Journal of Applied Research and Technology

www.jart.icat.unam.mx

Journal of Applied Research and Technology 22 (2024) 873-885

Original

Utilizing advanced machine learning techniques for accurate prediction of oxygen quantity in gas-fired boiler combustion to enhance environmental pollution control

K. Ganpati[a]* • S. Bhusnur[b]

[a]*Electronics and Telecommunication Engineering Department, Bhilai Institute of Technology, Durg, India*
[b]*Electrical and Electronics Engineering Department, Bhilai Institute of Technology, Durg, India*

Received 04 02 2024; accepted 07 29 2024
Available 12 31 2024

Abstract: PyTorch, an open-source machine learning framework built on the Torch library, is used in this application to apply deep learning to image classification in a boiler section and to design an entity algorithm for predicting the amount of oxygen available in the furnace section. The physical features of this flame are viewable using pictures obtained from a Charge Coupled Device (CCD). By removing the nonlinear elements, a multilayer CNN forecasts the amount of oxygen in the flue gas from a boiler. From the results of experiments conducted on-site in a real-time combustion system, images of boilers under various settings, including temperatures, air pressures, and gas conditions, have been obtained. Classification models are then applied. The precise quantity of oxygen content is calculated with these photos as input and comparing the outcomes with the test data set. More insightful information about the flame's physical features can be defined using a convolutional neural network (CNN) model and a multilayer representation of the flame images. The flame images captured on-site from an actual combustion system are utilized to illustrate this notion. The oxygen content is predicted using a multilevel-based, unsupervised, and semi-supervised deep entity algorithm by taking 12 classes and training 4,203,592 images each flame image in the tests has a resolution of 24 bits per pixel and a size of 658*492 pixels. After training the model, the loss is as low as 3%, and the attained accuracy is 97%.

Keywords: PyTorch, CNN, image classification, deep learning, oxygen prediction, environmental control

*Corresponding author.
E-mail address: ganpatishrinivas01@gmail.com (K. Ganpati).
Peer Review under the responsibility of Universidad Nacional Autónoma de México.

1. Introduction

The deep learning model trained in PyTorch can predict new data instances with a finalized model that uses CNN for image classification, object detection, image recognition, among others. PyTorch is an open-source Python library machine learning framework (Subramanian, 2018). It is widely used in artificial intelligence modeling, especially to create image classifiers. The efficiency of a boiler increases by this method, saves the fuel, and reduces heat losses in flue gases (Buhre et al., 2005; Zaporozhets, 2019). Optical radiation of a hot body (furnace) is the key- factor of a combustion process. Prediction of oxygen is a challenging task. With the aid of digital image processing, monitoring of live flame images can be done cost-effectively (Liu et al., 2017). Using high-definition flame images acquired by Charge Coupled Devices (CCD) and a grabber of flames, digitized images are obtained (Lu & Yan, 2006). Some noteworthy contributions towards the research area are as shown in Table 1. The NCDBN model's MAE and MRE values were reduced by 62% and 63%, respectively, in an author's research (Tang et al., 2020), while the MSE decreased by 80%. With respect to the testing data of datasets D2 and D3, the NCDBN model's error metrics significantly decreased. Furthermore, for each of the three datasets, the NCDBN model's error metrics were less than those of the LSSVM, RBF, LSTM, and BPs models. For every dataset, the NCDBN model's error metrics surpass those of the lone DBN model (Tang et al., 2020). Now in this research of entity model improve error set compare with NCDBN model after model training the data using entity model while training accuracy was around 99% testing accuracy is 97% These facts show that new techniques and technologies must be searched to optimize boiler operation. Efficiency will increase by the heat recovery and is an ecological aspect of burning carbon fuel. To forecast the oxygen content, different modeling algorithms, and training data sets have been applied to various models involving multiple color changes using efficient soft sensing methods (Shakil et al., 2009).

Table 1. Key findings and observations of existing literature.

Findings	Methods	Limitation/Observation	Ref.
CNN demonstrated a significant characteristic of local feature representation, suitable for soft sensor modeling.	A multichannel 3-D tensor multichannel CNN (MCNN) is suggested for representing different local dynamic features.	The fundamental issue that the proposed MCNN model addresses is the inability of CNN to cover process variables that are topologically far off, using the same convolution kernel.	(Yuan, Qi, Shardt, et al., 2020)
The material distribution is influenced by the instability present in the combustion system due to the circulating fluidized bed which hampers the operation. Accurate bed pressure prediction required	In this study, a bed pressure prediction system based on deep learning is suggested. To filter the input variables, the Pearson correlation coefficient with time adjustment was applied. The extraction of inertial delay characteristics from the data was carried out using Gaussian convolution kernels.	Model accuracy was not taken into account when considering the effects of coal quality change and coal slime mixing ratio. The technique required to characterize mixing ratios of the aforesaid quantities in the learning model needs to be taken care of in future development.	(J. Chen et al., 2022)
In this article, the author discussed the need to establish the precise rolling force beforehand to produce a coil with a precise thickness post the rolling operation.	The rolling force can be calculated using deep neural networks (DNN) and gradient boosting-based decision tree models, which can be applied in-line in actual plants. By using the inverse calculation of the conventional mechanical model of hot rolling, a particular temperature of the coil was determined and fixed as the output value.	The database is continually filled with data from the rolling process.	(Hwang et al., 2020)

Findings	Methods	Limitation/Observation	Ref.
To derive training and testing datasets for the MBFCNN network, tests on hydrogen-fueled scramjets with various equivalency ratios were done in a supersonic pulse combustion wind tunnel with an input Mach number of 2.5.	Convolutional neural network techniques were contrasted with the proposed deep learning architecture method.	The fuel injection system receives input from the combustor flow field image information, that aids in improving the combustor's real-time performance.	(Kim et al., 2022)
According to author Chuanwang Song, the channel attention technique is used extensively in deep learning. The local information of the feature image is stressed in this module and uses convolution to determine the regional channel weight, before integrating the data to fully utilize the regional information.	To identify the anomaly of the blast furnace tuyere, the local channel attention module and residual module are merged, and the local channel attention residual network LSERNet is built, datasets are obtained with the aid of experiments on the blast furnace tuyere.	The model might need to be retrained when moving to a new dataset because of the various camera placements and sensor resolutions. Retraining the model using a fresh dataset is all that is required. Although retraining is necessary, the training period is reasonable and does not necessarily have an impact on the method's applicability.	(H. Chen et al., 2022)
To optimize ultra-low emission systems, pollutant prediction for coal-fired circulating fluidized bed units is essential.	This study examined the interaction between the single-layer Gated Recurrent Unit neural network model and the differential equation model with the first-order Taylor expansion.	Optimization of the fluidized bed is not exactly described by single layer gated recurrent unit neural network model defined	(Sun et al., 2021)
(1) An early-fusion, time-invariant layer that can learn to pull out the power spectral density of succeeding image frames, which is a network layer that can be combined with any backbone network already in use. (2) A late-fusion layer that aggregates a backbone network's outputs at many time steps to forecast the current combustion state	Early-fusion layer to a backbone network as increasing the number of input photos. Furthermore, it is demonstrated that handcrafted weights are superior to learned weights for the late-fusion layer.	Two layers are proposed for a single gas turbine combustor which is a time-consuming process	(Choi et al., 2020)
Power plant clean production is evaluated using the selective catalytic reduction (SCR) denitrification efficiency of coal-fired boilers. The effectiveness of denitrification can be increased by making precise forecasts of NOx emissions at the SCR inlet.	A prediction method based on the random forest (RF) algorithm and lightweight convolutional neural network (CNN) was developed using deep learning.	The accuracy of Nox emission is not ever reduced anymore	(Wang et al., 2023)

In the combustion process, the entity technique is very rarely applied. The development of a CNN soft sensor system for a real-time combustion process quality prediction is attempted for the first time in this research (Mohammadi et al., 2018).Using the entity model, a reduction in the losses and increase in the efficiency can be done. The following topics are discussed in the present work:

- classification of boiler images,
- application of entity modelling method to gas-fired boilers and
- diminution in the number of process variables (Tsoumalis et al., 2022).

The combustion process is analyzed, and the actual oxygen content is monitored using the existing methods during the modelling stage. The value of the air, temperature, and fuel are acquired. From a real-time boiler system, the images of the process are captured, and the aforementioned variables are compared. The data is sectioned into training and test sets. With the aid of the training data set, a generalized model is developed, that is, further verified using test data sets. Prediction of the target variable for the unobserved data can be done using this model (Romero et al., 2005; Le Moullec, 2013).

The following five sections delineate the work: the first section is the introduction; Section 2 describes the details of the boiler system, its working, the Python-Pytorch framework, and a brief part regarding the CNN classification; Section 3 briefs the methodology; Section 4 explains, results, analysis, and the findings; and section 5 comprises results and discussions.

2. Working and efficiency of a boiler

2.1. Working of a boiler

By burning coal, heat energy is produced, which is further used for steam production to rotate turbine blades. Loss of heat in flue gases causes a major loss in efficiency. Other efficiency losses are heat radiation and convection to the boiler surroundings. In the BFG gas-fired system, there are two drums; one is termed a steam drum, and another is a mud drum. As seen in the image, two tubes-the down-comer and riser tubes-connect the upper drum and lower drum (Wu et al., 2021). The lower drum's water is heated, creating steam that naturally rises to the top drums through the riser attached. Steam spontaneously separates from water in the upper drum and is kept above the water line. Because cold water is heavier than the hot water in the lower drum and the water in the riser, cold water pushes the hot water upward through the riser when it is fed from the feed water inlet at the upper drum (Sarkar, 2015). Typically working of the boiler shown in Fig. 1.

2.1.1. Efficiency of a boiler

In this system, fuel and air are taken from a blast furnace and used as an injector for fuel in a boiler system. To save running expenses and to adhere to environmental requirements, emission level, and combustion efficiency should be managed at a suitable level. However, measurement of NOx and oxygen in the exhaust gas by the gas analyzers will be delayed. In such a case, an oxygen-content-based feedback controller is prone to overcompensate (Sirainen, 2016). A digital color camera

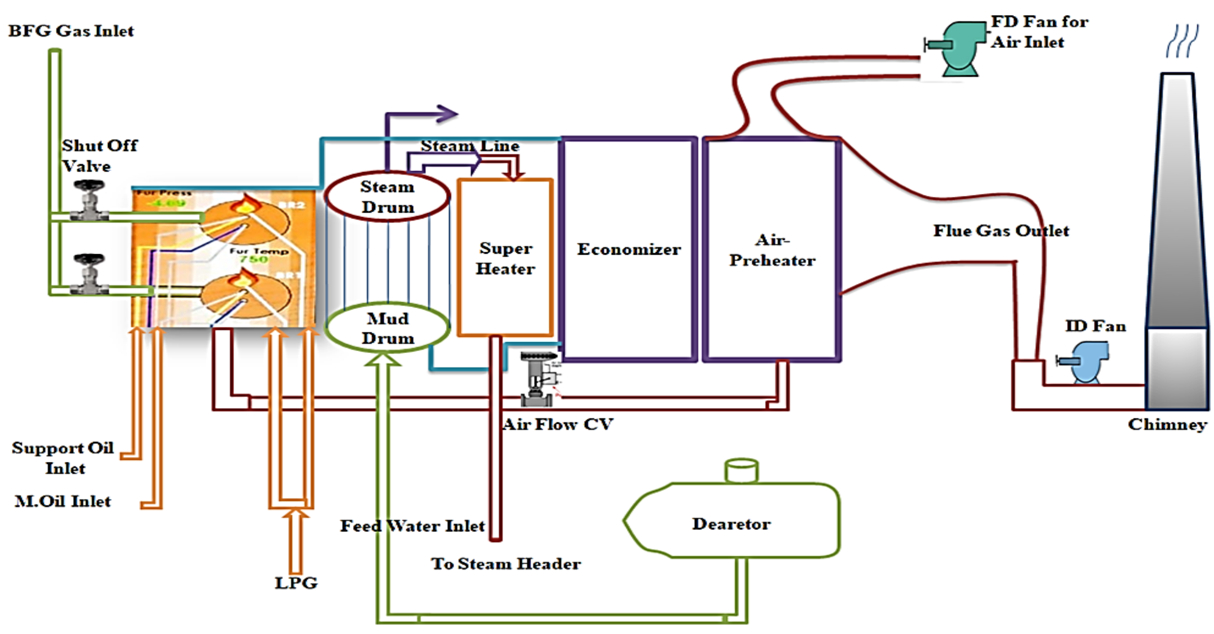


Figure 1. Boiler SCADA image.

was used to take photographs of the flames in the furnace. When sharing information from a CCD camera interface to a PC, a shield-like cooling mechanism is included (Huang et al., 2000). Each flame image used in the test has a resolution of 24 bits per pixel and measures 658 by 492 pixels. One frame every five seconds is the rate at which the pictures were taken (Chen et al., 2013; Huang et al., 2000).

2.2. Python PyTorch framework

Py-Torch is an open-source library for machine learning, using which deep learning models based on neural networks can be created and trained. The Facebook AI research team is principally responsible for its development. Both Python and C++ are used with PyTorch. Of course, the Python interface is better designed. PyTorch is very well-liked in research labs and supported by major corporations like Facebook, Microsoft, SalesForce, and Uber (Gao et al., 2020; (Jadon & Garg, 2020; Sharma & Bhusnur 2003b). PyTorch is gaining popularity quickly. However, it is not yet widely used in production systems, dominated by Tensor flow (backed by Google) and other similar frameworks (Chollet, 2021). A schematic PyTorch framework shown in Fig.2.

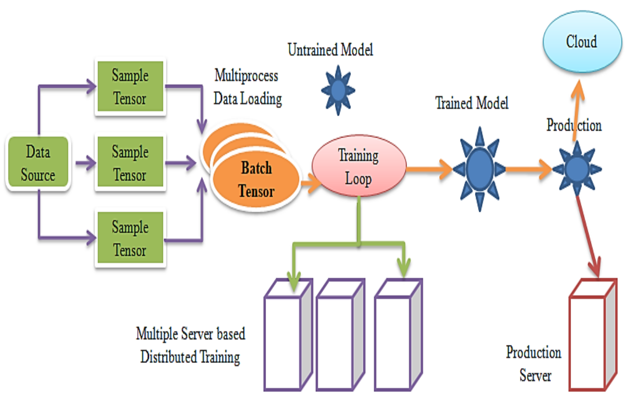


Figure 2. Python PyTorch framework (Yamashita et al., 2018).

Although other frameworks like Tensor flow are popular, PyTorch excels in dynamic computation rather than static computation and hence gives more flexibility for complex designs. The structures, classes, loops, and other constructs of Python provide better comprehension (Singh, 2022). Simple PyTorch implementation steps are described in Fig.3 (Längkvist et al., 2016).

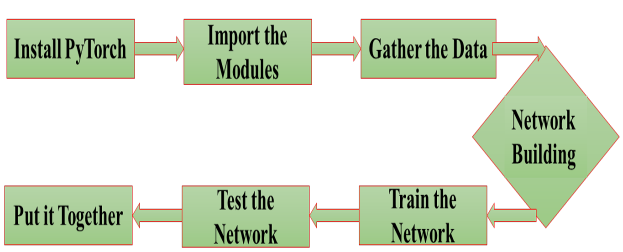


Figure 3. PyTorch implementation steps.

2.3. CNN classification

CNN architectures are of two primary types: segmentation and classification types. CNNs classify each pixel into one or more classes, given a set of real-world object categories (Längkvist et al., 2016). Steps of CNN layer structure is given below.

i. *Input layer:* Input images pass through this layer.
ii. *Convolutional layer 1:* This layer uses a series of filters to extract basic elements from the input image, like edges and corners. Convolutional layer output is input to the rectified linear unit (ReLU) activation function. Additionally, there are other activation features available. The model now has non-linearity due to this.
iii. *Pooling layer 1:* The feature maps created by the leading convolutional layer are down-sampled in this layer, which lowers their dimensionality and increases their processing efficiency.
iv. *Convolutional layer 2*: The output of the first max pooling layer is subjected to a series of filters in this layer to extract more intricate features, such as patterns and textures. The rectified linear unit (ReLU) activation function receives the output from the convolutional layer.
v. *Max pooling layer 2:* The second convolutional layer's feature maps are further de-dimensionalized by this layer's downsampling. (Yamashita et al., 2018).

Further refinement can be done in the third set of the convolutional and pooling layers.

CNN finds applications in learning tasks related to the classification of images, detection of objects, face recognition, among others. Researchers quite often use sentiment analysis while assessing opinions. In this study, a decision tree classifier and a sentiment analysis will be used.

3. Methodology

Classification and data entity models are used for image extraction and prediction of boiler images at different temperature and time variants to ensemble all the data and find error metrics. The gas-fired boiler combustion system's oxygen level lies in the range of 2.7 to 3.8, which makes it hard to train a prediction model. The primary reason is that the images corresponding to the oxygen range between all the values from 2.7 to 3.8 are unavailable as the boiler conditions change rapidly during combustion. Hence, a prediction model will not lead to a generalized model. A CNN architecture presented in Fig. 4.

To map the oxygen percentage predicted, with the original values, the most frequent oxygen levels observed by the boiler are selected to form a good dataset that is, robust and able to work in real-time. Classification has been used sparingly for finding the oxygen level in the boiler and predicting with a data entity model. The images were clicked using a high-end camera over some time at various temperatures, parallelly measuring the amount of oxygen in the boiler. After obtaining labeled images, CNN architecture was structured to assign the images to one of the 12 classes, depending on the oxygen content. So, given an image, the network is framed for a classification task, which will classify the image into one of the classes based on the oxygen level. The model consists of 7 convolution layers, three max-pooling layers, and three fully connected layers.

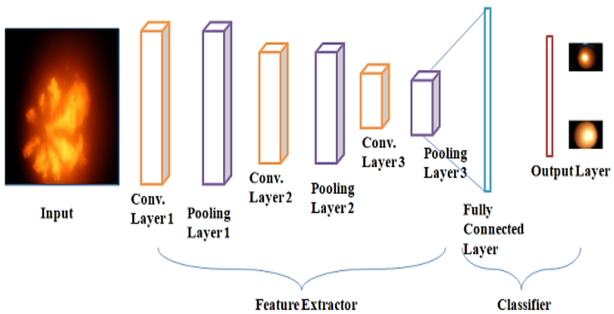


Figure 4. CNN Layered architecture.

3.1. Soft sensor modeling

Due to the coupling between mass and heat transfer mechanisms in any industrial process, there is an interaction between various process variables irrespective of whether they are topologically far or near. The conventional CNN is known to be good at extracting local features from the local region, and therefore the interaction due to process variables that are topologically far may not be learned entirely. To describe the correlations of the variables despite their topological organization, a multichannel CNN (MCNN) is proposed (Yuan, Qi, Wang, & Xia, 2020). The multichannel CNN concept involves a 3-D tensor that represents the information at one sampling instance, and each 2-D section of which is called a channel. It can include different orders of both dynamic and local features of variables that further enhance the prediction process (Panagakis et al., 2021).

Initially, the dataset is divided into training and testing datasets, as shown in Fig 5. Further training datasets are subjected to feature extraction and processed further for machine learning. Also, a pattern is analyzed, followed by labeling. In another way, classification is re-defined and combined with the entity model.

In order to predict oxygen level, two ensemble settings have been experimented with: one which directly uses the weighted sum of the two models and the other which combines the feature vectors from the two models to create a new set of fully connected layers. Few artificial neural network techniques, such as CNN, have been used to study combustion processes. The CNN techniques have been applied to combustion systems rarely. The CNN soft sensor system proposed in this research is a unique method in the combustion process for real-time quality forecast. The oxygen content is predicted using a multilevel-based, unsupervised, and semi-supervised deep entity algorithm by taking 12 classes and total 4,203,592 images are used for training each flame image in the tests has a resolution of 24 bits per pixel and a size of 658*492 pixels. There are 12 folders, each with an image of the boiler combustion process corresponding to an oxygen level. The folder name and the image label indicate the oxygen level. After obtaining the labeled images, a CNN architecture developed estimates the oxygen level from the photos. Therefore, the best line of action is to design the network as a prediction task and to estimate the oxygen percentage from an image.

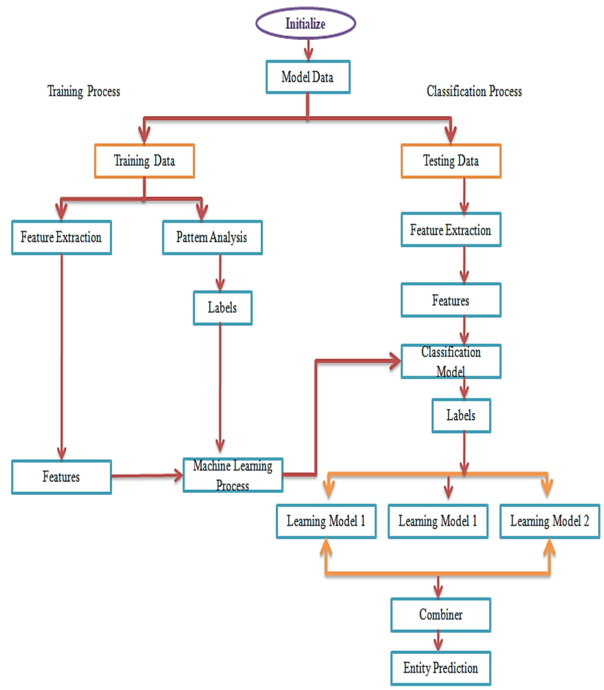


Figure 5. Flow chart of classification an entity prediction model.

$$\text{Classification accuracy } Y_c = \frac{Y_{cp}}{Y_{tp}} * 100 \qquad (1)$$

Y_{cp} denotes the number of correct predictions of images; Ytp represents the total number of predictions.

We quantify the performance of our model 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:

$$\text{Precision} = \frac{TP}{TP+FP} = 0.426$$

$$\text{Recall} = \frac{TP}{TP+FN} = 0.081$$

$$\text{F1} - \text{Score} = \frac{2 * \text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} = 0.0347$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = 0.98$$

3.2. Model evaluation

Performance metrics include F1-score, recall, precision, accuracy, and ROC curve. The goal is to achieve low error rates and high predictive accuracy for real-world applicability. After model training, the loss came as low as 0.9 after training the model, and the accuracy was 85%, which is very good for prediction tasks, which is excellent for tasks requiring prediction. The aim behind the recommended method is to enhance control of the boiler combustion process by continuously monitoring the oxygen concentration in flue gases, despite variations in gas quantity entering the furnace, with the aid of an oxygen sensor to regulate fuel combustion. As a result, the boiler room system experiences significant energy savings. Contribution to model robustness.

3.2.1. Diverse representation

3.2.2. Variability coverage

The large dataset includes images taken under a wide range of conditions, which helps the model learn the underlying patterns and relationships more effectively. This variability in the data ensures that the model can generalize better when encountering new, unseen conditions.

3.2.3. Class distribution

With 12 classes of oxygen levels, having a substantial number of images for each class helps the model to understand the nuances of each class and reduces the chances of bias towards any particular class.

3.3. Over fitting prevention

Performance metrics include F1-score, recall, precision, accuracy, and ROC curve. The goal is to achieve low error rates and high predictive accuracy

3.3.1. Exposure to various scenarios

As overfitting is frequently caused by the model learning particular patterns or noise that are only present in a small subset of the data, training on a large number of images exposes the model to a wide range of scenarios.

3.3.2. Data augmentation

The huge dataset makes it possible to apply techniques for data augmentation—like rotations, random cropping, and other transformations—effectively. These approaches further strengthen the model by enriching the training set and simulating many variants.

3.4. Improved generalization

3.4.1. Comprehensive learning

Rather than learning specific specifics, the model can learn more comprehensive and generalized properties with additional data, which are genuinely representational of the underlying physical process of combustion.

3.4.2. Noise reduction

By averaging out the data's inherent noise, a big dataset enables the model to concentrate on the real signal.

4. Data analysis and findings

Dataset composition: The entire dataset comprises 4,203,592 images, with each image having a resolution of 658 x 492 pixels and a color depth of 24 bits per pixel. (shown in Fig. 6).

Training and testing split: To create and validate the predictive model, the dataset is divided into training and testing sets. Typically, around 70-80% of the data is allocated for training, while the remaining 20-30% is reserved for testing.

Criteria for ensuring real-world variability: Images were captured from a real-time gas-fired boiler combustion system under various operating conditions. The operating conditions included different temperatures, air pressures, and gas compositions, which are critical to capturing the true variability found in real-world boiler operations. Temporal diversity: Images were taken one frame every five seconds to capture dynamic changes in the flame over time. This temporal resolution helps in understanding how the oxygen content in the flue gas varies with time and operational fluctuations. *Class-based labeling:* The images were categorized into 12 distinct classes, each corresponding to a specific range of oxygen content in the flue gas. This approach allows the model to learn from and predict a wide array of oxygen levels, which are essential for various combustion states. *High-resolution imaging:* By employing high-resolution images, the convolutional neural network (CNN) could capture fine details and subtle variations in the flame's appearance. These intricate details are crucial for accurately predicting the oxygen levels during combustion. The information gathered includes a video of the boiler at several different temperatures, each corresponding to a certain oxygen level. The video acquired is partitioned into frames and saved as images in the labeled folders with names based on the oxygen level in the broiler. Images in gas-fired 6 show different boiler images taken on-site from a gas-fired boiler at one industry from Raipur, at different temperatures and oxygen content.

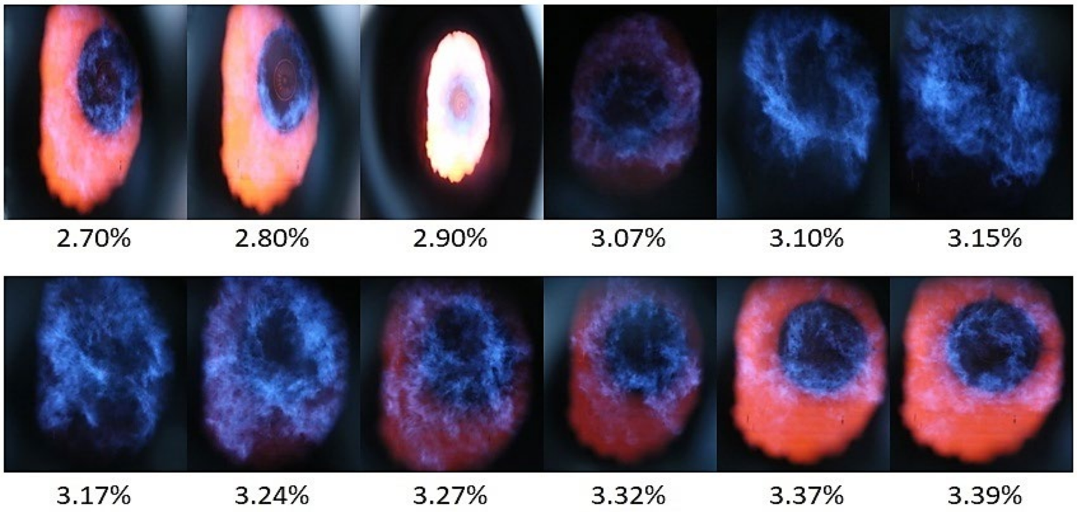


Figure 6. Real time flame images with their corresponding oxygen contents in ascending order.

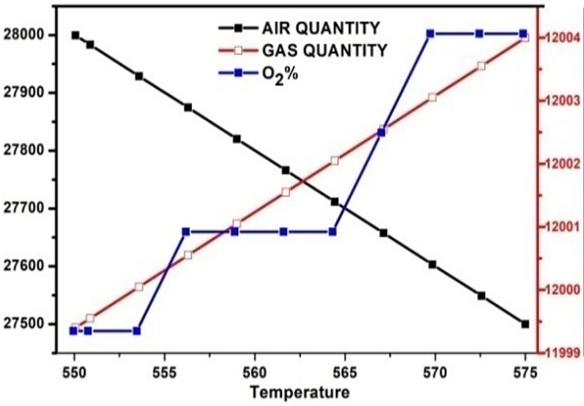
4.1. Result and implementation

The results shown in Table 2 depict the boiler oxygen percentage at different temperatures, different air and gas quantity inlet, observation time, for 12 different classes.

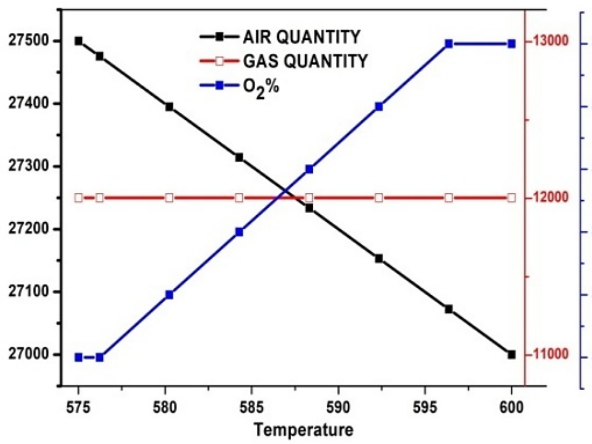
Graphs have been plotted to show variation in oxygen percentage at different levels of air and gas quantity considering different sections of temperatures in the range between 550°C to 750°C, as shown in Figure 7 and Figure 8.

Table 2. The boiler oxygen percentage at varying temperatures, air and gas inlet quantities, and observation times for 12 different classes.

Sr.No	Temperature	Air Quantity	Gas Quantity	O2 %	Image Taken Time
1	550	28000	12000	3.07	3:46 PM
2	575	27500	12004	3.1	3:43 PM
3	600	27000	12004	3.15	3:42 PM
4	625	27000	13500	3.17	3:39 PM
5	650	26200	13500	3.24	3:37 PM
6	675	27000	16800	3.32	3:27 PM
7	700	26000	18000	3.37	3:24 PM
8	725	18800	18800	3.39	3:17 PM
9	750	21600	22000	2.7	3:15 PM
10	775	22300	24500	2.7	3:10 PM
11	800	23400	26000	2.8	3:07 PM
12	818	32000	32000	2.9	3:03 PM



(a)



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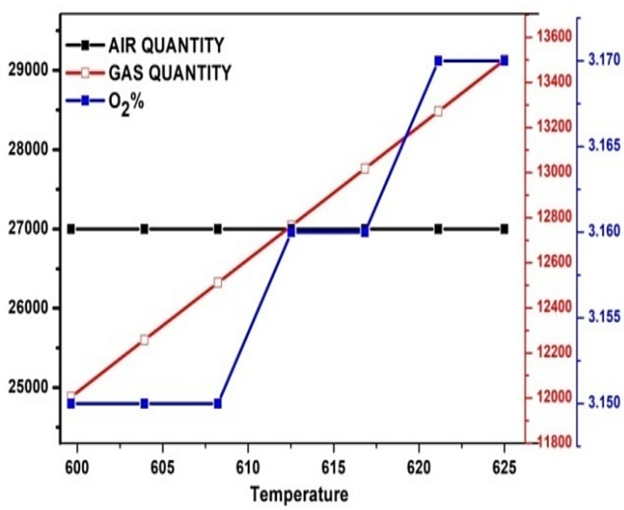
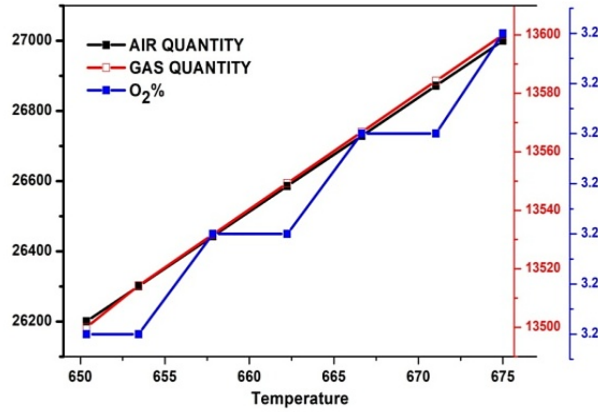
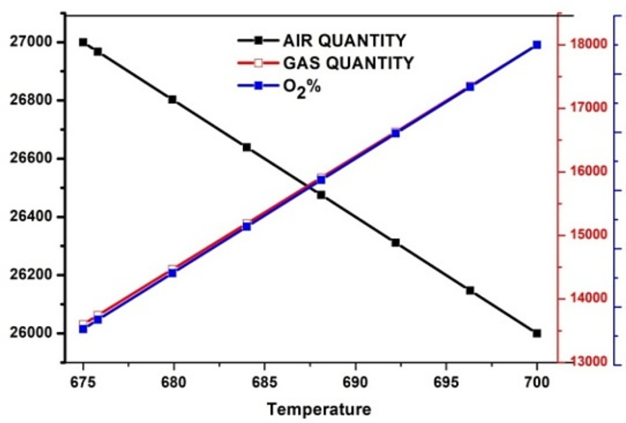


(c)

Figure 7. (a). Oxygen linearity with variable gas and air quantity between 550°C to 575°C; (b) Between 575°C to 600°C: (c) between 600°C to 625°C; (d) between 625°C to 650°C.



(a)



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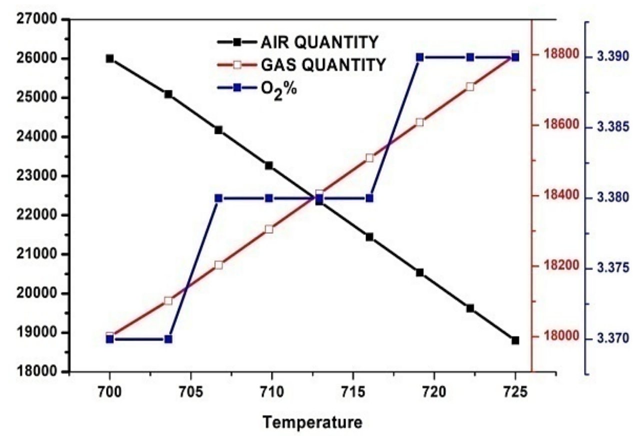
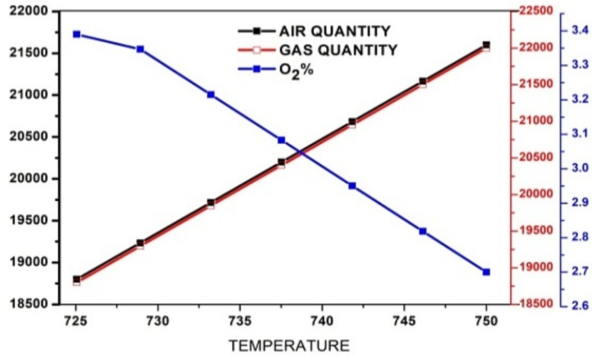


(c)



(d)

Figure 8. (a). Oxygen linearity with variable gas and air quantity between 650°C to 765°C; (b) between 675°C to 700°C; (c) between 700°C to 725°C; (d) between 725°C to 750°C.

Figs. 7 and 8 show the experimental results of the dependence of the boiler power from the concentration of residual oxygen in the flue gases at various boiler loads.

The combined characteristics of air amount, gas quantity, and oxygen level are shown in Fig. 8 at various temperature ranges between 550 and 850 degrees Celsius. A 256 x 256 color image is the network's input, made possible through preprocessing and normalizing the image's R, G, and B color channels. The image is then processed by several layers that reduce its resolution to 252 x 252, 126 x 126, and so on, until it reaches the fully connected layers, which employ the features gathered from the working layers to forecast the oxygen level. Here, the ReLU function is used as an activation function as it can converge quickly and solve the diminishing gradient problem. Using the L1 loss function, the difference back propagates between targets.

The experiment is simulated in Python 3.6, and PyTorch is the framework used. PyTorch is a machine learning tool kit built on the Torch library (Habib et al., 2011; Ketkar & Santana, 2017; Mannes, 2017) and widely used by Meta AI (Mohammadi, 2018) for applications like artificial intelligence and natural language processing (Patel, 2017). It is open-source software available for free, as per the Modified BSD license. Although PyTorch has a C++ interface, the Python interface has received the majority of development attention (Ketkar & Santana 2017).

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 training for 1600 epochs in one day. The parameters and hyper parameters of the models are selected. Finally, the learning rate was 0.0001, with cross- entropy loss and ADAM optimizer utilized, two high-level features provided by PyTorch, followed by Lightning and Catalyst (Ketkar & Santana, 2017). Tensor computation (similar to NumPy) with significant GPU acceleration (GPU) Using a tape-based automatic differentiation method, deep neural networks.

In Table 2, entity model prediction values acquired, namely, the mean average error (MAE), the mean square error (MSE), and the mean relative error (MRE), are shown. The model was found to be accurately estimating the oxygen content of the flue gas. The model is distributed within the minimum interval [0, 0.04], and as absolute error increases, its frequency gradually decreases. Although the absolute-error frequency of the algorithm declined quickly, and none of the distributions appeared in the higher absolute error interval, the frequency distributions of the models were similar to another algorithm. This outcome explains why the nonlinear combination increases the predictive power of two sub-models. As a result, the model's absolute error is at its lowest and exhibits good prediction accuracy. In the dataset testing data findings, the entity model's MAE and MRE exhibit reductions, with 64% and 67%, respectively, while the MSE reduced by 82%. The methodology includes a multilevel-based unsupervised and semi-supervised deep entity algorithm to handle the wide variability in the data (Sharma & Bhusnur, 2023a). This approach is designed to be robust against the operational variability by encompassing multiple layers of data abstraction and prediction refinement. Fig. 9 presents the distribution of training and testing curve of the entity model while the predicted result shown in Table 3.

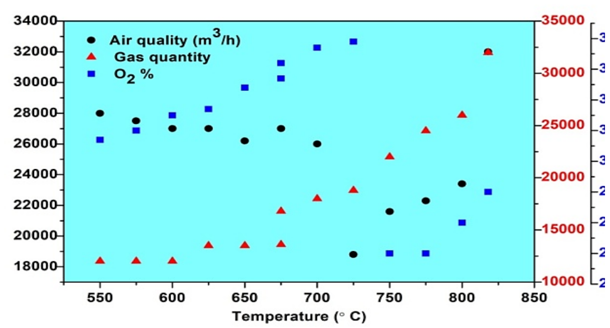


Figure 9. Training and testing curve of entity model.

Table 3. Entity model prediction result.

Data Set	Error Metrics	Entity Model Output
	Train	Test
MAE	0.0142	0.0152
MRE	0.4842	0.5052
MSE	0.0004	0.0004

Reported performance metrics

Accuracy: The model achieved training accuracy of around 99% and testing accuracy of 97%.

During evaluation, the accuracy was reported to be 85% when considering precision, recall, and F1-Score metrics.

Loss: The model's loss during training was reported to be as low as 0.9. After further optimization, the loss was reduced to 3%.

Comparison with industry standards and Current models The study contrasts their findings with a number of current models and techniques. This is how their performance compares: NCDBN model (Tang et al., 2020):

When compared to more conventional models such as LSSVM, RBF, LSTM, and BPs, the performance of the NCDBN model significantly improved in terms of mean absolute error (MAE) and mean relative error (MRE). The entity model employed in this study, according to the authors, has better error metrics than the NCDBN model, demonstrating a notable improvement in the prediction of the oxygen level during combustion.

Multichannel CNN (MCNN): Although this model is well-known for its proficiency in managing local dynamic features, it is not well-suited to capturing interactions between topologically distant process variables. According to the paper, these shortcomings are addressed by their model's multilevel-based unsupervised and semi-supervised deep entity algorithm, which offers a more thorough feature extraction and classification capabilities.

5. Conclusion and discussion

In a gas-fired boiler, combustion is an essential process that may be measured directly to cut down on losses. This study attempts to forecast the oxygen concentration in flue gases by utilizing the CNN model that was developed specifically to deal with this kind of issue. Based on an aggregation of 12 individual images, the entity model and CNN model were utilized to predict the amount of oxygen in a power plant boiler. Using the PyTorch library, the entire process was divided into three parts: feature selection, data pre-processing, and data analysis modeling. The entity model used in the CNN Technique generated accurate data, in contrast to the DBN Method. CNN architecture predicted the oxygen content from the pictures. Using the information acquired from the convolution and max-pooling layers, the fully linked layers predict the value of the oxygen level. With R2 = 0.9859, 0.9825, and 0.9879, the NCDBN model performs as it did in earlier research. When this performance is compared to that of the current research, designing a network for the purpose of estimating the oxygen percentage from a picture becomes viable. Using an entity model for data training after the model training accuracy was almost 99%, and testing accuracy was 97%. These numbers clearly indicate that the model is doing exceptionally well on untested data, is not overfitting, and is a great fit for prediction. In the future, pressure and ensembles with CNN-based models might be identified by gathering boiler timestamp information and creating a model based on a time series. Furthermore, multi- or hyper-spectral imaging as well as the use of 3D imaging techniques to capture a larger range of wavelengths outside of the visible spectrum are examples of better feature extraction techniques. This can provide more in-depth information about the characteristics of the flame and the conditions around combustion. In order to better handle complex linkages and temporal dependencies in the data, future iterations may look at more intricate deep learning architectures, such as Transformer models or hybrid models that mix long short-term memory with CNNs (LSTM) networks. With the help of this ensemble, pressure may be calculated for a predictive control application more precisely since it can detect every change in the boiler over time. Maintaining the optimal air-to-fuel ratio ensures a more thorough burning of the fuel. Reduced Fuel Consumption results from this because more efficient combustion uses less fuel to produce the same amount of energy. The production of harmful pollutants like carbon monoxide (CO), particulate matter, and unburned hydrocarbons is decreased by complete combustion. Lower excess oxygen concentrations stop NOx from developing during combustion. As combustion efficiency increases, less CO2 is emitted per unit of energy produced.

Conflict of interest

The authors have no conflict of interest to declare.

Funding

The authors received no specific funding for this work.

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