Engineering and Technology Journal e-ISSN: 2456-3358
Volume 07 Issue 07 July-2022, Page No.-1422-1427
DOI: 10.47191/etj/v7i8.05, I.F. – 6.484

A Deep Neuronal Network-Based Sensor for the Detection of Oxygen inside the Carbonization Furnace

Fredy Martínez[1], Angélica Rendón[2]
[1,2]Facultad Tecnológica, Universidad Distrital Francisco José de Caldas, Bogotá, Colombia

ABSTRACT: Agricultural production generates biological surpluses that can be used to produce additional products through thermal and/or chemical transformations, such as the carbonization of vegetables. The oxygen on the vegetable material during the carbonization process inside a furnace is an important parameter that determines not only the success of the process but also the quality of the final product. It is difficult to measure the oxygen inside the furnace in real time, partly because of the working environment of the sensor, and partly because of the operating characteristics of the furnace (continuous rotation on its axis). The goal of this project is to develop a reliable measurement system capable of operating in real-time. For the continuous and precise detection of the temperature inside the furnaces of a carbonization plant, we propose a method based on the characterization of the image inside the furnace using a deep neuronal network. First of all, the images of the interior of the furnace are captured through a digital camera in front of the material and the axis of rotation of the furnace. Then, the area of interest in each frame of the video is determined by image processing. Oxygen content information is then obtained using a deep model trained for the same furnace with pattern oxygen level sensors. Experiments conducted on actual operating conditions of the furnace demonstrate that the proposed method for estimating the working oxygen provides reliable data for the control of plant operation. The proposed measurement scheme demonstrated high reliability against the many changes present inside the furnace, also, its low computational consumption makes it a viable strategy for embedded implementation and operation in real-time.

KEYWORDS: Carbonization, Classification, Convolutional network, deep neural network, Temperature, Real-time.

I. INTRODUCTION

Activated carbon is a set of carbon derivatives with a high absorption capacity, highly crystalline, and highly developed internal porosity (Cerro et al., 2018). It is a material characterized by having a considerable amount of micropores (pores less than 2 nanometers radius), which is why it can have an area of 50 m^2/g or more, reaching values of more than 2500 m^2/g. This characteristic is used in purification processes (Senthil et al., 2016). Industrially it can be produced through the carbonization of organic material.

Carbonization is a process of thermal decomposition of organic material (e.g., plant residue from sugar production or similar processes) in the absence of air (Martínez et al., 2016). During the manufacturing process, the content of hydrogen, oxygen, and nitrogen is removed from the material to increase the proportion of carbon. This process is carried out in furnaces in which the level of oxygen, the heating rate, and the residence time must be controlled continuously and simultaneously. The continuous control of these variables defines the characteristics and quality of the final product. Given the high temperature and the harsh environment inside the furnace during the process, the direct detection of temperature and oxygen is a problem with great challenges.

Usually, the actual temperature of the hot material inside the furnace is measured intermittently by an operator using thermocouples or blackbody cavities with specialized equipment at a single point in the furnace (Tripathy et al., 2018, Wang et al., 2018). This is known as a measurement with contact with hot material, and although simple, it carries some level of risk for operators due to the high temperatures and dynamics of the furnace. This strategy only provides partial information about the temperature inside the furnace; for this reason, there is a lot of research in the development of thermal models of the behavior of the systems that allow determining from punctual readings the continuous value of the temperature of the system (Manara et al., 2017, Zhongyuan et al., 2016).

On the other hand, there are the non-contact measurement schemes, which in principle, prove to be safer for operators, allow continuous measurement, and provide a longer life to the sensor (Usamentiaga & García, 2017, Imaz et al., 2014). In the case of temperature, these schemes include infrared thermometers, colorimetric thermometers, and infrared thermal imagers. The infrared thermometer detects the infrared radiation of the object under measurement and converts the radiation level into an equivalent voltage signal that is finally scaled to the object's temperature. The colorimetric thermometer determines the object's temperature from the relationship of two infrared signals emitted by the object from two adjacent infrared bands. In both cases, the measured temperature corresponds to an average value that can be affected by the conditions of the environment. Infrared thermal imagers can provide two-dimensional infrared images that are not altered by the environment. The sensor uses a digital camera to capture the infrared radiation and from the image estimate, the temperature at all captured points (Pan et al., 2019a, Tyndall et al., 2016).

In the case of oxygen, the typical measurement scheme is the direct contact with a piece of specialized equipment with a probe introduced into the furnace to take air samples (Torres & Ramírez, 2012). As in the case of temperature, this is a punctual measurement scheme that does not provide information related to the distribution of gas inside the furnace and its effect on the carbonization process. Also, the rotary dynamics of the furnace make the measurement complex and dangerous for the operator. These punctual readings require a model of behavior inside the furnace to estimate the value at the points of interest, but the large variations of the actual plant introduce a large error in the measurements (Wang et al., 2018, Wang et al., 2016). Therefore, it is ideal to have an oxygen reading that does not require contact with the medium, and based on temperature sensors, it would be perfect to have a sensor that determines the oxygen content from an image of the hot material from some digital processing (Pan et al., 2019b).

To solve the difficulty of directly measuring the amount of oxygen in the organic material processed in the furnace and avoid the harsh working environment that the sensor would have to face inside the furnace, we propose a measurement scheme based on color images of the interior of the furnace and a classification model from a deep neural network (Martínez et al., 2020, Montiel et al., 2021). Firstly, a digital camera protected for the working environment is used to capture continuous images of the hot organic material inside the furnace (Barrero et al., 2015, Díaz & Pérez, 2004). The deep neuronal model then classifies this image. This neural model was trained from a dataset of images generated for the same furnace and classified with a laboratory instrument. The measurement scheme also considers the error caused by the dust, and the variations of the material inside the furnace, elements included in the training of the model.

The article is organized as follows. In Section II the problem is formulated and some preliminary concepts, the functional profile, and some other design considerations are presented. Section III details the design of the system, including the selection criteria and the final specifications adopted. Section IV presents the performance evaluation observed in the laboratory of the prototype. Finally, Section V concludes the article.

II. PROBLEM STATEMENT

The thermal decomposition of the plant material required during the carbonization process operates by removing the hydrogen, oxygen, and nitrogen content to increase the proportion of carbon. This process is carried out using a gas furnace with a process control that continuously regulates the level of oxygen fed, the heating rate, the temperature, and the residence time. Experimentally we have observed that it is possible to control the content of oxygen in the combustion regulating the entrance of air into the burner of the furnace.

The basic control of the level of oxygen in the combustion is carried out by the operators visually verifying the color of the flame. The level of oxygen affects the combustion process and therefore the behavior of the flame, making possible the visual inspection of the process. The proposed scheme for the estimation of the oxygen level within the furnace makes use of this principle. We propose to classify the state of the flame captured by a digital camera into one of four possible reference categories (or furnace states) in which the oxygen percentage is known (Martínez et al., 2016).

The four reference states correspond to the flame in four operating conditions established with specialized measurement equipment. The categories are, according to the opening conditions of the air valve:

- Flame with 0% air.
- Flame with 40% air.
- Flame with 80% air.
- Flame with 100% air.

The fuel used is natural gas, and the system can independently control the supply of fuel and air.

The research aims to develop an embedded system capable of estimating the oxygen content in combustion with a high degree of accuracy. Such a system must be able to integrate with the current structure of the production plant, which requires continuous communication, small size, and high mechanical strength. In addition, the performance is conditioned by the speed and correct estimation of the variable, so it is desirable to have a system that responds to the current operating conditions, which can be adjusted if these variables change or if it is transferred to a new production plant. These characteristics conditioned the profile of the prototype. Therefore, the system must have WiFi communication capabilities, withstand temperatures of up to 200 degrees Celsius (it will be located outside of the furnace), a focusing lens, and battery power with an autonomy of one week.

For the model, we use a deep NASNet (Neural Architecture Search Network). Of the models evaluated this network showed the highest performance with the least number of adjustable parameters, which is why it was selected and adjusted for this problem (this feature guarantees the lowest hardware resources, both in processing and storage memory). The training dataset consists of 500 images for each of the categories. These images were taken with the same digital camera and classified according to the reading of the oxygen sensor and the experience of the operator (thus replicating and automating the empirical system that the process was using). As these images were captured during normal furnace operation, the images (and therefore the model) consider the variations of the material and dust inside the furnace.

III.MATERIALS AND METHODS

Through the operation of the activated carbon plant, we characterize different operating states of the furnace. This pilot plant has an installed capacity of 10 kg/h of coal (Vallecilla et al., 2016). Using a digital camera, we record the behavior of the flame and construct the training dataset of the deep neuronal model (Fig. I).

Figure I. Dataset used for network training. (a) Flame with 0% air (c1 000). (b) Flame with 40% air (c2 040). (c) Flame with 80% air (c3 080). (d) Flame with 100% air (c4 100)

The dataset was used to train a NASNet (Neural Architecture Search Network) deep neural network. This network is characterized by having a high performance in the classification of images with a reduced number of adjustable parameters. We defined four categories for classification by the model according to the estimated oxygen content in the material. The categories were:

- Category 1: c1 000, flame with 0% air.
- Category 2: c2 040, flame with 40% air.
- Category 3: c3 080, flame with 80% air.
- Category 4: c4 100, flame with 100% air.

The deep network model was created in Keras with TensorFlow backend. The images (500 in each category) were randomly mixed in the data list to improve network performance. Besides, they are all resized to the same size (256 x 256 pixels) with the same goal. The model does not consider the aspect ratio of the images. Images are also normalized (each pixel) in the range of 0 to 1.

The training dataset is separated into two groups, one for training as such and one for testing. We use 70% of the data for training and 30% for performance evaluation. The number of nodes in the input layer is defined according to the size at which the images are resized, i.e. 256 x 256 x 3 (three matrices in RGB color format). The number of output nodes corresponds to the number of classification categories, i.e. four.

The neural network model was compiled by specifying as optimization function the stochastic gradient descent, as loss function the categorical cross-entropy, as metrics to evaluate the accuracy and the mse.

IV. RESULTS AND DISCUSSION

We created the deep network model in Keras (2.2.4) with TensorFlow (1.14.0) backend. The code was written in Python (3.7.3) with the use of OpenCV (4.1.0.25), Scikit Learn (0.20.3), NumPy (1.16.4), Scipy (1.3.0), and Pandas (0.24.2). The application was developed on a Linux machine with kernel 4.15.0-55-generic.

The summary of network parameters is as follows:

- Total params: 4,273,944
- Trainable params: 4,237,206
- Non-trainable params: 36,738

The result of the metrics calculated for training and validation are shown in Fig. II.

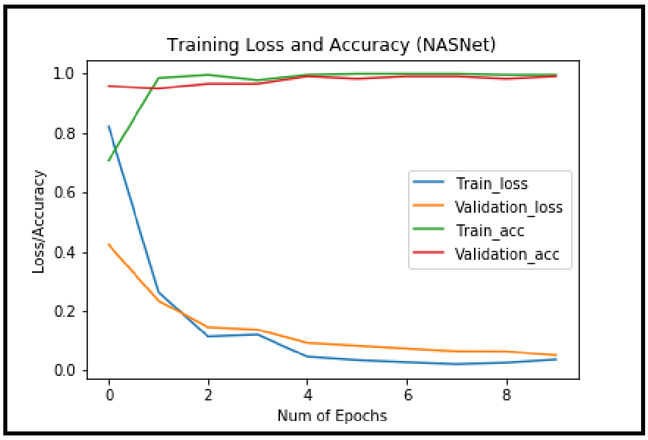

Figure II. Training Loss and Accuracy

The behavior of the training and validation data is very similar. Throughout the training, both the error of the training data and the error produced by the validation data are reduced in the same proportion. Something similar happens with the accuracy, which grows at the same rate for both training and validation data. This characteristic guarantees that the model is not over-fitted.

The model was also evaluated using the Confusion Matrix (Fig. III) and the ROC (Receiver Operating Characteristics) Curve (Fig. IV). From the confusion matrix, we also determined the metrics precision, recall, and F1-score (Table 1). In the case of the confusion matrix, the categories to which each image actually belongs were organized in rows and labeled on the left of the figure, while the types into which the model classified each of the evaluation images were placed in columns, marked at the top of the figure. In the case of the ROC curves, the average global behavior is shown at the top, while the upper left area of the curve is detailed at the bottom, and the curves of three of the categories are included.

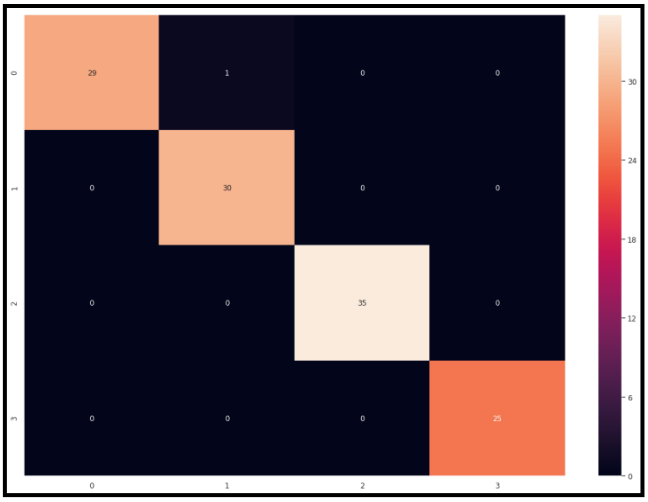

Figure III. Confusion Matrix

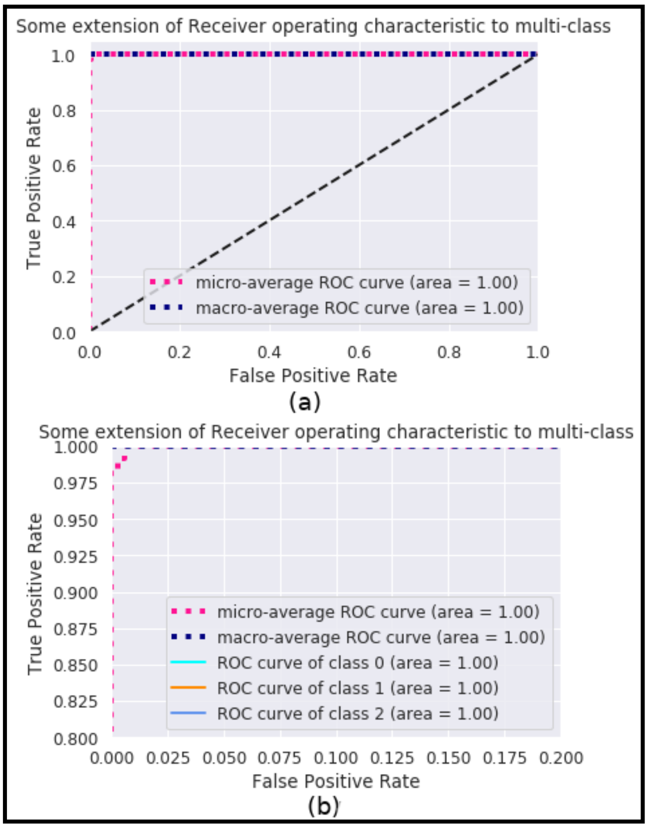

Figure IV. ROC Curve. (a) Receiver Operating Characteristics. (b) AUC (Area under the Curve)

Table 1. Metrics, Precision, Recall, and F1-Score

Class	Precision	Recall	F1-score	Support
c1_000	1.00	0.97	0.98	30
c2_040	0.97	1.00	0.98	30
c3_080	1.00	1.00	1.00	35
c4_100	1.00	1.00	1.00	25
Micro avg	0.99	0.99	0.99	120
Macro avg	0.99	0.99	0.99	120
Weighted avg	0.99	0.99	0.99	120

All metrics show excellent behavior with the validation data, i.e., excellent generalizability to real data captured by the camera. There is also no evidence of underfitting. The population selected for validation was chosen randomly, maintaining proportionally the sizes of the training groups. The sample consisted of 120 images, the majority (35%) coming from the category of 80% air in the combustion mixture. All images in this category were classified correctly. In the other three categories, the individual metrics were above 97%. The confusion matrix and ROC curve confirmed this performance. The movement of thresholds on the ROC curve yielded perfect classification for all categories. Analyzing the input images, and considering that the strategy performed well when visually classified by an operator, it is clear that no additional image processing is necessary for the model, and that its performance is good enough for the development of the embedded intelligent sensor.

V. CONCLUSION

This paper shows the design of a NASNet (Neural Architecture Search Network) based image classifier that is used as a strategy to estimate the oxygen content inside a furnace during a carbonization process of vegetal material. The image to be classified is taken in real-time by a digital camera in front of the flame of the process. The deep model is trained with separate images in four categories according to measurements made by expert operators. The model is trained and tuned to optimize classification capability. For performance evaluation, we use the confusion matrix, the ROC curve, and the precision, recall, and F1-score metrics. The confusion matrix (or error matrix) shows a high capacity of the model to classify the test data (30% of the data that the model did not know during the training process), only one of the images was wrongly classified. From the ROC curve, it can be stated that the model has a high capacity to distinguish between the four categories. These results are confirmed by the precision, recall, and F1-score metrics. The model has an excellent performance in image categorization and allows real-time operation with punctual and safe readings for the operator. Future developments will focus on the embedded implementation of the solution to form an autonomous and secure instrument.

ACKNOWLEDGMENT

This work was supported by the Universidad Distrital Francisco José de Caldas, in part through CIDC, and partly by the Facultad Tecnológica. The views expressed in this paper are not necessarily endorsed by Universidad Distrital. The authors thank the research group ARMOS for the evaluation carried out on prototypes of ideas and strategies.

REFERENCES

1. Barrero, A., Robayo, M., & Jacinto, E., "Board navigation algorithm in controlled environments based on image processing", Tekhnê, 2015, 12(2):23–34, ISSN 1692-8407.
2. Cerro, G., Ferdinandi, M., Ferrigno, L., Laracca, M., & Molinara, M., "Metrological characterization of a novel microsensor platform for activated carbon filters monitoring", IEEE Transactions on Instrumentation and Measurement, 2018, 67(10):2504–2515, doi:10.1109/TIM.2018.2843218.
3. Díaz, J. & Pérez, M., "Identificación de formas geométricas y colores mediante procesamiento y reconocimiento de imágenes", Tekhnê, 2004, 2(1):9–17, ISSN 1692-8407.
4. Imaz, E., Alonso, R., Heras, C., Salinas, I., Carretero, E., & Carretero, C., "Infrared thermometry system for temperature measurement in induction heating appliances", IEEE Transactions on Industrial Electronics, 2014, 61(5):2622–2630, doi:10.1109/TIE.2013.2281166.
5. Manara, J., Zipf, M., Stark, T., Arduini, M., Ebert, H., Tutschke, A., Hallam, A., Hanspal, J., Langley, M., Hodge, D., & Hartmann, J., "Long wavelength infrared radiation thermometry for non-contact temperature measurements in gas turbines", Infrared Physics & Technology, 2017, 80(1):120–130, ISSN 1350-4495, doi:https://doi.org/10.1016/j.infrared.2016.11.014.
6. Martínez, F., Martínez, F., & Montiel, H., "Low cost, high performance fuel cell energy conditioning system controlled by neural network", TELKOMNIKA (Telecommunication Computing Electronics and Control), 2020, 18(6):3116–3122, ISSN 1693-6930, doi:10.12928/telkomnika.v18i6.16426.
7. Martínez, F., Rendón, A., & Guevara, P., "Combustion quality estimation in carbonization furnace using flame similarity measure", Lecture Notes in Computer Science, 2016, 9939(1):125–133, ISSN 0302-9743, doi:https://doi.org/10.1007/978-3-319-46759-7_10.
8. Montiel, H., Jacinto, E., & Martínez, F., "A double-loop hybrid approach for the recognition of fissures in bone structures", ARPN Journal of Engineering and Applied Sciences, 2021, 16(11):1151–1156, ISSN 1819-6608.
9. Pan, D., Jiang, Z., Chen, Z., Gui, W., Xie, Y., & Yang, C., "A novel method for compensating temperature measurement error caused by dust using infrared thermal imager", IEEE Sensors Journal, 2019a, 19(5):1730–1739, doi:10.1109/JSEN.2018.2882201.
10. Pan, D., Jiang, Z., Chen, Z., Gui, W., Xie, Y., & Yang, C., "Temperature measurement and compensation method of blast furnace molten iron based on infrared computer vision", IEEE Transactions on Instrumentation and Measurement, 2019b, 68(10):3576–3588, doi:10.1109/TIM.2018.2880061.

11. Senthil, P., Saravanan, A., Anish Kumar, K., Yashwanth, R., & Visvesh, S., “Removal of toxic zinc from water/wastewater using eucalyptus seeds activated carbon: non-linear regression analysis”, IET Nanobiotechnology, 2016, 10(4):244–253, doi:10.1049/iet-nbt.2015.0087.
12. Torres, J. & Ramírez, L., “Adecuación del sistema de vacío FESTO perteneciente al laboratorio de automatización y control (LE-MC-01) del proyecto curricular de tecnología en mecánica UD”, Tekhnê, 2012, 9(1):69–78, ISSN 1692-8407.
13. Tripathy, H., Bej, D., Pattanaik, P., Mishra, D., Kamilla, S., & Tripathy, R., “Measurement of zone temperature profile of a resistive heating furnace through rvm model”, IEEE Sensors Journal, 2018, 18(11):4429–4435, doi:10.1109/JSEN.2018.2826722.
14. Tyndall, A., Cardell-Oliver, R., & Keating, A., “Occupancy estimation using a low-pixel count thermal imager”, IEEE Sensors Journal, 2016, 16(10):3784–3791, doi:10.1109/JSEN.2016.2530824.
15. Usamentiaga, R. & García, D., “Infrared thermography sensor for temperature and speed measurement of moving material”, Senosrs, 2017, 17(5):1–21, ISSN 1424-8220, doi: 10.3390/s17051157.
16. Vallecilla, L., Maestre, A., Salazar, R., Salamanca, N., Rincón, J., & Guevara, P., “Planta piloto de combustión para evaluación técnico ambiental de carbones”, Energética, 2016, 47(1):44–50, ISSN 0120-9833.
17. Wang, J., Shen, T., Zhao, J., Ma, S., Yao, Y., Chen, T., Shen, B., & Wu, Y., “Online measurement and control system development of combustion state for rolling reheating furnace”, in “35th Chinese Control Conference (CCC 2016)”, pp. 9530–9534, doi:10.1109/ChiCC.2016.7554870.
18. Wang, Z., Wang, L., Yun, Z., & Wang, J., “Temperature control based on fuzzy-PID algorithm for the blackbody radiation source”, in “IEEE International Conference on Mechatronics and Automation (ICMA 2018)”, pp. 797–802, doi:10.1109/ICMA.2018.8484315.
19. Zhongyuan, G., Shaosheng, D., Jinsong, L., Changhui, Y., C., Y., & Liangbing, Y., “Research on application of polynomial fitting technique in rotary kiln infrared temperature measurement system”, Infrared Physics & Technology, 2016, 79(1):160–164, ISSN 1350-4495, doi:https://doi.org/10.1016/j.infrared.2016.10.012.