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CONVOLUTIONAL NEURAL NETWORKS FOR THE AUTOMATIC CONTROL OF CONSUMABLES FOR ANALYTICAL LABORATORIES

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In recent years, the need for advanced systems and technologies for industrial process optimization using computer vision and artificial intelligence (AI) techniques has become increasingly pervasive. The specific focus of this study is to introduce an AI-based monitoring system within a production chain involved in manufacturing plastic consumables for analytical laboratories, specifically targeting the control of vials containing an anticoagulant substance. Currently, the inspection process relies on manual visual inspection conducted on a sample basis, resulting in the potential discarding of entire production batches if the absence of the anticoagulant substance is detected in a single vial. To overcome the inefficiency of the manual system, a comprehensive method is proposed to verify the presence of the anticoagulant substance in all produced vials, leveraging advanced computer vision and AI techniques. This innovative monitoring system offers promising solutions for enhancing industrial processes by enabling accurate and real-time monitoring. Specifically, we present our model and some preliminary results showing the potentiality of the proposed approach.

Keywords: *automatic monitoring, green economy, deep learning, convolutional neural networks*

1. Introduction

In recent years, the application of computer vision and artificial intelligence (AI) techniques in the industrial domain has shown promising results. These methodologies enable the analysis of images captured during the production process and the extraction of valuable information for monitoring and control purposes. By utilizing deep learning algorithms such as convolutional neural networks (CNN), it becomes possible to identify patterns, detect defects or anomalies, and provide instant feedback on the process's performance. The scientific literature highlighted several successful cases of applying computer vision and AI-based monitoring systems [1, 2, 3, 4].

In this work, we focus on the development of a computer vision and AI-based monitoring system to replace the manual visual inspection of a specific stage in a production chain. The goal is to leverage the potential of computer vision techniques so as to identify process irregularities in real-time. Specifically, we design a deep network model able to detect the presence of an anticoagulant substance inside transparent tubes. We use real images acquired through a camera to train our model for the ability to distinguish between presence and absence of the reagent.

This approach aims to optimize resource utilization, increase operational efficiency, and reduce waste in industrial processes, in order to: (i) align with the principles of sustainable manufacturing and (ii) contribute to the achievement of environmental and economic goals. Moreover, it offers several advantages, including the ability to monitor processes without the need for expensive dedicated sensors and the capability of identifying hidden problems that may escape other monitoring methods. Additionally, the use of images provides an intuitive visualization of the process, facilitating the understanding and enabling prompt interventions when necessary.

2. Method and results

As we stated in Section 1, this work addresses a specific industrial application, i.e. the detection of the presence of an anticoagulant substance inside vials within a production chain involved in manufacturing plastic consumables for analytical laboratories. To this end, we used a Deep Network architecture constituted by two main blocks:

- a 3-layer CNN neural network extracting relevant features;
- a 4-layer fully-connected network that performs the classification.

The model parameters have been chosen from scratch through an empirical process. The values of parameters of our deep network model are provided in Table 1.

Table 1: Deep network parameters. The symbol "-" for the fully-connected layers (ids 4-7) indicates that the corresponding parameter is meaningless.

Layer id	# of Input channels	# of Output channels	Kernel size	Stride	Input size	Output size
1	3	10	3	1	400x400x3	398x398x10
2	10	20	3	1	398x398x10	396x396x20
3	20	30	3	1	396x396x20	394x394x30
4	-	-	-	-	394x394x30	50
5	-	-	-	-	50	15
6	-	-	-	-	15	10
7	-	-	-	-	10	2

Our model has been trained by using images of the vials acquired through a camera situated on the top of the pipeline. We collected images of resolution 400×400 pixels. An example of the images is shown in Figure 1:

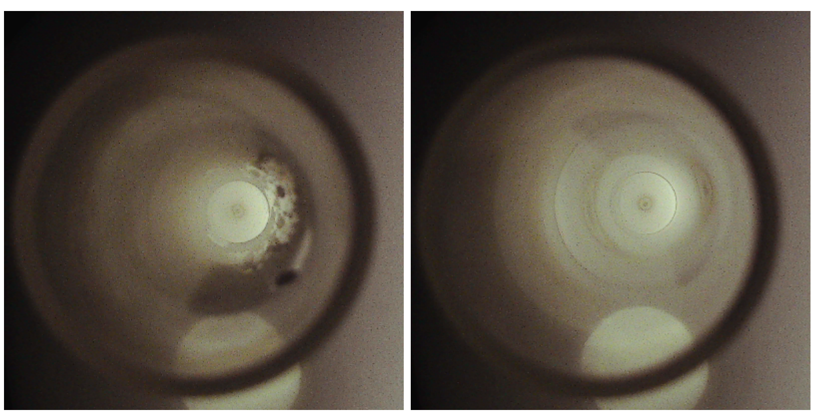


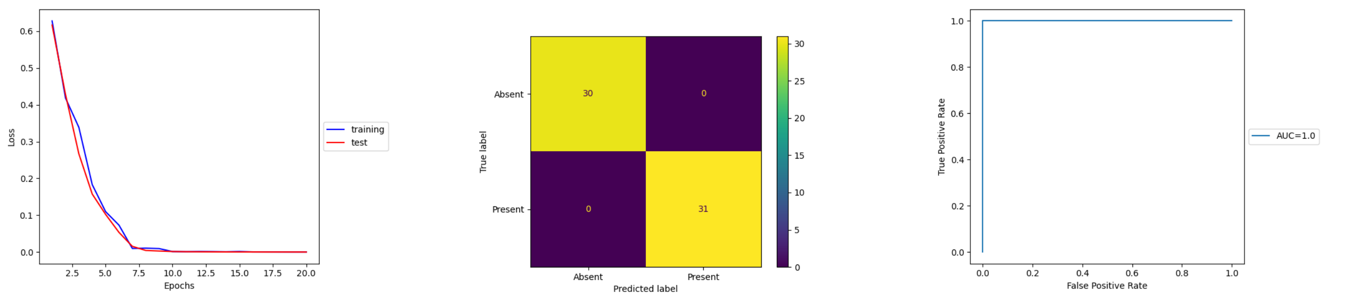
Figure 1: Two examples of images recorded by our system. **Left**: a tube containing anticoagulant. **Right**: an empty tube.

Specifically, we acquired 402 images split into a training set, which contains 341 images, and a test set including 61 images. In both sets, half of the images refer to tubes containing the anticoagulant substance, while the other half concerns empty tubes. The CNN block takes images as inputs and extracts features as outputs, which in turn will be used as inputs of the classification block. The first layer has a number of input channels corresponding to the basic colors (i.e., red, green and blue). For the other layers, the number of input channels is provided in Eq. 1:

$$num_{in\_channels}(l) = num_{out\_channels}(l-1), \quad l > 1 \tag{1}$$

where l indicates the layer id (see Table 1, first column).

The experiment has been replicated 10 times. Training lasted 20 epochs. We used the Adam optimizer [5] with weight decay. The learning rate has been set to 10^{-4} and the batch size to 16. With these settings, we achieved an average accuracy score of 100% over 10 replications of the experiment. This implies that all the trained models are able to correctly detect the presence/absence of the anticoagulant substance in the tube. The training and test errors are shown in Figure 2, left. By analyzing the detection ability of the best model, we can see that the confusion matrix (Figure 2, center) has no values outside the diagonal, i.e. no classification errors are performed. Furthermore, the ROC (Receiver Operating Characteristics) curve (Figure 2, right) corresponds to the ideal situation in which the classifier is able to distinguish between the positive class (presence of the anticoagulant) and the negative class (absence of the anticoagulant). Finally, the AUC (Area Under the Curve) score is equal to 1.0, thus indicating a perfect classifier.



(a) (b) (c)

Figure 2: (a) - Error curves during training. The blue curve represents the error on the training set, while the red curve indicates the error on the test set. We used the cross-entropy loss as an error metric. Data are obtained by averaging 10 replications of the experiment. (b) - Confusion matrix for classes "Present" and "Absent". The matrix represents the model capability of classifying images in the test set. (c) - ROC curve concerning the test set. Legend provides the AUC score. With respect to plots (b) and (c), data refer to the best model.

3. Conclusions

In this work, we describe an automated system able to correctly detect the presence/absence of an anticoagulant substance in vials. The model has been trained on a small dataset collected in a company dealing with plastic consumables. Preliminary results show that the approach is promising, as the system successfully classifies all images in the dataset. Nonetheless, real industrial applications deal with large amount of data. Future work should be devoted to validate this approach on a wider dataset. In addition, future research directions may focus on refining and optimizing the proposed computer vision and AI-based monitoring system, exploring its applicability in different industrial sectors, and investigating potential integration with other emerging technologies such as Internet of Things (IoT) and cloud computing for enhanced data analysis and decision-making processes.

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