Visual Analysis of Deep Learning Methods for Industrial Vacuum Metalized Film Product

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Abstract: Extract information to support decisions in a complex environment as the industrial is not an easy task. Information technologies and cyber-physical systems have provided technical possibilities to extract, store, and process many data. In parallel, the recent advances in artificial intelligence permit the prediction and evaluation of features and information. Industry 4.0 can benefit from these approaches, allowing the visualization of process, feature prediction, and model interpretation. We evaluate the use of Machine Learning (ML) to support monitoring and quality prediction of an industrial vacuum metalization process. Therefore, we proposed a semantic segmentation approach to fault identification using images composed of optical density (OD) values from the vacuum metalized film process. Besides that, a deep neural network model is applied to product classification using the segmented OD profile. The semantic segmentation allowed film regions analysis and coating quality associations through their class and format. The proposed classifier presented 86.67% of accuracy. The use of visualization and ML approaches permits systematical real-time process monitoring that reduces time and material waste. Consequently, it is a promising approach for Industry 4.0 on monitoring and maintenance support.

1 INTRODUCTION

The consistent growth of available data on manufacturing industries and the necessity for production and monitoring improvements promoted a fast development of complex systems and sensor technologies, as data-driven fault detection, diagnosis, and soft-sensors (Fan and Wang, 2014). These tools allow to obtain data information from production lines, environmental variables, machine parameters (Wuest et al., 2016), and possibilities the use of Machine Learning (ML) algorithms to extract knowledge and make predictions (Fan and Wang, 2014). Furthermore, the applications of ML algorithms can support surpass current difficulties on vacuum metalization process as elevated lead-time for quality analysis and limited inspection of the manufactured products.

Otherwise, large amounts of information in ML models make process comprehension an arduous task. Recent visual applications have tried to solve this issue by combining information technology and human intelligence to obtain insights from the data and support decisions under critical scenarios. Some examples for production planning (Wu et al., 2018), simulation (Dutta et al., 2018), production monitoring (Xu et al., 2017) and testing (Pajer et al., 2017) used the association between ML and visualization tools to improve industrial activities. So, we explored visualization techniques for algorithm and product variables interpretation to facilitate the use and comprehension of analysts and process engineers.

Attempting to explore ML potential and construct understandable models for a vacuum metalization process, this work proposes applying ML visual tools for interpretability and product classification through physical-properties images, reducing laboratory inspection and promoting production-time analysis.

The framework initiates with film density collected by 26 sensors. These values are processed and further targeted with quality classification from laboratory analysis. Then, we used the density film pro-

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file for semantic segmentation, and after, both objects segmented and not segmented are used to train and validate a deep learning classifier. Besides the accuracy metric, we evaluate the output layers to observe sparsity and information taken from the ML model (Fig. 1). Consequently, this work presents the following contributions:

- Use systematic visual information through ML algorithms instead of small film samples of products information from laboratory analysis.
- Predict product classification, reducing the standby time that the physical tests require.
- Indicate inferior quality products for film inspection in production time.
- Visualize coating quality in production time, supporting process monitoring and maintenance for the industrial vacuum metallization process.

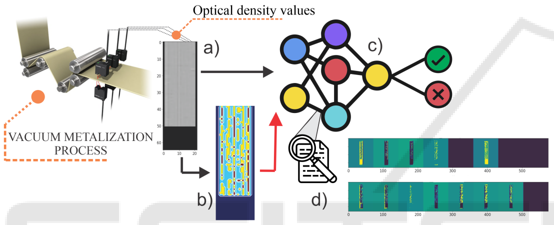

Figure 1: Illustration of the computational pipeline for industrial vacuum metallized film, the equipment light sensors measure the optical density (OD) values to represent features. a) We applied a semantic segmentation model to the OD object profile. b) Profile regions are associated by color to observe patterns and possible faults. c) We used a deep Neural Network (NN) in both profiles, the segmented and the not segmented one, to predict the film classification (as approved or disapproved). d) We evaluate the NN output layers to interpret the model prediction and information sparsity.

2 RELATED WORK

2.1 Physical Information for Industrial Process Monitoring

This work uses industrial machine data of a vacuum metallization process. In this process, a film substrate, or any oriented polymer as polypropylene (PP) and polyethylene terephthalate (PET), is loaded in the machine in the form of a roll. It unwinds and is coated by the aluminum evaporated on the substrate surface. This coating process occurs through a transversely disposed system composed of a ceramic boat heated by resistances and an aluminum wire fed with a wire conductor. During the coating process, the product optical density - OD is measured for automated control actions. An in-depth description of the process can be viewed in (Bishop, 2007; Perry and Lentz, 2009) and a process illustration in Fig. 2.

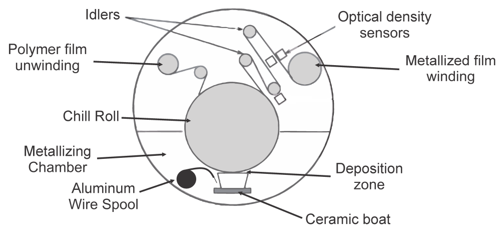

Figure 2: Vacuum Metallization process illustration. Where the polymer film is fed and metallized through vacuum metal deposition.

The coating quality can appear as a higher OD at a constant deposition rate, in the same way, that an improved surface provides a more continuous coating at a lower coating density. The OD of the coating usually represents the opacity of a thin metal coating expressed as a logarithm to base ten (1) (Bishop and Mount, 2016).

$$
\begin{aligned}
Opacity &= \frac{Incident\ light}{Transmitted\ light} \\
Transmittance\ (T) &= \frac{Transmitted\ light}{Incident\ light} \\
Opacity &= \frac{1}{T} \\
OpticalDensity &= \log_{10} Opacity = \log_{10} \frac{1}{T}
\end{aligned} \tag{1}
$$

The coating opacity expresses the light, water vapor, and gas barrier effects obtained by metal coating. For example, a package of potato chips with an opaque thin metal coating with OD of 1.7 achieve 49 days of shelf life, instead of the three days necessary to turn the chips rancid by light (I.F., 1993). Thus, it demonstrates the utility of the coating and its monitoring by film OD.

2.1.1 Visual Information for Fault Identification

The coating process by vacuum metallization occurs through boats heated by resistance, separated (0.1 m), and disposed transversely to the web orientation. Then, the wire metal is fed on resistance-heated boats by conductors and evaporated to be deposited on the web (Bishop, 2011). Following the metal deposition, we obtained OD values in a similar position and orientation, which propitiates a positional and individual evaluation of each evaporation local system rate, and the coating quality describes OD values or fault identification, as pinholes, debris, and scratches (Bishop,

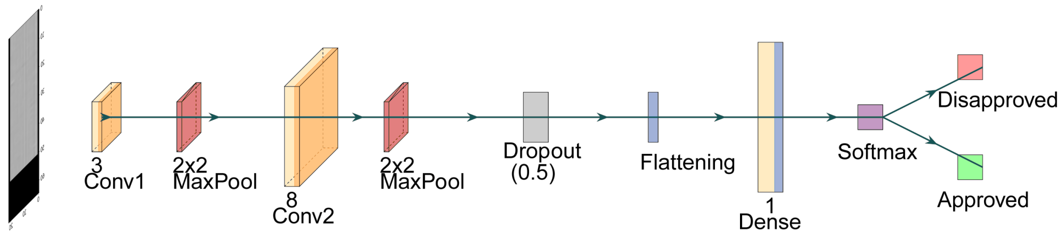

Figure 3: Deep Neural Network used to film class prediction obtained through sequential models from Keras API. We can observe two convolutional and max-pooling layers in the model that extract information, followed by the dropout regularization to avoid over-fitting and, at last, a softmax activation function for final classification.

2011). So, it is intuitive to explore the potential application of visual tools based on ML algorithms and OD film profiles to locate and identify these defects in the web profile.

2.1.2 Semantic Segmentation

Researches have shown a considerable potential of semantic segmentation applications on detecting and localizing objects in images. Borovec et al. (Borovec et al., 2017) proposed semantic segmentation to detect and localize Drosophila egg chambers in microscopy images. Lei et al. (Lei et al., 2020) applied deep learning and image processing to detect multiple objects on images. Recent applications of deep Learning models showed the capacity to detect and count plants and extract patterns and compression of images (Akbari et al., 2020). Thus, these applications demonstrate the potential employment of semantic segmentation algorithms for fault identification on film profile images and his description using the similar local and global context of the OD values.

2.2 Product Quality Prediction and Interpretation

The use of a data-driven system with statistical process monitoring (SPM) and ML models has been figured out as a significant research area over the last two decades (Qin, 2012). The data-driven quality improvement provided by ML algorithms can handle qualitative and quantitative variables in the same framework and model batch processes and optimize operation profiles through multivariate analysis (Kano and Nakagawa, 2008). ML algorithms' advantages have pushed researchers on industrial quality monitoring processes, mainly using deep Learning and ensembles algorithms.

2.2.1 Deep Neural Networks

Qin et al. point out as factual, kernel, or kernelization methods to explore nonlinear latent relations, as through neural networks (NN), besides, to retain linear computational cost, turning these models also been intensely studied for process monitoring (Qin et al., 2020; Alcala and Qin, 2010).

Also, existing deep learning platforms provide frameworks to construct distributed and parallel computing on the graphing processing unit. This strategy solves data struggling as speed restriction, typically observed in modeling large-scale massive datasets as industrial monitoring and quality prediction. For this work, we used a convolutional neural network model provided by Keras (Chollet et al., 2015) a Tensorflow high-level application programming interface (Wongsuphasawat et al., 2018).

We could determine the NN structure through experimentation with different multi-layer perceptrons configurations, varying layers, neurons, and adjusting dropout regularization. The Fig.3 shows the sequential NN model used to predict each film product's correspondent class analyzed using the Keras API's with inputs of 65x22 images of OD values, where the rows represent length positions and the columns represent the OD sensors. To extract image information and make the final product classification, we use two convolutional, max-pooling 2x2, and ReLU activation function layers with 3 and 8 neurons, respectively. The sequence uses a dropout of 0.5 to reduce the overfitting and a flattening with a dense layer of 1 neuron with a softmax activation function for the final film classification.

2.2.2 Model Interpretation

Even though most image analysis methods need to transform multivariate processes in raw forms that cause performance and spatial information loss, image data collection and processing advances have promoted miscellaneous industrial process applications research. Recent applications have demonstrated the capacity to solve multilayered problems propitiating a computational cost reduction and simplification on features description and distribution (Liu et al., 2017).

Once semantic segmentation provides regions contour and meaning, and the film quality depends directly on the uniformity and the presence of deprecated areas, we can analyze if the use of OD profile combined with the clustering mask and regions contour can improve the classification analysis. Academic studies had explored pixel values as a resource of fitness, sensitivity, and information (Bach et al., 2015; Shrikumar et al., 2017). So this work also proposes comparing NN layers outputs information when using different training images, the original OD film profile and the OD film profile with cluster mapping and contour made by the semantic segmentation.

3 METHOD DESCRIPTION

In this work, we evaluate the vacuum metalization process (Materials, 2016) of an international film manufacturing from the TOPMET 2450 machine, using data from 26 light detectors (B1 - B26) for optical density (OD) measures, equally disposed on transverse orientation to the web, more details in (Perry and Lentz, 2009). It was collected OD values with an interval of 2 min between each OD capture. Due to the size product variability, the width varies between 2,5 - 4,5 m and length up to 87 km, it was used padding to short objects up to 45 km and a crop for over this length. The width used was from B3 to B24 sensors positions due to the proportion of objects with valid OD values upper than 75%, as shown in the Figure 4.

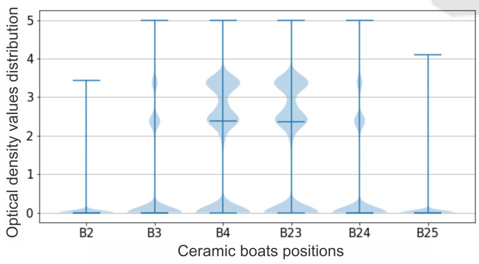

Figure 4: Optical density data set description for local coating systems with his values description according to the position of the sensors. The optical density distribution demonstrate that some positions presents a lack of valid values that should not be considered.

Over the 32.240 rows of data, we extracted 142 objects with the respective classification as approved or not. For clustering, we used all of the 142 objects. Otherwise, for class prediction, in the NN training, we used an oversampling on the disapproved class, turning 21 to 77 objects because of the class imbalance. The lack of objects for this project was the difficulty of obtaining objects target class through information crossing using experimental results obtained in the laboratory and registered on the enterprise system.

Initially, we process the data using TensorFlow and an image segmentation algorithm to observe OD distribution and area aggregation profile. After that, we applied a deep NN to classify the film as approved or disapproved. The code is available on GitHub[1].

4 EXPERIMENTAL STUDY

4.1 Class Prediction and Interpretation

The performance analysis provides the best sequential model presenting 86.67% of accuracy on the test and an average loss of 0.46 with an inference time of 4 ms, demonstrating, initially, the NN models' applicability for multilayered problems. Furthermore, the reduced number of objects compared with the features used to train and test the algorithm can impact the model performance, needing more tests and evaluation to validate the results.

4.2 Film Region Semantic Segmentation for Cluster Analysis

The clustering analysis used image processing through spatial regularization on super-pixels to make segmented regions more compact. The pipeline used comprises (i) computation of super-pixels; (ii) extraction of descriptors; (iii) soft classification, using the Gaussian Mixture Model for unsupervised learning; (iv) final segmentation using Graph Cut (Borovec et al., 2017).

This work experiment used a super-pixel size of 1 and regularization of 0.1, with the number of classes equal to four. These parameters were obtained by experimentation, observing the best OD profile division and comprehension. Fig. 6 shows approved and disapproved examples, where the yellow and red regions are interpreted as deprecated areas.

Fig. 6a is an approved object and presents a significant region of class 1 (blue light), differently from Fig. 6b, which shows a substantial part of class 2 (yellow) with class 3 (red) areas distributed inside this class. The class 3 region format of points and edges in different vertical positions indicates possible fault regions associated with pinholes and local coating system imbalance.

[1]https://github.com/tmrb/Master-project-codes

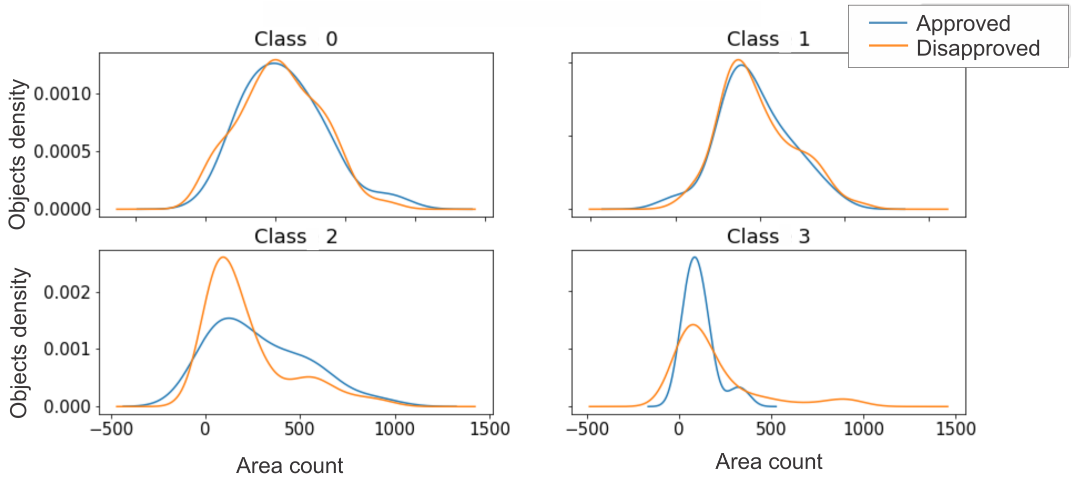

Figure 5: After addressing a class for each OD value of a product, we sum the number of OD classes by-product, representing area count. Dividing the objects according to his final classification, we could compare the area count occurrence in the objects approved and disapproved to observe possible influences in the product's final quality. The blue line represents the area counting for approved objects and the orange line for disapproved objects.

This visualization provides insightful observations. For the disapproved film, the local coating system on 2, 11, 13, 16, 22 positions present red as the significant class indicating potential local system problems or imbalances in one of the process variables: wire feed, wire aligning, or boat temperature.

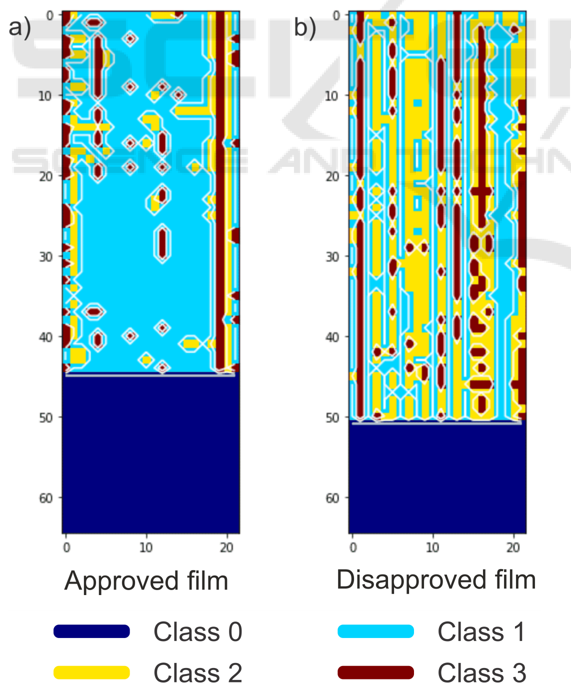

Figure 6: Film profile semantic segmentation for fault identification. Each region color represents a class obtained by clustering. The marine blue is class 0 and represents the padding area, the blue light class 1, yellow class 2, and red as class 3. a) It is an approved film object. b) A disapproved film object.

For the approved film, the predominant blue region indicates a good coating and uniformity. On the other hand, the spaced red points showed small areas with a soft covering associated with pinholes region, which can be caused mainly by smalls dirt or debris in the film profile that could be avoided by vacuum and venting variables adjustments.

Looking for objects analysis through class appearance, Fig. 5 count the class pixels area for each object. Observing that, class 3 demonstrated many high area counts for major disapproved objects, reinforcing the clustering analysis and the association of class 3 as undesired OD regions that contribute to object disapproval. For the further classes, no substantial class counting differences were obtained between approved and disapproved products.

4.3 Class Prediction with Semantic Segmented Images

Another interesting evaluation is in the layer's outputs, where we can observe the layer weights mapping and infer if the semantic segmentation could improve the classification process. Fig. 7 demonstrate the three first layers outputs, first, using the original OD values profile as the object input (Fig. 7a), and second using the images obtained through the semantic segmentation application (Fig. 7b). The three initial layers correspond to the convolutional layers with three neurons, max-pooling (2x2), and another convolutional with eight neurons.

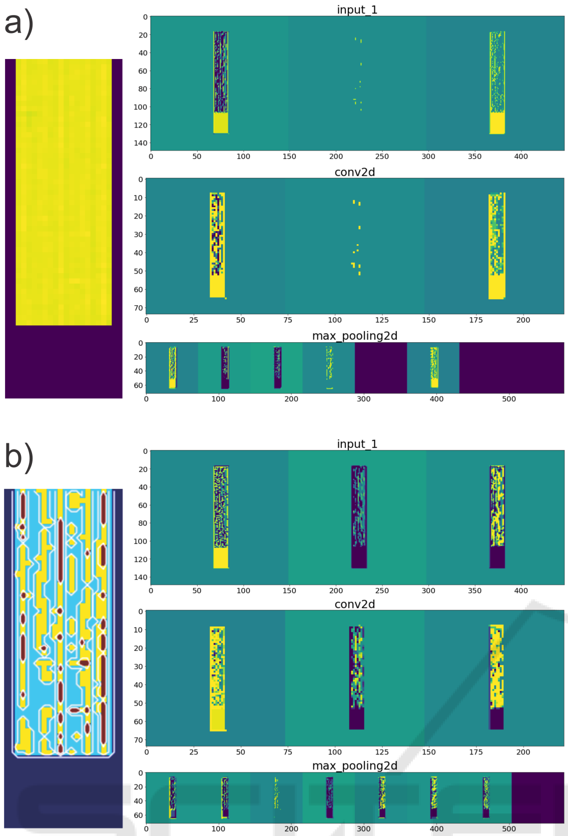

Figure 7: The three initial layers output analysis of using different types of images as input to train/test algorithm. a) Optical Density (OD) profile values of metalized film used as objects and the respective initial layers outputs. b) OD profile films after semantic segmentation with four OD regions classes representation used as input to train/test algorithm and his respective initial layers outputs.

It was possible to observe an improvement in layers output distribution attributed to semantic segmented images as the inputs. Fig. 7a demonstrates three empty outputs for the 5th, 7th, and 8th neuron, while Fig. 7b present only the 8th output empty of information. Besides that, the object contour and regions mapped by the layer's output values are more continuous and distinguishable for inputs obtained by the semantic segmentation, demonstrating improvements in the edges capture.

In terms of performance as accuracy and loss, we did not observe relevant differences. These metrics presented the same median values of 86.67% for accuracy and 0.46 for loss, owing to the lack of objects used to train/test/validate the algorithms. However, the output distribution reveals essential contributions of the previous image segmentation, with improved pixel-wise analysis and model sensitivity. In addition, the pixel importance was better propagated through the layers and represented in the final layers, demonstrating sensitivity enhancement to the model.

As the original OD profile does not present any difference in pixel relevance, a more distributed layer weights profile is expected, as closer to Fig. 7b. Moreover, the weights highlighted over the algorithms' layers trained with segmented inputs demonstrate a better sparsity of information. The refining of the importance of the features mapping reveals specific details in the shadow layers. Also, sparsity is a crucial feature and represents efficiency improvements by reducing resource use, like storage, communication, and computation requirements.

5 CONCLUSIONS

This work demonstrated that deep learning methods, like neural networks and semantic segmentation, can be applied to fault identification, not only for images but also for physical measures spatially distributed, propitiating semantic analysis, quality monitoring, and better quality prediction of the product. The use of semantic segmentation associated with image construction through physical measures represents a novelty for industrial applications and academic exploration, contributing to many other applications besides the Vacuum metalization process. The use of more objects and tests can propitiate further applications of the deep learning model applied, using as indicators for feature control, fault detection, and quality monitoring. Moreover, these algorithms can improve coating in real-time, demonstrating deprecate region identification, promoting feature manipulation, and guiding operator analysis.

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