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Quality control in manufacturing through temperature profile analysis of metal bars: A steel parts use case

Paolo Catti[a], Michalis Ntoulmperis[a], Vittoria Medici[b], Milena Martarelli[b], Nicola Paone[b],Wilhelm van de Kamp[c], Nikolaos Nikolakis[a], Kosmas Alexopoulos[a,*]

[a]*Laboratory for Manufacturing Systems & Automation (LMS), Department of Mechanical Engineering & Aeronautics, University of Patras, Rion, Patras 26504, Greece*

[b]*Dip. di Ingegneria Industriale e Scienze Matematiche, Università Politecnica delle Marche, Ancona, Via brecce bianche 10, 60131, Italy*

[c]*VDL WEWELER bv, 7325WC, Apeldoorn, The Netherlands*

* Corresponding author. Tel.: +30-2610-910160; *E-mail address:* alexokos@lms.mech.upatras.gr

Abstract

Non-uniform heating during metal bar hot forming may impact its straightness. In this study, an infrared non-destructive inspection system is proposed to acquire steel temperature profiles in runtime which should correlate to straightness deviations. Additionally, a machine learning algorithm detects outliers to identify oxides on the metal, which in turn is correlated to process parameters. This allows for proactive temperature adjustment to mitigate the risk based on historical profiles. The proposed approach has been tested in a use case coming from the steel industry.

Keywords: Machine Learning; Manufacturing; Non-Destructive Inpection; Quality Control;

1. Introduction

Quality control, in traditional manufacturing, is usually time-consuming, manual or difficult to implement in line. Additionally, it can be prone to errors and in the case of destructive testing can lead to waste [1].

In manufacturing, and specifically in the steel processing industry, the hot forming process involves heating a metal blank in a furnace up to a predefined temperature. With further processing, the metal blank is formed into its final shape [2]. However, non-uniform heating can lead to dimensional deviations in the product, which usually are challenging to detect in traditional manufacturing automatically [3].

Traditionally, measuring the temperature of a metal blank during the hot forming process, pyrometers have been used. However, they only provide point temperature measurements [4]. This creates a need for advanced non-destructive inspection systems that could capture the entire temperature profile of a metal blank, thus enabling proactive quality control in manufacturers through early anomaly identification during the hot-forming process [5].

This study proposes an advanced, infrared non-destructive inspection (NDI) system that acquires steel temperature profiles of metal bars. Additionally, machine learning (ML) is used to identify oxides on the metal bar, based on real-world data acquired through the inspection system. The ML algorithm's results are correlated with production parameters which enables the finetuning of process-related parameters, to achieve a more uniform heating. The approach is tested using real-world temperature profiles captured in-line through the proposed infrared non-destructive inspection system on steel bars.

2. Literature Review

Inspecting 100% of production is becoming key for smart factories to enable the early detection of defects and avoid their propagation [1]. Manual inspections as well as Statistical Process Control is less efficient to ensure a defect-free surface of products.

Automated inline quality inspection is the core concept of NDI systems, based on Non-Destructive Testing (NDT) [7]. An NDI is specifically designed to obtain measurements for quality

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control of a part during production, in a non-intrusive approach. NDIs detect features of the product during the manufacturing process enabling the evaluation of material quality without compromising the integrity of the product and without affecting the production steps. Thus, strategical integration of NDIs [8]is critical to ensure the interoperability of different systems, to allow for easier data correlation, and to provide consistent and valuable feedback for continuous improvement [8].

The concept of non-destructive inspection has evolved with the advent of Industry 4.0, bringing advancements in capability, reliability of evaluation, system design, customisation, safety, and maintenance [9]. Non-Destructive Evaluation 4.0 signifies a paradigm shift in industrial inspection, offering real-time data, cloud-based management, access to a vast knowledge base, and fostering more informed decision-making. Innovative technologies enable near real-time data streaming, and the integration of Artificial Intelligence (AI) facilitates quick and dependable decision-making [9].

The design of an NDI varies depending on the type of quantity being measured. The type of inspection is related to the under-measurement product, the environment, and the requirements of the final product. Different types of non-invasive measurement techniques could be performed, such as vision-based techniques, infrared thermography (IRT), acoustic and ultrasonic testing, electromagnetic methods, and so on [10].

In this study, thermography is employed to address the recognized gap in the analysis of defects in high-temperature steel applications in a full-field manner. While pyrometers are commonly used in such environments, they fall short of providing a comprehensive temperature distribution, offering a localized view of the product's temperature without capturing differences across a surface [4]. This limits the ability of manufacturers to assess the integrity of products, components, or systems, particularly in industries dealing with high-temperature processes.

Thermography "uses the distribution of surface temperatures to assess the behaviour of what is under the surface" [11]. It is based on the detection of infrared radiation emitted by any object at a temperature above absolute zero. IRT enables the acquisition of measurements of a two-dimensional temperature and emissivity distribution, making it possible to observe whether there are abnormal temperature profiles [12]. In recent years, thermography has increasingly been suited for automatic inline use, thanks to improved electronic systems and sensors. As discussed in [13], thermography has been applied in industry in electrical, mechanical, and other applications.

In modern manufacturing, there is an increasing demand for the use of advanced ML algorithms for improving quality inspection and control. In [14] a systematic review of the usage of ML algorithms in manufacturing in the context of predictive quality in manufacturing. The review's results affirm the potential of ML and Deep Learning (DL) techniques for data-driven quality estimations. Similar findings were presented in [15]. Additionally, in manufacturing, apart from predictive ML models to predict quality control, ML techniques have been utilized for classification and outlier detection purposes. In [16], a base extreme gradient boosting model was used where, through classification, defects on PCBs were detected. Furthermore, in [17] classification algorithms were used to extract the probability of manufacturing equipment requiring maintenance, directly linking it to the quality of the product.

Anomaly and outlier detection are also a key topic in the context of using ML algorithms for quality inspection in manufacturing [18]. A systematic literature review was conducted in [18] comparing the findings of 290 research articles. In addition, the capabilities of ML anomaly detection algorithms in manufacturing have been demonstrated in [19] where through an XGBoost algorithm [20], outliers in the final test stage of integrated circuit manufacturing were detected.

In the context of modern manufacturing, an abundance of sensors can be utilized to capture production and process-related data, however, during the creation of ML algorithms targeting quality control, dimensionality reduction of the acquired set of data is often required [21]. Several dimensionality reduction techniques are available each serving a specific purpose [21]. As presented in [22], modern techniques include principal component analysis (PCA) which is more suitable in cases where linear relationships between the data dominate and isometric mapping which is better suited for data with non-linear relationships.

In conclusion, it is evident from the reviewed literature that there is a growing need for advanced non-destructive ZDM inspection solutions [7]. In this study, a vision-based non-destructive inspection solution, that utilizes thermography, is proposed and is in-line tested and deployed in a steel parts manufacturer. Additionally, while there is an increasing demand for advanced ML algorithms targeting quality inspection and control in manufacturing [14], the field of using unsupervised outlier detection algorithms in conjunction with data from advanced in-line installed ZDM solutions is not fully explored [23], [24], [25]. Therefore, this study aims at providing a methodology where through temperature profiles of a metal bar, acquired from an in-line installed NDI system, an outlier detection algorithm identifies oxides on the blank and through a human-centred process reconfiguration mechanism, heating process parameters are adjusted.

3. Methodology

In this manufacturing context, the observation of variables within a multi-stage process is fundamental to capturing comprehensive product knowledge. The acquisition of variables is conducted in a multi-dimensional space, considering critical factors such as process stage, time, and product identification. A holistic approach to data observation, acquisition, processing, and correlation aims to improve the efficiency and effectiveness of production processes.

Raw data from inline NDI systems are processed to obtain value-added information that can be used for decision-making. A thermographic NDI facilitates a critical role within this framework, offering the ability to assess the temperature distribution in a product's surface after thermomechanical treatments. This enables the extraction of meaningful features from the manufactured product.

Using the temperature profile, captured by the NDI system, of the product the presence of oxides on the bar can be identified. To achieve this a deep learning unsupervised algorithm is employed. The proposed algorithm is based on a CNN DL model with autoencoders. The algorithm's architecture can be found in Fig. 1.

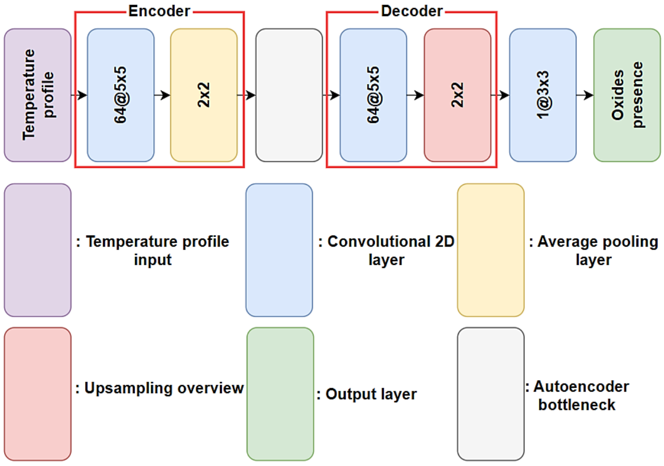

Fig. 1. Architecture of the proposed unsupervised deep learning model

To identify defects in products as they progress in the line and adjust process conditions accordingly, the correlation of data is needed. Correlation analysis measures the strength and the direction of an association between some variables.

Different types of correlations can be evaluated. Pearson correlation coefficient measures the linear relationship between two continuous variables. It ranges from -1 to 1, where -1 indicates a perfect negative linear relationship, 1 indicates a perfect positive linear relationship, and 0 indicates no linear relationship. Spearman rank correlation coefficient assesses the strength and direction of monotonic relationships between two variables. It is non-parametric and does not assume linearity.

The proposed NDI system produces a multidimensional array containing information from each captured pixel. The contained information is the temperature of the bar at the given point. Due to the nature of the temperature profile, PCA is performed for dimensionality reduction. PCA reduces the number of columns of the multidimensional array representing the acquired temperature profile to facilitate the correlation analysis between NDI data and production parameters.

To further decrease the temperature profile's dimensions, while maintaining critical information, descriptive analytics are applied on top of each principal component column. Through the application of descriptive analytics, the minimum, maximum, mean and standard deviation of each principal component column is generated due to its criticality in the oxide's identification process.

The next step includes the dataset creation based on which the correlation analysis is applied. The dataset contains the reduced dimensions temperature profile as well as production and process parameters. To assess the correlation, Pearson's and Spearman's correlation techniques are used to identify possibly correlated production and process parameters with the reduced dimensions temperature profile as well as product defects.

Using the identified correlated parameters with the temperature profile data and product defects, as well as the proposed deep learning algorithm for oxide detection recommendations are made to human experts to fine-tune production parameters to reduce the oxide presence on the metal bar, thus directly affecting its straightness during the hot forming process. An overview of the presented approach can be found in Fig. 2

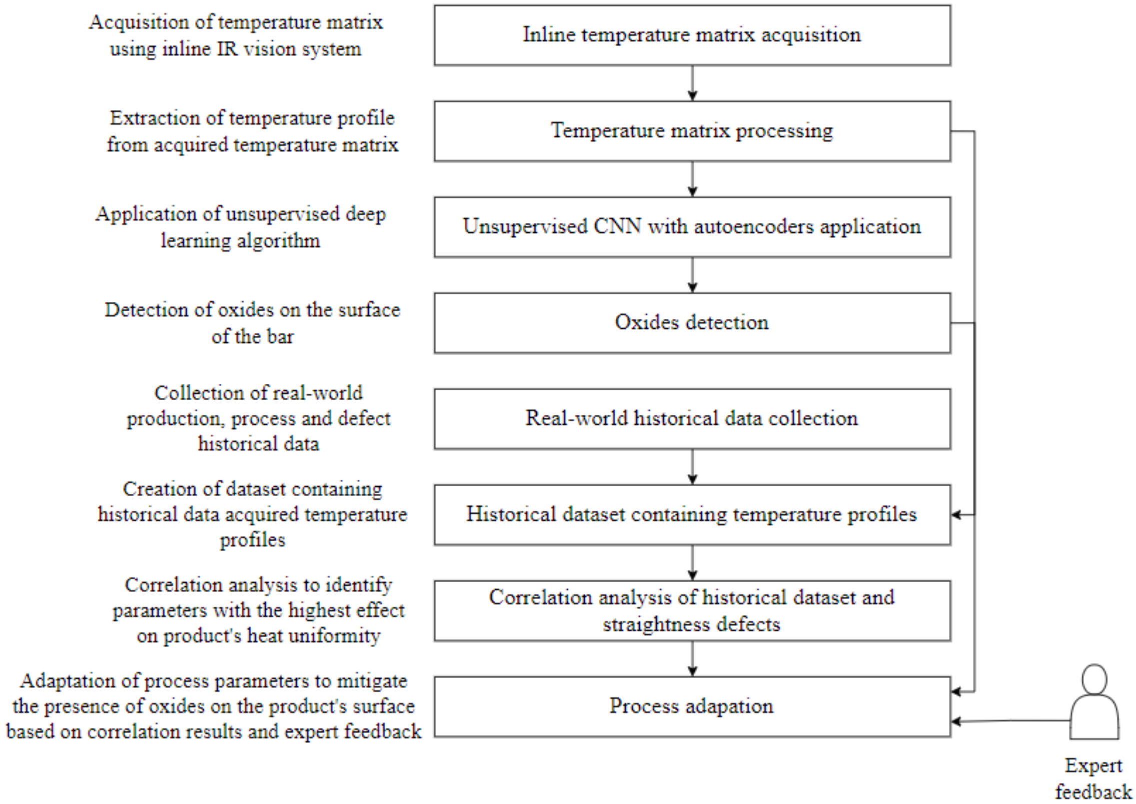

Fig. 2. Overview of the proposed methodology

4. Implementation

In an Industry4.0 scenario, an NDI system based on thermography and image processing has been designed, developed, and implemented to monitor the high-temperature distribution of objects passing through a production line (Fig. 3).

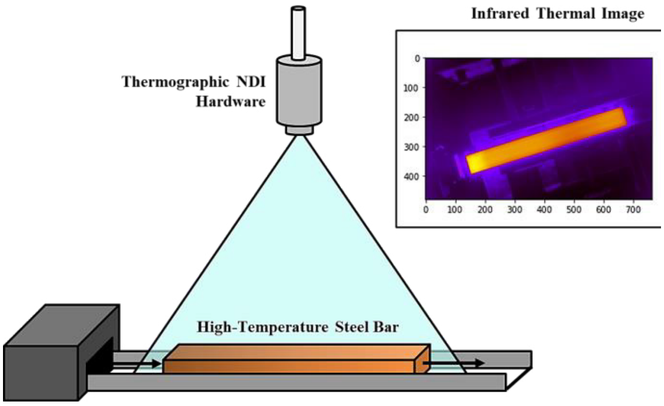

Fig. 3. Inline Thermographic Non-Destructive Inspection system

The NDI system is installed after the oxide removal step of the hot-forming process. At this stage of the process, the product has a maximum temperature of approximately 1100°C.

The main component of the NDI is the IR thermal camera. The camera is an Optris PI 1M model operating in the NIR (Near-InfraRed) spectrum λ=0.85 ÷1 µm, where emission from high-temperature metals is intense while radiated heat from the colder surroundings is small, thus allowing a better signal-to-noise ratio and thus a lower measurement uncertainty. The thermal camera and the related electronics are housed in a cooling jacket to withstand harsh environmental conditions. The thermal camera communicates with the industrial PLC to receive a gate signal to acquire a thermal image of the product synchronized with the product position on the line. The thermal camera has a CMOS sensor with a full resolution of 764 x 480 and a temperature range of 450° - 1800°C.

The emissivity has been calibrated to perform quantitative measurements and it is about 0.85. The emissivity has been calibrated on non-oxidized high-temperature steel. Oxides have different emissivity from non-oxidized steel, and therefore the temperature detected on it is different from the background and quantitatively non-correct. This however allows the image oxides.

The acquisition software allows the acquisition of one infrared thermal image for each bar passing through the line. The processing software was developed to reduce the size of the raw data by cropping the thermal image to the size of the product and extracting early useful indicators. The resulting image is a matrix of temperature values that can be used to easily extract useful features of the product. Temperature values and profiles (Fig. 4) can be extracted and correlated with other process parameters.

To fine-tune the model used in the proposed approach, grid search has been employed to determine the model's hyperparameter values that result in the highest-performing model. The hyperparameters of the proposed model are:

- Activation function: "elu",
- Pooling type: "average",
- Optimizer: "Adam" [26],
- Batch size: 16,
- Maximum number of epochs: 200,
- The loss function used was: Mean Squared Error.

Additionally, the early stopping function is used in the model. The function monitors the validation loss of the model and is set to be triggered after 3 consecutive epochs where there is no improvement in terms of the model's validation loss. The early stopping function is coupled with a learning rate reduction function which reduces to half the learning rate of the "Adam" optimizer.

The effect of the presented approach on process reconfiguration has been tested in a simulated environment. Using preexisting simulation models of the manufacturing line, the presence of defects on the trailing arm was simulated and using experts' feedback process parameters of the hot forming process were altered based on their identified importance, through the correlation analysis, on the presence of straightness defects on the trailing arm. The simulation was conducted using real-world data from the manufacturer.

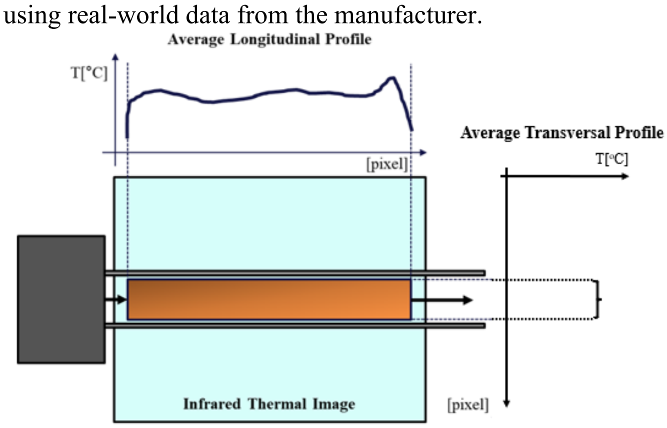

Fig. 4. Thermal profiles extraction

5. Use Case

The raw data, acquired by thermography, have been transformed into useful information through post-processing. The transformed data includes the temperature matrix, which represents the surface temperatures of the product, and is used to extract longitudinal and transverse profiles on the steel bar, from which indicators of uniformity can be extracted.

A dataset containing every production and process parameter, acquired through various IIoT sensors across the manufacturing line, was created. In the dataset, the temperature 2D distribution captured with the presented NDI was included. The temperature distribution is a matrix of 80x660 dimensions that can be seen as a sequence of 660 transversal profiles. In total, the final dataset contained the temperature data, production and process parameters and defect metrics of real-world data of two weeks of production.

The inclusion of the temperature profiles in the dataset required the application of PCA as presented in the proposed methodology. Through PCA the dimensions of the original matrix (80x660) were reduced to 80x6, with the 660 columns being reduced to six principal components. The number of

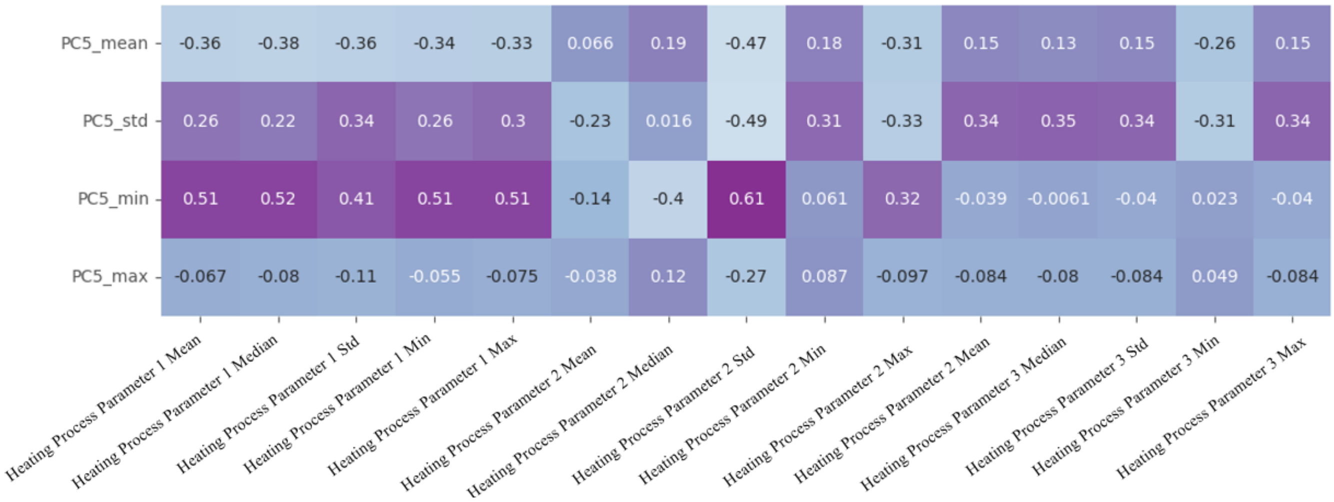

Fig. 5. Spearman's Correlation results of hot forming process parameters with the fifth principal component of the temperature profile.

principal components was determined using the explained variance ratio. The combined explained variance ratio was 0.95which in turn indicated that the number of principal components to be used is six. Additionally, to further decrease the dimensions of the temperature profile data the minimum of each principal component was calculated due to its importance with the presence of oxides on the metal bar.

The reduced temperature profile was correlated with the dataset containing production and process parameters as well as with the presence of straightness defects on the bar. Pearson's and Spearman's correlation techniques were employed to identify the linear and non-linear correlation between the data. The results of the correlation analysis indicated a high correlation of a principal component with process parameters related to the hot-forming process as seen in Fig. 5. Additionally, the correlation between the reduced temperature profile and the presence of straightness defects on the trailing arm was calculated. However, a lesser correlation was observed, which can be attributed to the low number of defects present in the dataset.

Following the correlation analysis, the proposed unsupervised deep learning algorithm was trained and tested using the available temperature profiles. During training and testing, an 80-20% split in the data was utilized. Additionally, the model was instructed to classify as anomalous those that belonged to the 95th percentile of errors. The model was constructed using the hyperparameters detailed in section 4. To assess the model's performance the training and validation loss was monitored. The model's performance was evaluated using the mean squared error and the mean absolute error between the reconstructed decoder data and inputted temperature profiles. Additionally, the loss and validation loss were used to determine the fitting of the model. The evaluation results can be seen in Table 1.

Table 1: Performance metrics of proposed unsupervised deep learning algorithm

Performance metric	Value
Mean Absolute Error	0.093
Mean Squared Error	0.041
Loss	0.039
Validation Loss	0.058

An example of a portion of the trailing arm with detected oxides (white spots) by the proposed model can be seen in Fig. 6 where the identified oxide can be seen encircled in the two images. However, the algorithm has detected as oxides additional spots on the bar (white dots on the bottom half of the image). These are numerical anomalies and do not constitute the presence of an oxide, and with further fine-tuning of the model such false positive detections will be avoided.

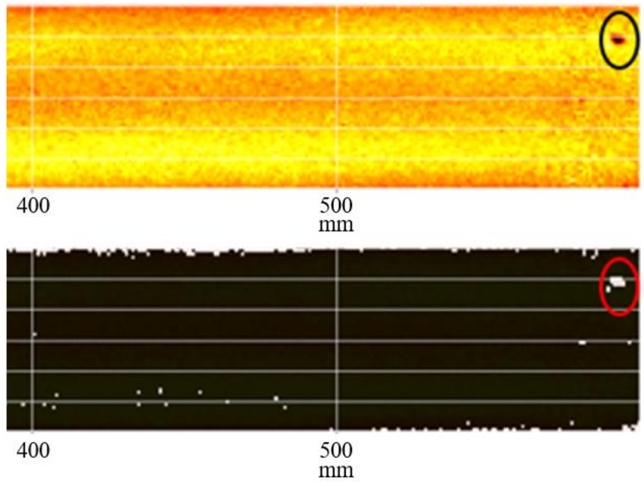

Fig. 6. Detected oxides on the trailing arm.

Lastly, a simulation was conducted to measure the effects of reconfiguration of the hot forming process based on the identification of oxides on the trailing arm using as a basis the highest correlated process parameter. The simulation was conducted using an existing simulation model of the production line and specifically of the hot forming process. Based on feedback on the hot forming process from field experts, the temperature at which the trailing arm is being heated was adjusted. Based on the production line simulation this resulted in a more uniform heating of the trailing arm, thus reducing the number of oxides present on the surface of the bar.

6. Conclusion

A methodology aiming at using trailing arm temperature profiles acquired from an inline vision-based NDI system in conjunction with an oxides detection model based on a deep learning algorithm was presented. In the study, the NDI system was used to acquire approximately two weeks' worth of production temperature profiles. Additionally, real-world data of production and process parameters related to the products whose temperature profiles were acquired were used to determine the highest correlated parameters with the temperature profiles.

The presented approach demonstrated relatively high accuracy in detecting oxides on the metal bar using the acquired NDI temperature profiles. Nevertheless, false positive oxides were detected on the bar. To address this, in future iterations, a filter will be applied to the generated by the algorithm results where detected oxides should occupy an area larger than a few pixels and the local intensity of the image should be significantly lower than the surroundings.

Nevertheless, future research is needed to fine-tune the presented approach. Specifically, future work will concentrate on fine-tuning the percentile of errors that the unsupervised algorithm deems as anomalous, thus having oxides on the bar surface. Additionally, the reconfiguration approach will be automated to enable the process online adaptation.

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