Cyber-physical system supporting the production technology of steel mill products based on ladle furnace tracking and sensor networks

Piotr Hajder[1][0000−0002−0437−3328], Andrzej Opaliński[1][0000−0002−9730−9594], Monika Pernach[1][0000−0002−0091−5329], Łukasz Sztangret[1][0000−0003−4872−406X], Krzysztof Regulski[1][0000−0001−8080−2254], Krzysztof Bzowski[1][0000−0002−1784−2584], Michał Piwowarczyk[2], and Łukasz Rauch[1][0000−0001−5366−743X]

[1] AGH University of Science and Technology, Kraków, Poland
{phajder,opal,pernach,szt,regulski,kbzowski,lrauch}@agh.edu.pl
[2] CMC Poland Sp. z o.o. michal.piwowarczyk@cmc.com

Abstract. The use of information technologies in industry is growing year by year. More and more advanced devices are implemented and the software needed for them becomes more complex, which increases the risk of errors. To minimize them, it is necessary to constantly monitor the condition of the system and its components. This paper presents a part of a complex production support system for steel mill, responsible for monitoring and tracking the current state on the production hall. Data on currently performed melts and their condition, collected from two sensor layers - Level1 and Level2 - combining with a camera system that allows tracking the position of the main ladle in the hall, was used to create metamodel based on linear regression and neural network for the temperature drop which is occurring during the transport of liquid steel to the casting machine. This approach enables optimization of production volume and minimizes the risk associated with a temperature drop below the optimal one for casting. Several neural network models were used: YOLOv3 for object detection, CRAFT for text detection and CRNN for text recognition. This information is published to the sensor subsystem, enabling precise determination of the state of each performed melt. The system architecture, prediction accuracies and performance analysis were presented.

Keywords: cyber-physical system · machine learning · sensors · vision processing · steelmaking automation

1 Introduction

One of the industry sectors, which is the main research area in this work, is the steel industry. Steel is a product whose use can be found in almost every other industry, even in everyday life. Depending on its purpose, various compositions are used, by dosing appropriate alloy additives, and variable process conditions,

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

such as melt temperature and casting time, or the degree of superheating. In the case of the most rigorous alloys, deviations from the process and its schedule are unacceptable, as this may result in the creation of a different steel grade, which translates into both company losses and the purpose of its use. Therefore, there is a need for continuous monitoring and control, from the very beginning of the process. An important step in the production of specific steel grades in the continuous casting process is the transfer of the main ladle (ML) from the electric arc furnace (EAF) through the ladle furnace (LF) to the continuous steel casting machine (CSC). This takes time, which causes the temperature of the molten steel to drop and may make casting difficult or impossible, possibly lowering the quality of the product.

In this paper, the development of ladle position monitoring modules, measuring systems and metamodeling of the temperature drop of liquid steel in the ML is presented. A sensory layer was created, deployed in the production hall. The measurements are aggregated with data from the database and then used in the temperature drop metamodel. Historical data were used to train this model, which is based machine learning techniques, in particular linear regression and neural network. In addition, available industrial cameras were used to track the movement (determining the position) of the ML in the production hall, enhanced with three machine learning models: one for ML detection, as well as two for detecting and recognizing text in the form of numerical labels. We present the architecture of these modules, the results of their integration and sample results, including performance and accuracy of the predictions of the models used. This work are part of a hybrid IT system designed to optimize and model continuous steel billets.

2 Preliminary arrangements

In this work, we describe the module of the production technology support system at the steel plant, concerning the modeling of the temperature drop of liquid steel in ML. For the alloy to be properly cast, the temperature must not fall below the set value. For this purpose, we created a metamodel that evaluates the current temperature according to the time passed after ML's departure from EAF. In order to assess whether the alloy can be cast, in addition to the metamodel, we have created a subsystem for monitoring the position of the ML in the hall, to be able to assess as early as possible whether the ML will arrive on time at the CSC or whether it will need to be reheated at the LF station. This subsystem consists of two main components: sensors, measuring and collecting information about current activities in the hall, and video monitoring of the ML position, based on multiple industrial cameras. Preliminary arrangements for each of these components are described in the following sections.

2.1 Sensors

The main task of the sensory layer in the described problem is to provide the necessary data and information to the component responsible for metamodeling,

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

based on which they will be able to model the current state of the process and control it in order to obtain its optimal result. For the proper operation of process steering component, it is necessary to provide data from the sensor layer, which will be:

- Up-to-date – delivered on an ongoing basis, preferably in real mode, immediately after obtaining them in the environment, so that the system's reaction can be immediate,
- Precise and accurate – reflecting the parameters of the real process as closely as possible in order to obtain the best representation of the metamodel,
- Complete and consistent – mapping all technical and technological parameters necessary to develop and launch a metamodel mapping the technological process carried out in the electrosteel plant hall.

In the existing hardware layer concerning sensors and measurement of the environment to which this task relates, there are already a lot of elements that can provide useful data related to sensors and parameters of such a technological process. We can distinguish three main sources among them:

1. **Level1 system**. At the lowest level – in the hardware layer – there is embedded software for devices located in the electrosteel plant hall. It is known as Level1 and stores information about the status of devices located in the hall. This data can be obtained directly from the device controllers in real mode, although in the standard mode of operation of the steel plant, the data on the process itself is not used for automatic (intelligent) process control and steering.
2. **Level2 system**. It is sensor layer available in the electrosteel plant hall, which stores part of the parameters related to the technological process carried out on main process devices. These are parameters related to the melting schedule (grade, recipient, sequence in the melting sequence), characteristics of end products related to a given ML (chemical composition, size and type of cast element) or parameters of individual stages of processing at specific positions in the steelworks plant hall (batch weight, amount of oxygen or coal used, total processing time per step). The imperfection of this layer in terms of its use in the production control process based on the metamodeling is that data are available only after the completion of the processing process on a particular device in the electrosteel plant hall (EAF, LF, CSC). Due to the characteristics of the technological process, they appear in the system every 30-50 minutes, because these are the standard processing times on individual devices included in the process.
3. **CCTV monitoring system**. The video monitoring system available in the steelworks plant hall is based on 12 cameras covering most of the hall area. The data is available in the live view system and the image is also archived, but in the current mode of operation of the plant hall, the only image analysis mechanisms available in the system are the mechanisms of motion detection in the image, without any identification of the sources of these events. There is no distinction whether the movement in the image was generated by a person, a vehicle or a moving ladle (ML).

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

The main problem, common in this field of research and industry [1, 2], in the sensory layer of the current infrastructure of the steelworks plant hall is that data on the steelmaking process that could enable automatic control mechanisms for such a process (based on machine learning mechanisms) are available in different hardware layers of the environment (described above), are not integrated and partly inconsistent.

The task that needs to be solved is so that they can be used as a data source for the metamodeling component based on machine learning mechanisms is the integration, aggregation and unification of data from the three sensor systems mentioned above and providing them to the metamodel component in a coherent version in real mode.

2.2 ML position tracking

As described in the previous subsection, there are 12 industrial cameras, providing current view of the production hall via RTSP protocol. They may be used to track position of every used ML. The main problem to be solved in the described part of the system is the detection of ML and recognition of its label. The basic solution that has been indicated for this problem is the detection of objects and text, along with its recognition. For this purpose, available Avigilon industrial cameras were used, along with machine learning models. To achieve the goal of this module, following tasks can be defined:

1. **Object detection** - detecting the ML on the image frame, which determines its position in the hall;
2. **Text detection and recognition** - detecting and recognizing the ML label, which will allow it to be identified.

Both of these tasks can be solved using machine learning methods, in particular based on convolutional neural networks [3, 4]. However, since the task is not standard and publicly available training sets for the networks do not contain ML, we had to build our own dataset. For this purpose, the images from each camera were analyzed, the key ones for modeling the hall and steelmaking process were determined. Then, with the interval set per camera, the frames were uploaded to the disk. After image gathering was completed, they were selected and labeled in order to prepare them for training machine learning models. Labeling was performed for both ML and numeric labels painted on ladles. In addition, due to lot of similarities between dumped frames, we used ImgAug [5] to augment dataset with modified versions of images, in particular by 'emulation' of smoke, which can occur while during slag pouring (visible on few cameras) and may influence results obtained from models.

With an already prepared training data, the main problem to be solved is to prepare neural network models and its implementation for the indicated tasks. These models must be trained and tested for accuracy and performance. Then, they can be aggregated into one solution that receives a frame from the camera as an input and returns the position and ML label as an output.

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

2.3 Metamodeling for temperature drop prediction

Measurements of temperature distribution of liquid steel inside a ladle is very difficult or sometimes even impossible task in industrial conditions, due to the safety reason and high cost of equipment. On the other hand precise knowledge about the overheating level is crucial to maintain optimal range of temperatures during Continuous Steel Casting process to obtain the highest quality of casted billets. Application of FEM models to predict the temperature of liquid steel in industrial conditions is impossible due to the long computation time. Therefore, in this paper, two machine learning techniques were applied for this task: linear regression (LR) and artificial neural networks (ANN) [6, 7].

All computations were performed using MATLAB software. Deep Learning Toolbox was used to create and train ANNs and Optimization Toolbox was applied for gradient optimization of cost function in case of linear regression. In both cases, the aim of the model was to predict the steel temperature after specific time period based on: the type of the steel (GradeID), temperature obtained after heating (StartTemp), cooling time (TimeDiff) and the steel weight (Weight). Eventually, based on the temperature difference and cooling time, the cooling rate was computed. The collected data, after filtering, consists of 7362 records. The data concerned 81 grades of steel. Unfortunately, the number of records for individual grades of steel varied greatly. The most common type of steel was represented by over 3000 records, while for five types of steel only one record was in the dataset. Despite such differences in the number of records, preliminary training of the models revealed, that the number of steel types included in the training set did not have a major impact on the accuracy of the model. Therefore, all computations were performed for all 81 types of steel.

2.4 Related works

There is a visible trend in the steelmaking sector to increase investment in R&D activities to optimize production [8]. The development is observable from the scientific side, which is reflected in the available literature, where many works showing the improvement of efficiency and quality of steel production can be found [9, 10], including through the use of sensor networks [11]. These works are mainly focused on optimizing the steelmaking process by reducing carbon emissions into the atmosphere. An indirect impact is also observed in the form of a process whose optimization criterion is minimization of energy consumption. High emissions and energy consumption result from the high temperature that a given steel grade must reach during casting. Numerical simulations are often the basis for conducting such research, which allow for non-invasive testing of the possibilities of improving the available technology [12, 13]. A situation that should be avoided at all costs in the steel production process is a drop in temperature below the casting temperature, as this will require transport of the ML for re-heating. This can be a logistically difficult task, which is why monitoring is essential.

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

Monitoring in the industrial sector is not a new phenomenon. This is an important element in Industry 4.0, as it also allows you to control the correct operation of support systems. One of the tasks in this paper is tracking ML. Since the appearance of the ML is almost identical for all these types of vats, this task can be treated as an Object Detection. In the industrial field, there are applications of machine learning algorithms for this class of problem [14], in particular the recognition of various workpieces on the production hall [15]. Machine learning models were used in the work, in particular convolutional networks, e.g. YOLO (You Only Look Once) and residual networks, e.g. Resnet. Their application in industrial conditions can also take place in tracking the movement of objects or detecting their absence or presence [16].

3 Proposed methodology and architecture

The main idea of solving the described problem was to create an IT system that implements two main functionalities:

- supporting the control of the technological process by the metamodeling component, which allows detecting potentially unfavorable situations (e.g. superheating or crystallization of the melt) and enabling the avoidance of such situations
- monitoring the state of the technological process by technologists and technical staff using mobile devices

In order to implement such a system, it was necessary to develop a component for integrating the sensory layer, which would enable the aggregation of data from all sensory systems available within the infrastructure of the steelworks plant hall. Such data would then be delivered to the component responsible for supporting the steering and monitoring of this technological process (based on machine learning mechanisms). The diagram of the main components of this system is presented in Fig. 1.

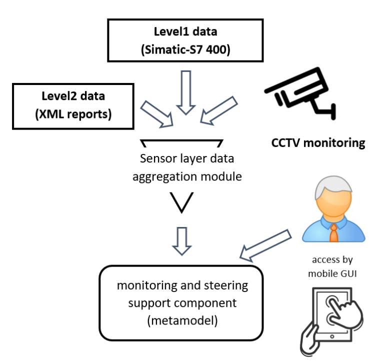


Fig. 1: Scheme of integration of the main components of the system

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

The details of the implementation of the main components of this system are presented below.

3.1 Sensors layer

In order to implement the main functionality – supporting the control of the technological process based on the process metamodeling component – it was necessary to provide this component with the correct data necessary for its operation. For this purpose, a sensor layer data aggregation component was developed that integrates the three main sensor sources (Level1, Level2, CCTV) and unifies the data available in them, which then makes it available to the process steering component.

The requirement of the metamodeling component is to provide this data on an ongoing basis and in a coherent, unified form. The same data provided by the sensory data aggregation component is also used to implement the second basic functionality of the entire system - enabling monitoring of the process status of the steelworks hall using a mobile application for service personnel.

A component that aggregates data from the base sensor systems available at the electrosteel shop in the following way:

Level1 integration – this hardware-level system provides data on individual devices involved in the technological process (EAF, LF, CSC). Integration with this system was carried out based on the connection with the Siemens Simatic-S7 400 controller programmed with the use of the Sharp7 library which is the C# port of Snap7 library. The data is delivered in real time and read and saved in the database with the time interval set in the configuration. Among the data obtained from this source are (among others): the current temperatures of the ML armor and the bottom of the tundish, the values of the last measurements of the liquid metal temperature, the current duration of the charge processing in the EAF or at the LF, the amount of energy consumed at individual processing stations.

Level2 integration the mechanism of integration with the Level2 system is based on report documents generated by this system in the XML format, made available via a network drive after the completion of subsequent stages of processing in the technological process (at the EAF, LF and CSC). XML documents are automatically detected using FileWatcher, xsd and standard C# libraries used to parse XML documents. Data from parsed reports are placed in the system database in separate tables for each of the monitored devices. The data obtained by these mechanisms relate to the process stages carried out in the EAF (e.g. charge melting time, melting process efficiency, amount of energy and oxygen used, charge weight), LF (e.g. argon mixing parameters, energy consumption in the station, current chemical composition alloy), CSC (e.g. casting mode, weight of steel, transport time to the station, number of cores).

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

CCTV integration – details of the operation of the ladle detection component have been described in a separate chapter of this work, while the integration of this component has been implemented through the definition and implementation of software interfaces transferring the following information from the ladle detection component to the integrating component: camera id, detected ladle number, ladle position within the scene, detection time. The entire exchange of information is carried out by the open source message broker RabbitMQ.

Data from the sensor systems described above, operating on various hardware layers of the electrosteel plant hall, have been aggregated, unified and made available in real time as a component of sensory data aggregation. The data aggregated in this way is stored in the system database and made available to component that enable the implementation of the main functionalities of the system: the process monitoring component of the steelworks hall using an application for mobile devices and the metamodeling component, enabling support for controlling the technological process carried out in the steelworks plant hall.

3.2 ML position tracking

The problem of ML position monitoring has been divided into two tasks: ML detection and identification of its label. The decision was made to use machine learning to solve them. In the first approach, only the Tesseract OCR library was used for text detection and recognition, because all MLs have numerical labels, and their occurrence elsewhere is very rare on the cameras used. Unfortunately, this solution turned out to be ineffective due to the very low accuracy of detecting areas with text - in the best cases at the level of 63%.

The second approach was based on the detection of one class of objects in the ML form. Four machine learning models were used for this purpose: Mask-RCNN, MobileNet, YOLO v3 and its tiny version. All models were trained using a total pool of 7072 images, of which approximately 2000 were modified with ImgAug. Additionally, after initial testing, 700 images were added from the hall where none of the vats were located. This was due to the single-class detection - adding images without an object resulted in an increase in detection accuracy by 8%. These data were split 80-20 for training and validation, respectively. In the case of label identification, two models were used: pretrained CRAFT (Character-Region Awareness For Text) for text detection [17] and a custom convolutional recurrnet neural network as text recognizer, consisting of 28 layers (mainly Conv2D, Maxpool, BatchNormalization, and LSTM). The latter one was trained used Synth90k set enhanced with approx. 10000 cropped labels from MLs. Output from CRAFT, which are heatmaps, is postprocessed using OpenCV in order to obtain transformed boxes with text. These boxes are then processed by recognizer.

The prepared models were used to determine the position of individual ML in the hall. After ML is detected, it is cropped from original image and this crop is sent to label detection and recognition. This approach allowed to improve text detection accuracy. However, in some cases label can be detected on original image. Therefore, we decided to execute both detection models concurrently

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

and then match boxes (ML and text) with each other using intersection. Then, ML position and its label are sent to message broker. The algorithm describing the operation of the ML tracking is shown as a flowchart in the Fig. 2.

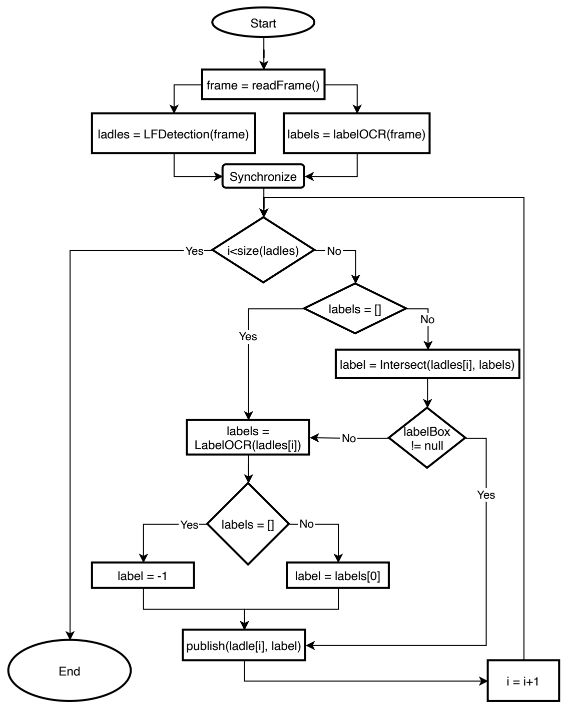


Fig. 2: ML detection and label recognition pairing algorithm

From the implementation side, the Python 3.10 with Tensorflow 2.10 was used to develop and train machine learning models. Models were built with Keras in such a way as to process image batches, e.g. text detection on multiple ML crops is possible with one inference.

3.3 Metamodeling of temperature drop

Linear regression The value predicted by linear regression model is computed using the hypothesis in the following form:

$$h_\theta(\mathbf{x}) = \boldsymbol{\theta}^T\mathbf{x} = \theta_0 + \sum_{i=1}^{n} \theta_i x_i$$

where: $\boldsymbol{\theta}$ – vector of model parameters, $\mathbf{x}$ – vector of features (input of the model with added element $x_0 = 1$), $n = 4$ – number of features

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

Model training consists in finding the optimal values of vector $\boldsymbol{\theta}$, which minimize the cost function:

$$J(\boldsymbol{\theta}) = \frac{1}{2m}\sum_{i=1}^{m}(\hat{y}_i - y_i)^2$$

where: m - number of training points, $\hat{y}_i$ - model prediction, y_i - training value.

The crucial for model accuracy is selection of the features (elements of the input vector). The selection of the four, listed above features was made after performing the analysis of importance. However, the small number of features makes model very simple and, as consequence, unable to learn complex relationship which may be hidden inside the training data. This situation is called underfitting or high bias problem. To avoid underfitting, new features should be added to the hypothesis. The new features may contain completely new data or, as more often, be a combination of data (features) already used. Within this paper, new feature were designated as higher power (up to the 4th) of already chosen inputs and all possible products between them. As the result, the number of features was increased to n=69, and each of the new ones was defined as:

$$x_i = x_1^{p_1} x_2^{p_2} x_3^{p_3} x_4^{p_4}$$

where: $i \geq 5$, $p_1, p_2, p_3, p_4 \in [0, 4]$, and $1 \leq p_1 + p_2 + p_3 + p_4 \leq 4$

On the other hand, introducing additional features into the hypothesis may cause the model to be too complex and it can learn the relationship hidden in the data by heart. This situation is called overfitting or high variance problem. It can be easily detected by comparing errors computed for training and testing (validation) sets. If the training error is low while the validation error if high, there is a high variance problem. To avoid the overfitting the regularization term was added to the optimized cost function:

$$J(\boldsymbol{\theta}) = \frac{1}{2m}\sum_{i=1}^{m}(\hat{y}_i - y_i)^2 + \frac{\lambda}{2m}\sum_{i=1}^{n}\theta_i^2$$

where: λ - regularization parameter, n - number of features.

Artificial neural network The second model was built using artificial neural networks. Artificial neural network is an information processing system built with a given number of single elements called artificial neurons which are arranged in three layers: input, hidden and output layers. Number of neurons in the input (output) layer depends on the number of input (output) values, while the number of hidden layers is defined as the result of the user experience (usually, no more than two hidden layers for the nonlinear problems). Mostly, there is one neuron in the output layer corresponding to the predicted value. In case of ANN, adding the new features is not necessary. Therefore, only four features formed the input vector. However, the network topology (i.e. number of hidden layers and number of neurons in each one) is essential for model accuracy. Unfortunately, there are

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

no rules that indicate the best number of hidden layers and neurons. Therefore, 49 neural networks were tested, each trained 50 times. Among them there were networks with one hidden layer and the number of neurons equal to: 6, 8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28, 30 and with two hidden layers and the number of neurons in each equal to : 5, 10, 15, 20, 25, 30.To compare trained models two Mean Absolute Errors (MAE) were calculated:

$$MAE = \frac{1}{m}\sum_{i=1}^{m} |\hat{y}_i - y_i|$$

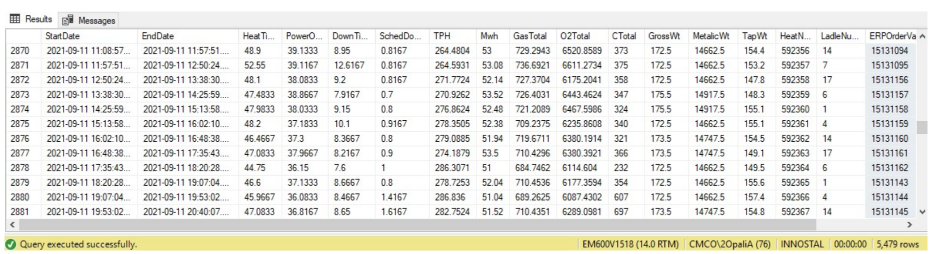
$$R^2 = \left(\frac{\sum_{i=1}^{m} (\hat{y}_i - \overline{y})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{m} (\hat{y}_i - \overline{y})^2 \sum_{i=1}^{m} (y_i - \overline{y})^2}} \right)^2$$

4 Obtained results

The environment used in this work is a server equipped with 2x Xeon Gold 6264 @ 3.10 GHz (36 physical cores in total), 768 GB RAM and NVidia Tesla M10, equipped with 4 graphics processors (4 CUDA visible devices). Only one GPU of this card was used for testing.

4.1 Sensor layer data aggregation module

One of the results of the component of data aggregation from sensory systems is the storage and sharing of information about the technological process carried out in the steelworks hall. The data relate to the implementation of this process at the main points of its processing - EAF, LF and CSC. Examples of processing data in the EAF are shown in the Fig. 3.


Results Messages

	StartDate	EndDate	HeatTi...	PowerO...	DownTi...	SchedDo...	TPH	Mwh	GasTotal	O2Total	CTotal	GrossWt	MetalicWt	TapWt	HeatN...	LadleNu...	ERPOrderVa
2870	2021-09-11 11:08:57...	2021-09-11 11:57:51....	48.9	39.1333	8.95	0.8167	264.4804	53	729.2943	6520.8589	373	172.5	14662.5	154.4	592356	14	15131094
2871	2021-09-11 11:57:51...	2021-09-11 12:50:24....	52.55	39.1167	12.6167	0.8167	264.5931	53.08	736.6921	6611.2734	375	172.5	14662.5	153.2	592357	7	15131095
2872	2021-09-11 12:50:24...	2021-09-11 13:38:30....	48.1	38.0833	9.2	0.8167	271.7724	52.14	727.3704	6175.2041	358	172.5	14662.5	147.8	592358	17	15131156
2873	2021-09-11 13:38:30...	2021-09-11 14:25:59....	47.4833	38.8667	7.9167	0.7	270.9262	53.52	726.4031	6443.4624	347	175.5	14917.5	148.3	592359	6	15131157
2874	2021-09-11 14:25:59...	2021-09-11 15:13:58....	47.9833	38.0333	9.15	0.8	276.8624	52.48	721.2089	6467.5986	324	175.5	14917.5	155.1	592360	1	15131158
2875	2021-09-11 15:13:58...	2021-09-11 16:02:10....	48.2	37.1833	10.1	0.9167	278.3505	52.38	709.2375	6235.8608	340	172.5	14662.5	155.1	592361	4	15131159
2876	2021-09-11 16:02:10...	2021-09-11 16:48:38....	46.4667	37.3	8.3667	0.8	279.0885	51.94	719.6711	6380.1914	321	173.5	14747.5	154.5	592362	14	15131160
2877	2021-09-11 16:48:38...	2021-09-11 17:35:43....	47.0833	37.9667	8.2167	0.9	274.1879	53.5	710.4296	6380.3921	366	173.5	14747.5	149.1	592363	17	15131161
2878	2021-09-11 17:35:43...	2021-09-11 18:20:28....	44.75	36.15	7.6	1	286.3071	51	684.7462	6114.604	232	172.5	14662.5	149.5	592364	6	15131162
2879	2021-09-11 18:20:28...	2021-09-11 19:07:04....	46.6	37.1333	8.6667	0.8	278.7253	52.04	710.4536	6177.3594	354	172.5	14662.5	155.6	592365	1	15131143
2880	2021-09-11 19:07:04...	2021-09-11 19:53:02....	45.9667	36.0833	8.4667	1.4167	286.836	51.04	689.2625	6087.4302	607	172.5	14662.5	157.4	592366	4	15131144
2881	2021-09-11 19:53:02...	2021-09-11 20:40:07....	47.0833	36.8167	8.65	1.6167	282.7524	51.52	710.4351	6289.0981	697	173.5	14747.5	154.8	592367	14	15131145

Query executed successfully. | EM600V1518 (14.0 RTM) | CMCO\2OpaliA (76) | INNOSTAL | 00:00:00 | 5,479 rows

Fig. 3: Integrated data from EAF station.

The numerical characteristics of the data from the 18 months of collecting data from the sensory layer are as follows:

– over 16,000 reports on melts at CSC, LF and EAF stations were collected,

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

– number of temperature measurements taken: over 33,000 at the EAF, over 94,000 at LF stations, over 81,000 at CSCs,
– over 58,000 tests of the chemical composition of steel were carried out at LF stations,
– 75 different grades of steel were made.

More detailed information is a company secret and cannot be disclosed in this publication.

4.2 Training, accuracy, and performance of LF identification

The results obtained for the indicated models are presented in the Table 1.

Table 1: Training and accuracy results of models used

Parameter	Mask R-CNN	MobileNet	YOLOv3	YOLOv3 tiny
Training time [h]	6.32	3.57	2.51	0.89
Detection time CPU [ms]	1840	1380	430	101
Detection time GPU [ms]	680	450	173	37
Accuracy (typical pos.) [%]	96	95	94	92
Accuracy (overall) [%]	88	85	82	68

Based on the obtained results, it can be seen that the accuracy of detection in typical positions of the ladle does not differ significantly - the maximum observable difference is 4%. In unusual positions, less relevant to the continuous casting process, the accuracy can vary, more depending on the specific position, less on the choice of network. However, a significant difference can be seen in the case of detection and learning times. With this criterion in mind, the YOLO network performs best, in particular its simplified version, called YOLO-tiny. The accuracy of detection slightly decreased (by approx. 13% in the general case and approx. 3% in typical cases), but the detection time decreased almost seven times (173 ms full vs 37 ms tiny). This model is therefore great for quick testing of the entire module, also on machines without GPU acceleration. Example of ML detection results from camera looking on LF is presented in Fig. 4.

Due to the high similarity of the labels on the vats, it was decided that the use of external sets would give better text detection results than the set of labels cut from ML. Final testing was performed on cut images of the ML only and achieved 89.3% prediction accuracy: 361 out of 404 images were classified correctly. We defined accuracy as percentage of cases where the network found the label on the ML at least once (some have more than one label). Obtained accuracy is very high for images without any smoke (96.5%, 250 out of 259), high for small amount of smoke (87.5%, 84 out of 96). For images where manual recognition by human eye is very hard, obtained accuracy was low (55.1%, 27 out of 49 tested images were correct). Images for final tests were captured separately and were not included in any of training sets. Results from aggregated ML detection and its identification are shown in Fig. 5.

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

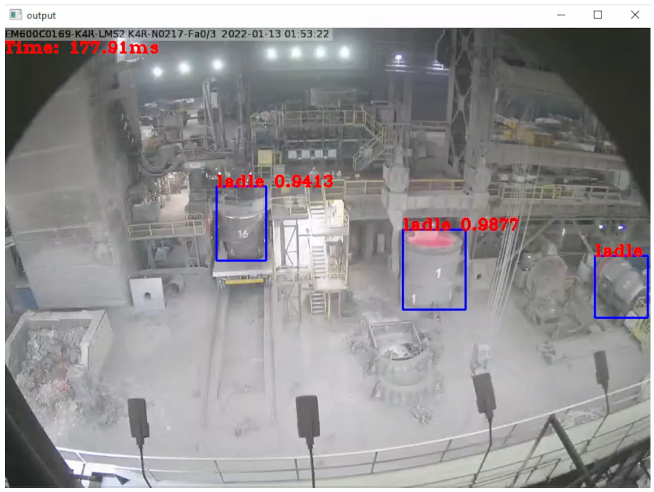
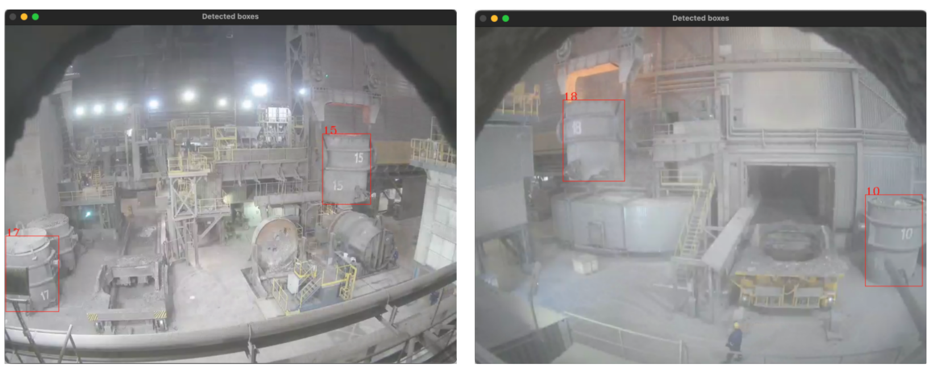


Fig. 4: ML object detection results



(a) ML detection on LF

(b) ML detection near EAF station

Fig. 5: ML Label detection results

4.3 Metamodeling

The smallest mean absolute error (MAE), equal 0.109, was obtained for a network with two hidden layers containing 5 and 25 neurons, respectively. The value of the coefficient of determination R2 for this network was equal to 0.764, and the training time was 7.7 s. Comparison models based of LR and ANN (Table 2) showed that neural networks allows to get more precise results.

5 Summary and further works

The aim of the work was to create a multilevel system to monitor the steelworks production hall. Two modules were created to monitor the condition of the ML

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

Table 2: Assessment of models' prediction to the real values

Model	MAE	R^2
Linear regression	0.12	0.70
Artificial neural network	0.109	0.715

and the production hall, which, combined with the metamodeling module, make it possible to determine whether casting of the material is possible due to the temperature drop after leaving the EAF. The system was tested in CMC Sp. z o.o. in Zawiercie (Poland) and allows for an assessment of whether the steel can be cast after the specified time has elapsed, which may vary between each cast. The ladle monitoring module made it possible to determine the location of each ML in use, which, combined with the sensors, allowed for a precise determination of the status of each of the orders carried out by the steelworks.

At the moment, it is not used in production yet because the other components are being implemented. Among others, these include scheduling steelmaking campaigns, user interface, or aggregation with other systems in the company. The modules described in the thesis will be improved in terms of code quality, performance, and prediction accuracy, if the data collected before implementation allow it.

References

1. R. H. Myers, D. C. Montgomery, and C. M. Anderson-Cook, *Response surface methodology: process and product optimization using designed experiments.* John Wiley & Sons, 2016.
2. J. Sacks, W. J. Welch, T. J. Mitchell, and H. P. Wynn, "Design and analysis of computer experiments," *Statistical science*, vol. 4, no. 4, pp. 409–423, 1989.
3. M. Krzywda, S. Łukasik, and A. H. Gandomi, "Graph neural networks in computer vision - architectures, datasets and common approaches," in *2022 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–10, 2022.
4. U. S. Shanthamallu and A. Spanias, *Neural Networks and Deep Learning*, pp. 43–57. Cham: Springer International Publishing, 2022.
5. A. B. Jung, K. Wada, J. Crall, S. Tanaka, J. Graving, C. Reinders, S. Yadav, J. Banerjee, G. Vecsei, A. Kraft, Z. Rui, J. Borovec, C. Vallentin, S. Zhydenko, K. Pfeiffer, B. Cook, I. Fernández, F.-M. De Rainville, C.-H. Weng, A. Ayala-Acevedo, R. Meudec, M. Laporte, *et al.*, "imgaug." https://github.com/aleju/imgaug, 2020. Online; accessed 25-Jan-2023.
6. S. Haykin, *Neural Networks: A Comprehensive Foundation.* USA: Prentice Hall PTR, 2nd ed., 1998.
7. A. V. Joshi, *Machine Learning and Artificial Intelligence.* Springer International Publishing, 2020.
8. B. Gajdzik and R. Wolniak, "Framework for r&d&i activities in the steel industry in popularizing the idea of industry 4.0," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 8, no. 3, p. 133, 2022.
9. Y. Graupner, C. Weckenborg, and T. S. Spengler, "Designing the technological transformation toward sustainable steelmaking: A framework to provide decision

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36

support to industrial practitioners," *Procedia CIRP*, vol. 105, pp. 706–711, 2022. The 29th CIRP Conference on Life Cycle Engineering, April 4 – 6, 2022, Leuven, Belgium.

10. Z. Xu, Z. Zheng, and X. Gao, "Energy-efficient steelmaking-continuous casting scheduling problem with temperature constraints and its solution using a multi-objective hybrid genetic algorithm with local search," *Applied Soft Computing*, vol. 95, p. 106554, 2020.
11. C.-J. Zhang, Y.-C. Zhang, and Y. Han, "Industrial cyber-physical system driven intelligent prediction model for converter end carbon content in steelmaking plants," *Journal of Industrial Information Integration*, vol. 28, p. 100356, 2022.
12. P. V. de Cassia Lima Pimenta, J. R. de Sousa Rocha, and F. Marcondes, "Thermomechanical investigation of the continuous casting of ingots using the element-based finite-volume method," *European Journal of Mechanics - A/Solids*, vol. 96, p. 104724, 2022.
13. Z.-s. Yang, L.-z. Yang, Y.-f. Guo, G.-s. Wei, and T. Cheng, "Simulation of velocity field of molten steel in electric arc furnace steelmaking," in *9th International Symposium on High-Temperature Metallurgical Processing* (J.-Y. Hwang, T. Jiang, M. W. Kennedy, D. Gregurek, S. Wang, B. Zhao, O. Yücel, E. Keskinkilic, J. P. Downey, Z. Peng, and R. Padilla, eds.), (Cham), pp. 69–79, Springer International Publishing, 2018.
14. A. D. O. Riordan, D. Toal, T. Newe, and G. Dooly, "Object recognition within smart manufacturing," *Procedia Manufacturing*, vol. 38, pp. 408–414, 2019. 29th International Conference on Flexible Automation and Intelligent Manufacturing (FAIM 2019), June 24-28, 2019, Limerick, Ireland, Beyond Industry 4.0: Industrial Advances, Engineering Education and Intelligent Manufacturing.
15. L. Malburg, M.-P. Rieder, R. Seiger, P. Klein, and R. Bergmann, "Object detection for smart factory processes by machine learning," *Procedia Computer Science*, vol. 184, pp. 581–588, 2021. The 12th International Conference on Ambient Systems, Networks and Technologies (ANT) / The 4th International Conference on Emerging Data and Industry 4.0 (EDI40) / Affiliated Workshops.
16. R. Ward, P. Soulatiantork, S. Finneran, R. Hughes, and A. Tiwari, "Real-time vision-based multiple object tracking of a production process: Industrial digital twin case study," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 235, no. 11, pp. 1861–1872, 2021.
17. Y. Baek, B. Lee, D. Han, S. Yun, and H. Lee, "Character region awareness for text detection," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 9365–9374, 2019.

ICCS Camera Ready Version 2023
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-36030-5_36