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Machine Learning models to forecast defects occurrence on foundry products

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Abstract: Manufacturing defects negatively affect production cost and environmental impact. This impact is even heavier for production processes that are particularly energy intensive, such as in the metallurgical industry. In the cast iron foundry sector, components manufacturing can be affected by various defects that depend on quality of raw materials fed to the melting process, process parameters, cast iron final temperature, ferroalloys additions and final composition. Defects formation is a multifactorial phenomenon, for which relevant factors are not easy to identify, as it is also a rare event. This paper presents a set of models based on machine learning methodologies for predicting and classifying defects on foundry production lines to assist process operators in managing the process and, eventually, stop production when it is not possible to adjust process parameters. The modelling phase exploits decision trees methodologies enhanced with algorithms for augmenting unbalanced datasets related to defects occurrences. The combination of these methodologies produces efficient models showing very encouraging results.

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Keywords: Machine Learning, ML, cast iron foundry, manufacturing defects prediction, anomalies, decision tree, unbalanced datasets, data augmentation.

1. INTRODUCTION

Maintaining a high-quality final product while ensuring compliance with increasingly stringent environmental constraints and cost sustainability is one of the most relevant current challenges for the process and manufacturing industry. The role of foundries is crucial: they are the main source of castings and produce indispensable components for other industries. The presence of defects in final products has a negative impact on a foundry's profits. Production defects often result in reworking costs, additional energy consumption, or casting waste generation. Defects can also be discovered at later stages, such as machining, assembly or, even worse, during product use, with increased risks or rejection and complaints from customers and costs for foundries (Pribulová, Bartošová and Baricová, 2013).

In the past decades, several works were conducted to prevent defect generation. Defect identification, characterization and classification were explored in different papers. Sütőová and Grzinčič take an in-depth look at the casting defect classification and cataloguing system, a fundamental tool in the organization of a foundry. The authors propose an example of a catalogue, which classifies and describes the defects in an aluminum foundry and its advantages in supporting production and quality control operators. (Sütőová and Grzinčič, 2013) Juriani provides a detailed overview of critical casting defects and their causes, also focusing on technically feasible remedies to minimize various casting defects and improve casting quality (Juriani, 2015). The topic of defect identification and classification is explored also using Artificial Intelligence (AI) methodologies as reported in the work of Pastor-López et al., who propose a technique for the detection of surface defects by applying a segmentation method that flags potentially defective regions on the casting and then applies the machine learning (ML) technique BCLP (Best Crossing Line Profile) to classify the regions into correct or different types of defects (Pastor-López et al., 2015).

Defect detection in foundry and steel production routes is often performed through image-based inspection and automated methodologies (Riaz et al., 2017), effective only during the manufacturing process (Vannocci et al., 2019, Brandenburger J). However, this approach can only identify the defects on already manufactured pieces and cannot prevent their occurrence. Examples of this approach are reported in several works, where Deep Learning is exploited (Filip Nikolić, Štajduhar and Marko Čanađija, 2022). To detect surface casting defects from labelled images from a foundry, Pastor-López et al. applied a new methodology, called BoDoC, developed to optimise the performance of machine learning algorithms using computer vision when a small training dataset is available (Pastor-López et al., 2021).

Another field of analysis is preventing the defect generation through forecasting techniques, as studied by BramahHazela et al., who applied a ML classifier and regression method and compare several techniques to identify the micro shrinkage and ultimate tensile strength (BramahHazela et al., 2022). Models based on supervised machine learning classification are applied by Uyan et al. to find the operating conditions that affect the defects in low-pressure die casting aluminum products (Uyan et al., 2023).

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Another interesting work focusing on preventing the defect occurrence exploits a Bayesian inference approach for determining the safe range of process parameters (Sata and Ravi, 2016).

In conclusion, avoiding the production of defective or parts not meeting customer requirements is mandatory: it saves the energy required to produce the same product several times, avoids the generation of waste and increases the productivity of the plant (Colla, 2022). AI techniques can help achieving this objective by guiding and supporting industries in the transformations needed for more sustainable and competitive production processes (Colla et al. 2020). However, AI techniques often need massive datasets for the learning process and their accuracy is strictly dependent on the amount of data. Production defects are often a rare event, leading to very unbalanced data distribution between nominal and defect classes target of the classification task. In this sense, several works propose data augmentation techniques (Cateni, Colla and Vannucci, 2014) for overcoming overfitting problems in classification (Vannucci and Colla, 2016) and regression tasks.

In this context, this work proposes a set of models for predicting in advance the occurrence of defects on foundry production, by considering chemical and thermal analyses of the cast iron before the molding process and the inoculant control strategy through AI models based on decision tree. In this work, the classification accuracy, and the generalization capability of the models in presence of very rare defect events are guaranteed through some state-of-the-art data augmentation methodologies. In particular, the models focus on two specific cast iron qualities, and in two different defects: the micro shrinkages and cementite formation. The proposed work has been carried out within the Alchimia project, which is funded by the European Union through the Horizon Europe framework.

The paper is organized as follows: Sec. 2 describes the Alchimia project; Sec. 3 describes the plant and process involved; Sec. 4 presents the design phase of the machine learning models; Sec. 5 presents the results of the modelling phase and finally Sec. 6 draws some conclusions.

2. THE ALCHIMIA PROJECT

The European project "Alchimia - Data and decentralized Artificial intelligence for a competitive and green European metallurgy industry" aims at finding the optimal input material mix to reduce the environmental footprint of the complete value chain of steelmaking and metallurgical processes.
The project is organized in two practical case studies. The first one regards an important European steel company contributing to the project with three industrial plants. The second one is related to Fonderia di Torbole (FdT), one of the leading foundries in the production of automotive components located in Italy. The present work focuses on this second case study.

The methodology is based on the development of a platform based on Federated Learning (FL) approach (Li et al., 2020) and Continual Learning (CL) (Hadsell et al., 2020) according to a human-centric design. This platform will act as a Decision Support System (DSS) supporting plant managers and process operators in decision-making for optimal material and energy management. The main components of such DSS are the models that reproduce the core part of the considered production processes.

The ambition of the project lies in the application of FL and CL: the models developed for each plant are trained in a decentralized way, avoiding the creation of centralized datasets, but each plant contributes to an optimized global model. The CL mechanism allows continuous improvement of ML model accuracy, ensuring the long-term adaptivity and upgrading of systems. Further Alchimia ambitions are:

- the "human factor" analysis of new digital technology insertion within industrial processes;
- the replicability, scalability, and transferability of developed tools for different industrial sectors.

3. PLANT AND PROCESS DESCRIPTION

FdT is a component producer for the automotive sector: it produces and sells brake discs and drums, castings, and machined parts. The FdT foundry plant schematic is shown in Fig. 1.

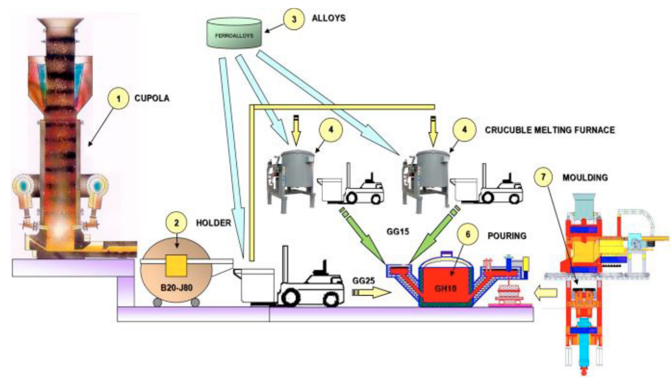


Fig. 1. FdT foundry plant schematic.

The input material mix is mainly composed by pig iron, return, steel scrap and coke. It is melted in the cupola furnace (Unit 1) and after the melting stage it is transferred into two induction furnaces named holders (Unit 2). Then the material is divided into paths: the majority goes to the pouring system (Unit 6) and feeds the moulding process (Unit 7); the remaining is devoted to production with higher requirements, therefore adjustment of the material chemistry is needed between holders' outlet and pouring inlet and it occurs in two tandem crucible melting furnaces (Unit 4). Usually, the complete cooling of the products requires an average time of three hours and only at this time is possible to perform the final quality tests. When faster testing procedures are required (e.g., to provide feedback for process parameter settings and adjustments), one-hour accelerated cooling can be implemented for a single mould, which takes about 1 hour.

The overall goal of the research work is to forecast the final products characteristics, and to avoid producing parts that do not meet customer's requirements and losing time (typically at least 3 h) before adjusting process parameters, by saving energy, raw materials and labor. The application of ML-based models can help achieving this objective by assisting in process monitoring and prediction of product quality parameters using cast iron analysis as input data. In particular, the available input dataset is composed by thermal and chemical analysis performed in two different positions, casting temperature and inoculant additions. The analysis points are selected according to product type and their correlation to product quality. The output dataset regards the quality test parameters and presence of defects (cementite and porosity). In the present work data related to two different types of cast iron were used: high-carbon cast iron (GG15HC) and standard cast iron (GG25). For GG15HC thermal and chemical analyses are performed at points 4 and 6 and for GG25 at points 2 and 6 (Fig. 1).

4. METHODS

4.1 Decision Trees

Decision Tree (DT) is a powerful tool in data analysis and ML, offering intuitive representations of decision-making processes, as they are structured as decision graphs that sequentially solve a list of tests, comparing numerical values with a set of threshold values. DTs are applied in various fields for different tasks. Classification and regression analysis (Pathak, Mishra and Swetapadma, 2018) are the most common applications, but they are also widely exploited for feature selection (Rao et al., 2019), anomaly detection (Barbariol et al., 2021), and cyber-attacks detection (Alqahtani et al., 2020).

Interpretability is the main strength of the DT, as the decision mechanisms and related results are widely understandable by human operators. Additionally, DT can solve nonlinear modelling problems and are easy to implement. They are particularly suitable for Programmable Logic Controllers (PLCs) and embedded systems and are used in real-time in edge-computing applications. On the other hand, DT are sensitive to noise and outliers, and are prone to overfitting in the training phase, thus they must be carefully tested.

This paper focused on developing interpretable and real-time models that can benefit a FL approach in the training phase. These models will be implemented within a DSS helping process operators in the decision-making process to minimize raw materials and energy consumption and waste generation by predicting production defects. To this aim, all the models presented are based on DT Classifiers (DTC), designed through SkLearn library in Python environment.

4.2 Data oversampling

Data quantity and quality play pivotal roles in the performance of ML methodologies, especially in the case of unbalanced datasets, where some classes (for classification tasks) or operation points (for regression tasks) are numerically not well represented in the dataset. Supervised learning using unbalanced dataset often leads to bias and poor generalization capabilities, resulting in learning only the majority class instead of generalizing the data information content. In the last 20 years, several methodologies were developed for data oversampling to mitigate the mentioned issues and enhance model accuracy and reliability, through algorithms that augment the data of the minority classes.

The Random OverSampling Examples (ROSE) algorithm (Menardi and Torelli, 2012) and Synthetic Minority Oversampling Technique (SMOTE) algorithm (Chawla et al., 2002) and its variations (e.g. ADASYN) are probably the most known among data augmentation techniques, due to the simplicity of the algorithm and their effectiveness. ROSE generates artificial data for the classes, exploiting a smoothed bootstrap approach, and undersampling for the majority classes. SMOTE creates synthetic data through interpolation for the minority classes, minimizing the risk of overfitting. Interesting works that use respectively ROSE and SMOTE algorithms are presented by Zhang and Chen (2019) and by Sridhar and Sanagavarapu (2021).

This work exploits both ROSE and SMOTE algorithms for augmenting the datasets of production including samples of both nominal and defects, to balance the dataset and avoid modelling overfitting. The **imbalance-learn** library in Python environment is used for this purpose.

5. DATASETS AND MODELS DESIGN

The modelling phase focuses on identifying defects in the production of subclasses of product based on two different cast-iron qualities (GG25 and GG15HC) characterized by different chemical and mechanical characteristics. Such qualities show a different sensitivity to two main problems: cementite formation and micro-shrinks. The final mechanical properties of the products depend on cast iron chemical composition and on the presence of these defects.

The quality measurements are generally performed even several hours after casting, thus, defects detection does not enable timely intervention on the process, leading to potential production of a significant amount of scrap if the final quality does not meet the target one and connected waste of energy and other resources. In this context, the models focus on predicting cementite and micro-shrinks to anticipate production stop or to suitably adjust the process.

The data acquisition campaign focused on identifying the most correlated measurements with the defects forecasting. For GG25 and GG15HC the data collection resulted in two different datasets that are characterized by the same measurement points: (i) the chemical and thermal analysis of cast iron at the refinement furnace (Unit 6, Fig. 1), the casting temperature and the inoculant quantity; (ii) the quality measurements of the final products in terms of cementite measurements and micro-shrinks assessed via X-ray. More in details, the chemical analysis includes the percentual content of carbon, silicon, manganese, phosphorus, sulfur, chromium, copper, molybdenum, tin, titanium, aluminum, lead, tungsten, nickel, vanadium and niobium. The thermal analysis focus on the cooling curve of the sample, including also the characteristics of the first derivative of the curve. In particular, the main features extracted from the curves are the liquidus temperature, the eutectic temperatures (minimum, maximum and of the transformation), solidus temperature, and the recalescence (the difference between the maximum and minimum eutectic temperature). For each feature but recalescence, also the related cooling time are used. From the first derivative curve are extracted the index of the efficiency of the precipitation of eutectic austenite, and the speed of transition from semi-solid to fully solid state.

The raw datasets collected for the GG25 cast-iron quality is composed of 534 real samples, referring to a short period of production of specific target products. The dataset is composed of 3 different quality classes: (i) "nominal", i.e. products meeting quality targets; (ii) products with micro-shrinks; (iii) products with cementite defects. The dataset is highly unbalanced, as the number of defects is low. The classes are shown in Table 1. The number of samples and percentage over the total number of samples are given for each class. Finally, the problem is defined as a binary classifier for each defect and not as a single multi-class classifier because the two defects of cementite and micro-shrinkage are not self-excluding, i.e.: the two defects may in principle occur simultaneously.

Table 1. Dataset for the cast-iron GG25

Final product quality	Number of occurrences	Percentage
Nominal	521	97.57 %
Micro-shrink defects	3	0.57 %
Cementite defects	10	1.87 %

Model 1 focuses on predicting the presence of micro-shrink defects for products in cast-iron GG25. The model classifies each sample k of the input data $\boldsymbol{I}_{\mathrm{GG25_{xray}}}$ in two classes:

$$c_{\boldsymbol{I}_{\mathrm{GG25_{xray}}}}(k) \in \{\mathrm{nominal} = 0, \quad \mathrm{defect} = 1\}$$

The dataset for training such model is extremely unbalanced, as only 3 samples are available, that are insufficient to train a reliable model. Therefore, the ROSE algorithm with smoothed bootstrap was used to synthetically augment the defects dataset, resulting in 523 examples for each class (normal / defect). A DTC model was trained with the augmented dataset. The maximum depth of the tree is selected through grid search for maximizing the generalization of the model.

Model 2 focuses on predicting the presence of cementite defect for products in cast-iron GG25. The model classifies each sample k of the input data $\boldsymbol{I}_{\mathrm{GG25_{cem}}}$ in two classes:

$$c_{\boldsymbol{I}_{\mathrm{GG25_{cem}}}}(k) \in \{\mathrm{nominal} = 0, \quad \mathrm{defect} = 1\}$$

The dataset for training such model is very unbalanced, as only 10 samples are available for the defect class, that are insufficient to train a reliable model. Also in this case, ROSE was used to augment the defect dataset, by obtaining 416 examples for the defective class and 409 for the nominal one. A DTC model was trained with the augmented dataset and then tested with real test data. The maximum depth of the tree is selected through grid search for maximizing the generalization of the model.

The raw datasets collected for the GG15HC cast-iron quality is composed of the same measurement point of the GG25. In this specific case, the number of samples is 409, referring to a short period of production of specific target products. Also this dataset is composed of the 3 previously listed classes, that are shown in Table 2. Also in this case the dataset is highly unbalanced as expected. In particular, for this specific cast-iron quality the number of samples showing micro-shrink defects are sufficient, while cementite was not detected.

Table 2. Dataset for the cast-iron GG15HC

Final product quality	Number of occurrences	Percentage
Nominal	375	91.69 %
Micro-shrink defects	34	8.31 %
Cementite defects	0	0 %

For this specific cast iron quality, a model (**Model 3)** has been designed for predicting the micro-shrink defects on the X-ray measurements. The model classifies each sample k of the input data $\boldsymbol{I}_{\mathrm{GG15HC_{xray}}}$ in two classes:

$$c_{\boldsymbol{I}_{\mathrm{GG15HC_{xray}}}}(k) \in \{\mathrm{nominal} = 0, \quad \mathrm{defect} = 1\}$$

To overcome the issue of unbalanced dataset, SMOTE was used to augment the dataset related to the minority class. SMOTE generates synthetic samples for the minority class, resulting in 365 synthetic sample for the defective class over 730 samples. The DTC was trained on the augmented dataset.

6. RESULTS

As stated above, for each specific model, the training procedure starts with the dataset augmentation. Each model was trained by exploiting the augmented dataset and then tested by exploiting the test datasets. In this section, the testing results are described, by reporting the standard performance indices calculated for classification tasks: (i) precision, (ii) recall, (iii) accuracy and (iv) F1 score, computed as follows:

$$\mathrm{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\mathrm{Precision} = \frac{TP}{TP + FP} \quad (2)$$

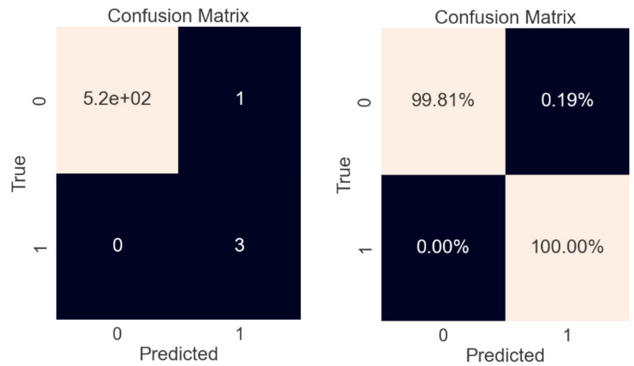
$$\mathrm{Recall} = \frac{TP}{TP + FN} \quad (3)$$

$$\mathrm{F1} = \frac{2\,TP}{2\,TP + FP + FN} \quad (4)$$

where FN and TN are, False and True Negatives, FP and TP are False and True Positives. The classification results evaluated in the test dataset are reported in Table 3. The confusion matrices, evaluated for the test dataset, for each model are shown, respectively, in Fig. 2, 3 and 4. In particular, left figures show the confusion matrix reporting the results in absolute terms (the number of samples classified in the specific class), while right figures show the percentage results.

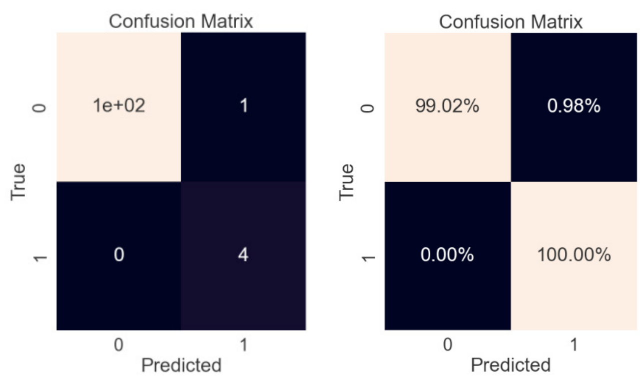
Table 3. Model performances on test dataset

Model	Accuracy	Precision	Recall	F1 Score
1	0.998	0.875	0.999	0.928
2	0.991	0.9	0.995	0.942
3	1.0	1.0	1.0	1.0



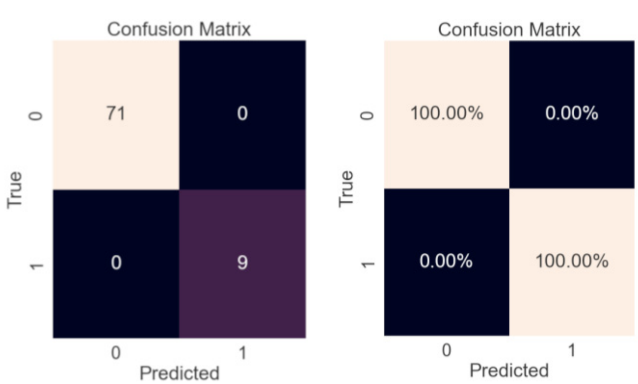
(a) **(b)**

Fig. 2. Confusion matrix for model 1, test results in absolute values (a) and percentual with respect its class (b).



(a) **(b)**

Fig. 3. Confusion matrix for model 2, test results in absolute values (a) and percentual with respect its class (b).



(a) **(b)**

Fig. 4. Confusion matrix for model 3, test results in absolute values (a) and percentual with respect its class (b).

To sum up, **Model 1** is a DTC trained to forecast the presence of micro-shrink defects for GG25 cast iron quality. Data augmentation technique based on ROSE algorithm allowed to artificially augment the defects samples. The final depth of the tree, selected through grid search, was 10. The testing results on dataset composed of real data are very promising. **Model 2** is a DTC trained to forecast cementite presence in the final product for the GG25 cast iron quality. Also in this case, the ROSE algorithm allowed efficient augmentation of the dataset for the defective class. The final depth of the tree, selected through grid search, was 15. The DTC model trained with the augmented dataset was tested on real test data, showing very promising results.

Model 3, forecasts the presence of micro-shrink defects on GG15HC cast iron quality-based products, was trained on a dataset augmented via SMOTE, and was tested on real data of the test dataset, with promising results. The final depth of the decision tree, selected through grid search, was 12. In particular, this model shows a perfect classification performance.

7. CONCLUSIONS

The paper presents a set of models forecasting defects formation in a foundry production line, focusing on micro-shrink and cementite defects for two specific cast iron qualities. The models, designed through dataset augmentation techniques (ROSE and SMOTE) and DTC, allows forecasting defects occurrence starting from early measurements of the process in terms of chemical and thermal analysis of the molten cast iron. The models are designed to be used within a DSS supporting process operators in decision-making process allowing anticipation of the suitable countermeasures and process control actions or of production interruption to avoid further waste of raw materials, energy and resources.

Although the original industrial datasets were rather unbalanced, as few samples belong to the defective classes, the results on the test datasets are rather encouraging. Such results demonstrate that a reliable forecasting of defects occurrence is possible starting from the main process data. Further tests are planned to increase the datasets for both training and testing, to verify the models on numerically more significant datasets. Since the augmentation of the dataset introduces synthetic data, the reliability of the models should be further assessed through additional data of defective products. Additional tests will be performed in the future exploiting data gathered in an additional acquisition campaign to make the analysis more robust and enhance the generalization ability of the models.

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