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Review of Data-driven Decision Support Systems and Methodologies for the Diagnosis of Casting Defects

A. Burzyńska
University of Warmia and Mazury in Olsztyn, Poland
Corresponding author: e-mail address: burzynskaalice@gmail.com

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Abstract

The concept of 'Industry 4.0' has introduced great dynamism into production environments, making them more integrated, connected and capable of generating large volumes of data. The digital transformation of traditional companies into innovative smart factories is made possible by the potential of Artificial Intelligence (AI), which is able to perform predictive analytics inspired by the development of Industrial Internet of Things (IoT) technologies or to support highly complex decision-making, in the era of zero-defect manufacturing. The need for innovative techniques and automated decision-making in diagnosing the causes of casting defects is increasing due to the growing complexity and higher level of automation of industrial systems. Particularly important are fully data-driven predictive approaches that enable the discovery of hidden factors influencing defects in castings and the prediction of the specific time of occurrence by analyzing historical or real-time measurement data. In this context, the main objective of this article is to provide a systematic overview of data-driven decision support systems that have been developed to diagnose the causes of casting defects. In addition, different methods for predicting casting defects are presented. Finally, current research trends and expectations for future challenges in the field are highlighted. It is hoped that this review will serve as a reference source for researchers working in the field of innovative casting defect prediction and cause diagnosis.

Keywords: Casting defects, Quality 4.0., Digital transformation, Zero defects manufacturing, Smart manufacturing systems

1. Introduction

Data-driven intelligent systems can generally split into three types: rule-based (RBS), case-based (CBS) or a hybrid reasoning as combination of both above-mentioned systems. The first type was developed by researches of artificial intelligence and meant mainly expert systems based on the if-then rule applied to derive a solution of the problem [1]. The second one offers the possibility to extract information about incidents that have occurred by treating the incident and its resolution as a specific case [2]. A strategic concept of data-driven management can be applied in every field of manufacturing to make decisions on the basis of advanced analysis and interpretation of the production data. According to the foundations of the Fourth Industrial Revolution (Industry 4.0. or 4IR [3][4][5]) we can say that production data is the most valuable raw material in manufacturing companies. The main goal is to extract from the acquired process data, the information, knowledge, and wisdom (DIKW)[6]. All three types of data-driven intelligent systems can be a part of another type, which is Artificial Intelligence-based systems [5].

Artificial intelligence (AI) is one of the leading technologies of the Smart Factory, which is one of the main tenets of the Industry 4.0 concept [5]. AI provides an opportunity to construct automated, fully autonomous systems and machines capable of making real-time decisions in accordance with the changing needs of manufacturing companies. Creating effective models of this type of system presents some difficulties, due to the dynamics of the production environment and the variability of production problems. Nevertheless, the technological advances allow researchers to create and use artificial intelligence methods to solve complex problems in various fields including the manufacturing sector [7], [8], [9], [10], [11], [12], [13]. This is also the case in one of the most popular manufacturing processes which is metallurgy sector, more specifically in metal casting processes, to diagnose the causes of casting defects. Acting on the definition of the term "Quality 4.0." [14],[15], which refers to the identification of the relationship between the production of quality products through its management and the 4IR concept. Nowadays, companies are aiming to digitize quality management processes in general through the application of AI techniques and including machine learning (ML) methods [16].

The prognostic of defect creation and diagnosing of its causes become more important for the manufacturing industry. This is related to the constant need to improve the competitiveness of enterprises including foundries. It seeks to constantly increase production efficiency while maintaining the quality of manufactured products while reducing operating costs. Considering this fact, the number of defects created significantly reduces production efficiency and quality results and, consequently, increases operating costs [17]. For example, proper defect diagnostics (in a medium-sized foundry) to identify and reduce 1% of defects can yield a few million in savings per year [18]. It should also be borne in mind that the costs of finishing processes and quality control compared to the costs of production and, more precisely, the casting process are comparable. Therefore, proper defect diagnostics can help save about 50% of total production costs [19]. However, achieving this is a significant difficulty, as manufacturing processes and in particular casting processes are considered to be very expensive, the most complex and complicated process, described in detail in [20].

Data from the casting process can be an important input for producing defect-free castings. They can be used as input data for machine learning techniques to detect various types of production errors. ML in this case allows advanced interpretation of casting processes referred to as a 'black box', which, by their complex nature, are not algorithmized and can only be analyzed in terms of inputs and outputs, with no known characteristics or comprehensive knowledge of what is happening inside them [21].

Given these facts, it can be concluded that the diagnosis of product defects and their causes is an important issue of great interest to scientists, technologists and experts of manufacturing companies. Over the past two decades, numerous attempts have been made to apply rule-based and case-based data-driven intelligent systems to determine the cause of deterioration in the quality of manufactured castings. The techniques tested by the researchers have shown varying results and have been characterized by variability in their performance. Therefore, it was noted the need to provide a complex overview of data-driven decision support systems and methodologies for diagnosing the causes of casting defects according to the presented research chain in order to present the direction of development of the studied problem for future researchers The most recent work on this topic will be discussed in the following chapters.

2. Overview of Casting Defects

Defects in castings are an important element in the quality performance of foundries. The issue of the quality of cast products is directly related to the correctness of the shapes and dimensions obtained, including the correct mass properties, the mould preparation processes, the preparation of the liquid metal and the pouring process. The technology for the creation of castings is complex, depending on many uncontrollable factors, at various stages of production. Each casting must have the required quality defined in the technical conditions for its acceptance, which at the same time constitute the basis for deeming a given casting defective [22]. Consequently, the objective is to detect them at an early stage through the implementation of differentiated quality tests [23]. Methodologies for improving the quality of manufactured castings include determining the type of defect, identifying its causes and correcting the set process parameters [22]. A comprehensive understanding of the factors influencing the occurrence of certain defects in castings is crucial for the optimization of casting processes [24].

Defects in castings are classified according to international and national standards. Any deviation of dimensions, shape, weight, external appearance, breach of material continuity, structure or mechanical or physico-chemical properties from the applicable requirements according to the standard are called defects. Defects are classified according to where they occur, into shape defects (on the external surface of the casting), raw surface defects, discontinuities and internal defects. In this order, casting quality is controlled by non-destructive and destructive testing, but mainly during machining [22]. Common inspection procedures are often limited to visual and dimensional inspections, weight and hardness testing. However, for castings used in critical applications such as aerospace or automotive components, additional methods of nondestructive inspections are used like radiographic, eddy current, magnetic particle or liquid penetrant inspections (described in detail in [25]).

A well-known defect is porosity, which is a serious problem observed in foundries, especially in die casting processes [26], [27]. Porosity is the formation of holes, air pockets, depressions or pores on the surface or inside of cast parts [28]. Their presence compromises the structural integrity of the casting and can cause corrosion or leakage. Such defects are unacceptable for critical high-strength parts [28]. The reasons for the formation of porosity can be various, most commonly as a result of the release of gases from the metal during solidification, or from the moulding compound [22]. There can also be a high occurrence of bubble breakage of aspirated air by the turbulent flow of metal and thus by the injection speed of the metal into the mould [29], most frequently in high-pressure castings. It should be mentioned that hydrogen is the most common source of porosity in aluminum alloys of all gases, as its solubility in liquid aluminum decreases with temperature [30], [31], [32]. All types of porosity can form in alloys depending on the location in the casting and geometry. In thicker walls, these are most often shrinkage and mixed porosity, while gaseous porosity, depending on the process, can occur anywhere. This defect is often recognized through X-ray, visual quality inspection of the casting surface or during leak tests [19].

Another defect is the formation of a shrinkage cavity [33], which occurs during solidification when the metal shrinks and is caused by volume contraction of the metal. The result is the formation of cavities and voids in the casting, usually funnel-shaped, sometimes extended with small, separated cavities [22]. They are prevented by changing the gating and riser design. However, they are diagnosed during radiographic testing and visual quality inspection [23].

Inclusions of foreign particles such as oxides and sand may appear in the casting, which are deposited in the casting during the casting process [34]. Foreign particles may originate from moulds, contaminated materials, ladles, furnaces or the environment. Sand inclusions are often caused by leaching of moulding sand from the surface of the mould cavity or by an improperly constructed gating system [22]. It is one of the most widespread defects and at the same time the cause of so-called production rejects. The aim of this defect detection is visual inspection or microscopic analysis [23].

Incomplete filling of the casting mould with liquid metal can also result in misruns or cold shuts [35], [36]. Cold shuts occur when the two relatively cold streams of molten metal from different gates do not fuse properly during the casting process [37]. A misrun results in an unfilled portion of the mould due to the freezing of the molten metal before it reaches all parts of the mould cavity [37]. These castings exhibit blurred edge shapes, missing or incomplete reproduction of certain elements. Potential causes of this defect include premature solidification of the metal in the initial solidification phase due to insufficient flowability, insufficient pouring speed or excessive metal flow resistance in the mould. The prevention of this type of defect is achieved by modifying the design and dimensions of the pouring system, increasing the casting temperature, and preparing a more efficient air discharge.

Despite the existence of established diagnostic techniques for identifying defects in castings, there are intricate and concealed relationships between process parameters and product performance parameters that are challenging or even impossible to discern without the utilization of appropriate tools based on production data [36].

3. Data-Driven Decision Support Systems

Decision-making is a kind of meta-problem that is ubiquitous in every field of human activity. The phenomenon of decision making has therefore become the subject of intensive research into various aspects and areas of the problem. The subject is approached from the psychological and cognitive sciences, but also from the systems sciences, mathematics and information technology.

In the case of living systems, the key factor is the human decision maker, which is a kind of criterion for evaluating the comparative performance of created systems [38]. From this it can be deduced that the design of such systems must take into account human capabilities, which can be the key to success, but also a kind of difficulty, through inherent characteristics such as human inconsistency, variability of judgements or imprecision. These characteristics are an important difficulty for mathematical models [39]. For complex decision problems with implicit relationships, mathematical analyses could go beyond the limits of formal concepts.

Efforts have been made to develop effective and efficient decision support systems (DSS) [40], [41], [42] to assist decision makers, but not to replace them. To this end, they have been divided into different types, such as document-driven, model-driven, knowledge-driven, web-based, inter-organizational, communication-driven and data-driven DSS [43]. Data-driven modeling of manufacturing processes with all specific types of models and management of process failures is described in details in [44]. Data-driven decision support system can be a powerful tool for gathering insights into the essence of manufacturing data in order to extract knowledge from it to help decision makers. It is of the utmost importance to utilize advanced data-driven modelling, encompassing the full spectrum of AI potential as defined by the Industry 4.0 concept [45].

The main goal for manufacturing companies is to have easy and fast access to a large amount of accurate and well-structured multidimensional data, which is also key to the success of a data-driven DSS. In [46] it was stated that these systems should be characterized by special analytical capabilities (with for example statistical analysis, ad hoc data filtering and retrieval, alerts and triggers, data management, data summarization, excel integration), flexible reporting (with for example advanced data displays, report design, generation and storage and view production reports), intuitive data manipulation, multi-user support, easy for users to access and understand and multidimensional conceptual view [47].

As previously stated in Chapter 2, the conventional approach to identifying quality defects in casting processes relies primarily on manual visual inspection and the subjective judgement of foundry personnel. Although this approach has been successful thus far, it is limited in its ability to analyze complex and intricate data sets that contain hidden relationships. Consequently, the implementation of data-driven decision support systems (DSS) for the diagnosis of casting defects has commenced. These systems are designed to analyze large data sets collected from a variety of sources in real time. Such systems are frequently based on machine learning algorithms, statistical analysis fundamentals, and predictive modelling. The systems are often capable of identifying patterns, detecting anomalies and trends in common data, while at the same time possibly indicating the formation of a defect in a specific casting or group of castings.

The main advantage of this solution is its ability to detect defects at an early stage of production, which can help prevent so-called production rejects. Through constant monitoring and data analysis, the systems can alert operators to deviations from normal operating conditions, allowing immediate intervention to prevent the defect from occurring. The existence of these systems allows operators and technologists to make more scientifically informed decisions based on objective evidence and data-driven insights, rather than relying on individual intuition. At the same time, reducing the time and resources required for manual inspection. Another advantage of applying data-driven DSS to the subject under consideration is their ability to analyze the root causes of emerging quality problems. This is achieved by correlating process data with historical records to identify specific factors causing defects. Such a holistic approach enables the implementation of preventive measures to avoid certain defects in the future. Furthermore, the concept of continuous improvement (Kaizen [48]), is emerging in line with the fundamental principles of lean management methodology, as the application of artificial intelligence (AI) algorithms to the systems enables them to learn continuously from new data and feedback, thereby enhancing their diagnostic capabilities and becoming flexible by adapting to evolving casting processes.

The arguments presented allow us to conclude that the integration of data-driven DSS in the diagnosis of the causes of casting defects represents a significant advance in modern manufacturing practices. The potential to exploit the capabilities of advanced data analysis and machine learning techniques allows for significant advances and improvements in casting processes, ultimately leading to improved quality, reduced downtime and increased operational efficiency. Given the importance of the subject, Chapter 4 provides an overview of the application of the systems and methodologies described in the analyzed subject.

4. Review of Data-driven Systems and Methodologies for the Casting Defect Diagnosis

The application of data-driven DSS in the manufacturing industry is diverse, with numerous examples of their use in the context of casting defect diagnosis and prediction.

The data-driven approach to the aforementioned topic can be applied, for example, to the identification of technological parameters that affect the quality of the final product, namely the finished casting. A recent paper [49] describes a data-driven DSS based on ANOVA and contingency tables methods used to select important process parameters influencing the output variable and based on Artificial Neural Networks (ANN) of the multilayer perceptron (MLP) type used to build a list of influences of the most important process parameters on its result. The authors emphasized that a substantial quantity of data, even if imperfect, can provide insights into the production process, in this case the aluminum extrusion process. By analyzing data using data-based advisory systems, it is possible to reduce the proportion of defective products. This reduction is possible by correctly identifying the source of production defects. As a result, the system can propose product design rules and recommend the most appropriate production process parameters for existing and new products. The developed case-based system, through the application of AI models, is capable of utilizing case studies derived from historical data and comparing them with the current results. The system designed by the authors is notable for its innovative approach, which utilizes knowledge derived from neural models (in contrast to the conventional extraction of knowledge from human experts, expressed in the form of rules). This enables the system to not only support decision-making but also to predict the specific consequences of the decisions taken, as proposed in [50]. The developed CBS system was considered to represent a combination of the three types of DSS, namely data-driven, knowledge-driven and model-driven, through the use of neural models to determine the direction and magnitude of the impact of technological parameters on production results, while utilizing exemplars from the production database. Consequently, the authors enhanced the dependability of the advisory system's recommendations. This approach enabled the authors to utilize neural models in the advisory system, despite the limitations of these models in predicting outcomes for new data.

Article [51] delineates the concept of a recommendation system (analogous to the aforementioned example) based on automatically recorded historical data. The system is initially designed to select relevant variables through correlation analysis and Kruskal-Wallis (K-W) analysis and reverse ANOVA (see [19] for further details). Subsequently, the system identifies the influence of process parameters on product quality through MPL-type neural models. The research presented here was conducted as part of a project carried out at a production plant. It is noteworthy that the authors distinguished between two categories of casting defects. The initial category comprised pitting, excessive surface roughness, tearing, lines, and blisters. The subsequent category encompassed dimensional variation, waving, flatness variation, broken walls, lack of rectitude, angle variation, twisting, and dents. The division was made on the basis of the information available in the company datasets, which described the defect class in question as either surface or dimensional. The neural model demonstrated a 89% accuracy rate for surface defects and a 79% accuracy rate for dimensional defects. In this context, the objective of the advisory system was to identify the parameters that contribute to the formation of a defect belonging to a specific category. The authors' proposal for an advisory system involved utilizing historical data for analysis, with the objective of identifying the optimal set of technological parameters for non-defective castings. In the case of new product ranges, the program would identify the optimal parameters, taking into account the characteristics of the product and the tools employed. The authors concluded that the implementation of the proposed recommendation system would result in a notable reduction in the number of defective products and announced its implementation in the production plant. A further avenue for research would be to test the efficacy of neural models in predicting the effects of simultaneous changes to multiple process parameters and their impact on the quality of the final product.

Additionally, there are intriguing articles that delineate analogous methodologies for diagnosing the underlying causes of defects in castings [19], [52]. These methodologies are based on ANOVA (reversed and direct) and K-W (reversed and direct) analyses, as well as Pearson and Spearman correlation coefficient analyses for the selection of significant variables. These variables are identified from the perspective of the output value that describes the quality of the analyzed casting. Three methods of advanced process modelling were employed, namely artificial neural networks (ANN), regression trees (RT) and support vector machines (SVM), with the objective of identifying the optimal technological parameters and quantifying their impact on the quality of the casting. The authors compared the results of the aforementioned methods and demonstrated that the most optimal root mean square error (RMSE) of 0.86 was attained through the utilization of ANN for modelling purposes. On this basis, the most effective ANN models were employed to ascertain the specific value levels of given process variables that influence defect formation in the product. This was achieved through model testing for multidimensional optimization of process parameters, including non-linear GRG with multistart and evolutionary methods. The authors identified three principal challenges associated with data-driven modelling. These were: the challenging application of SVM models; the inherent randomness of ANN models (due to the different weights); and the limited performance of RT models. This and analogous methodologies (which form the basis of Smart Factory operations) [53], [54], utilizing, among others, the Random Forest (RF) and Synthetic Minority Oversampling Technique (SMOTE) algorithms [55], achieve efficiency of up to 89% [56], could serve as the foundation for an intelligent decision-making system as outlined in reference [51].

An intriguing case study was conducted on the advancement of a quality-related machine learning algorithm for the forecasting of slag inclusions defects in a continuous casting process, as detailed in the topic under review [57]. The data obtained from the process state sensors was subjected to an empirical mode decomposition (EMD) algorithm, which was deployed for the purpose of processing the multi-modal time series. The authors conducted an empirical investigation of six machine learning methods: ANN [58], SVM (with nonlinear and linear kernels) [59], [60], K-Nearest Neighbors (K-NN) [61], Decision Trees (DT) [62], RF and Adaptive Boosting (AdaBoost). A significant aspect of the study was the methodology applied to handle the issue of data imbalance data, particularly the representation of critical values, which was relatively limited. The authors applied random under-sampling (RUS) and random over-sampling (ROS) algorithms to achieve data balancing. The resulting predictive models, constructed using the aforementioned advanced process modelling techniques, were evaluated using a combination of calculated accuracy and a proposed evaluation tool: the receiver operating curve in the total area under the curve (ROC-AUC), as detailed in [63] and [57]. The study indicated that the most effective machine learning method was optimized RF, which demonstrated the highest accuracy 0.77 and ROC AUC 0.64. The model demonstrated the highest sensitivity to samples representing castings with a defect, while maintaining the capacity to accurately classify castings without manufacturing defects. In this instance, the performance of the ANN model was found to degrade when some cases were removed from the training set using the RUS method. Despite the development of a comprehensive methodology that could form the basis of a decision-support system, the authors believe that further research and experimentation are necessary to enable the solution to be applied to the production plant in the future.

A very interesting paper [64] was presented at the 2nd International Conference on Power Electronics & IoT Applications in Renewable Energy and its Control (PARC), presenting a model for the inspection of castings based on a deep learning binary classification method. In the paper, the authors describe an inspection system based on image classification that is designed to perform fully effective quality analysis while minimizing inspection costs by eliminating the human factor. In this paper, a convolutional neural network (CNN) architecture has been developed to diagnose defects in finished castings. A dataset of images of the cast part, i.e. the impeller of a submersible pump, was used for the analysis. The images were taken in top view and represented by a greyscale mesh. The algorithm created was able to identify and classify various surface manufacturing defects and decide whether the analyzed casting was acceptable or unacceptable from a quality point of view. The subject is extremely important as surface and shape defects have the highest proportion of defects directly related to the manufacturing process [51]. Other articles have described decision systems for the diagnosis of surface defects in castings based on the CNN method [65], [66], [67], [68], [69], [70], [71] with a high success rate of between 98-99% [65]. This suggests that, in general, CNNs are capable of detecting objects and classifying images [65]. Furthermore, a deep learning model has been employed to develop a U-Net system, based on CNNs, which is capable of detecting casting defects with high efficiency. This approach has been demonstrated in several studies, including [72], [73], and [74]. Another study concentrates on the prediction of defects using interpretable machine learning models. The models are trained on solidification and microstructure data, with the objective of predicting the occurrence of transverse cracks in castings produced using a continuous casting process. The authors achieved a prediction accuracy of 94.6% [75]. In another paper, the authors employed machine learning algorithms to predict and analyze defects associated with the surface of steel and cast iron castings [76]. Furthermore, a paper [77] put forth the idea of integrating a hybrid model comprising convolutional neural networks (CNNs) and random forest classifiers to anticipate casting defects such as misruns, blowholes, shrinkage defects, inclusions, and sand inclusions. The developed system is capable of detecting manufacturing defects based on the presented set of images, with an accuracy of 95.91% [77] or, in the referenced publication [78], as high as 99%.

The article [79] similarly puts forth the utilization of machine vision through the establishment of the system, designated 'CASTvision', which is an automated vision system based on camera readings. The system was developed by the Cooperative Research Centre for Cast Metals Manufacturing (CAST) at Deakin University. The objective of the system is to perform dimensional and visual inspections of castings produced for the automotive industry. The system is based on three principal execution procedures. The first concerns the acquisition of camera image data, the second the processing of this data, and the third the decision-making process. Image analysis was conducted using mathematical morphology, as detailed in [80]. However, to accelerate the processing of data, the original images were smoothed using a Gaussian pyramid filter [81]. A significant accomplishment was the successful integration of the developed system into the manufacturing plant. In the actual process, the system demonstrated an extremely low false positive rate, with only 0.25% of normal parts incorrectly identified as defective out of 200,000 castings inspected. The research indicates that image analysis using hybrid methods can also be an effective means of diagnosing and predicting product defects. It is also pertinent to mention the expert systems developed based on RBS, such as 'ESVOD' developed at the VSB-Technical University of Ostrava. This is a knowledge-based computer system (KBCS) whose purpose is to identify defects according to external attributes, diagnose defects, identify their causes and finally propose prevention and remedies [82]. In addition, publicly accessible applications such as the Open Atlas of Casting Defects (OACD) have been developed with the objective of supporting the assessment and classification of casting defects [83].

A highly innovative technological solution has also been developed in this area, namely the Digital Twin. This relatively novel technology was first proposed by Michael Grieves in 2003 [86] and has since garnered increasing interest from both academic and industrial circles. The technology forms part of the Industry 4.0 initiative, which is designed to facilitate the emergence of so-called

Smart Manufacturing Systems (SMS). An SMS can be defined as a physical system comprising intelligent machines, products, materials and the intricate interconnections between them. The SMS can be divided into two distinct spaces: a physical space in which physical processes and products exist, and a digital space in which models of these processes exist. Consequently, a digital twin-based approach has been applied to the manufacturing system design sector [88] and to SMS configuration [89]. This is a highly innovative approach due to the digital continuity of modelling compared to conventional simulations. The Digital Twin has an architecture that allows for the real-time prediction of die casting quality based on process data. This technological solution enables production cells to interact in a virtual environment in real time. The objective is to simulate different process alterations and gain insight into the resulting production outcomes, which is crucial for effective change management in production enterprises. Systems have been developed that employ XGBoost-based learning methods for the prediction of quality in pressure casting and a deep learning-based neural network (named Refine-ACTDD) for the accurate detection of minor visual defects in complex aluminum castings [84]. This represents a novel approach to the identification and diagnosis of casting defects.

5. Challenges and Future Directions

In conclusion, the articles present evidence of the efficacy of diverse machine learning and deep learning methodologies for the diagnosis and prediction of casting defects, demonstrating high accuracy and effectiveness in the detection and analysis of defects. The systems presented put forth solutions to achieve zero defect manufacturing objectives based on advanced process analysis using big data. This is consistent with the principles of Industry 4.0. Concurrently, the pioneering diagnosis of the root causes of defects constitutes an integral component of the Quality 4.0 concept.

The accurate identification of the underlying causes of casting defects is of paramount importance, yet it is also a challenging objective, largely due to the intricate nature of metallurgical processes and the persistent lack of comprehensive understanding thereof [19]. The process of decision-making based on data from different stages of highly complex, non-linear processes is inherently complex. The discovery of relationships between process parameters derived from different stages of the casting process is a highly complex undertaking that is currently almost impossible to achieve. It is noteworthy that the utilization of data-driven DSS in the foundry industry remains relatively limited. This is due to the fact that real-world environments present a range of complex and distinctive challenges, which organizations are frequently inadequately prepared to address. Only a small number of the articles reviewed provided information on the complete implementation of the solution in a production environment. The authors acknowledge that much of the work requires further investigation, which is understandable given the importance of ensuring the reliability of the forecasts and manufacturing costs. It is important to note that any casting that is incorrectly classified as defective, despite not exhibiting any defects, will result in additional costs for the foundry. Conversely, the incorrect classification of a casting as defect-free could result in the use of a casting containing a defect in a critical component in the automotive industry. This could lead to a significant reduction in operational safety and other serious consequences. It thus follows that this topic remains a highly active and relevant one. Additionally, a considerable number of companies have yet to establish a comprehensive roadmap with a defined framework and user guide for the implementation of AI methods [85]. This is an important aspect to consider in the pursuit of enhanced competitiveness.

The efficacy of the systems and methodologies developed is contingent upon the manner in which the process data are prepared for advanced modelling of the foundry processes. A salient characteristic of the data under examination, as frequently discussed in the literature, is its inherent imbalance. This indicates that while a substantial quantity of data is available for analysis, there is a paucity of data pertaining to castings with defects. Consequently, advanced data analysis techniques have frequently been able to exclude this data, resulting in a reduction in the accuracy of the predictions. It can be concluded that preliminary data analysis, frequently employing statistical techniques, is a crucial determinant of success in attaining satisfactory results. As previously stated in Chapter 3, the use of an artificial neural network (ANN) as a foundation for developing decision support systems for predicting product defects and diagnosing their causes is a highly advantageous approach. Nevertheless, it has been observed that ANN predictions are frequently arbitrary, with disparate weightings, which frequently necessitates the extension of research and the creation of multiple models. With regard to the employed deep learning techniques, it was observed that, in the majority of cases, convolutional neural networks (CNNs) were capable of identifying defects in the analyzed castings (based on machine vision techniques) and of predicting their occurrence.

A significant finding of the literature analysis was the creation of a digital twin, which facilitated the prediction of defects and the identification of their causes. This technology facilitates the design of intelligent manufacturing systems, enabling the maintenance of the function-structures-behavior-control-intelligence-performance (FSBCIP) framework for SMS [86]. It also enables effective production planning and suggests an optimal factory layout. A living digital twin enables real-time anomaly detection through predictive and prescriptive analysis to minimize not only the number of defects produced, but also to minimize downtime and optimize foundry operations. The digital twin concept can be created for a machine, such as a key bottleneck machine, for the entire process, including models for all machines, and for the entire enterprise, even if geographically dispersed - which is the highest level of implementation of this technology [87]. These represent avenues for further research on the topic under analysis, which, despite extensive analysis, still presents a challenge for researchers and foundry companies.

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