Design of Machine Learning method for decision-making support and reliability improvement in the investment casting process

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Abstract
The need to improve reliability and support decision-making in manufacturing has drawn attention to the application of diagnostic and decision-support tools. Particularly in the investment casting industry, data-driven methods can be the enabler for process diagnostics and decision support. Images from the microscopic examination in the investment casting process are used as data input, to detect defects in produced pieces. The microscopic examination usually relies solely upon the ability of the operator to determine whether an image from the microscope contains a defect. Therefore, an effective strategy for this decision-making process is crucial to improve the reliability of the examination. The use of the machine learning classifier Random Forest is introduced to derive predictions on the existence of a defect in the input image. This work focuses on employing machine learning tools for image recognition and the developed approach constitutes a decision support model to assist the operator and improve the reliability of their assessment.

1. Introduction

During the last decade, machine learning (ML) techniques have been widely implemented in different production processes, aiming to enhance the quality of the products, apply process diagnostics, or support decision-making (Esmaeilian et al., 2016) Utilization of ML methods has found application in production operational management centers to facilitate decision-making processes (González Rodríguez et al., 2020), or use predictions to support decisions in inventory management (Mohamed & Saber, 2023). The need to improve the reliability of decision-making for fault detection and diagnostic processes represents one of the strategic objectives of many industries. In manufacturing, reliability refers to machines, equipment, and systems being able to perform their intended functions with consistency and predictability. Providing reliable products is vital to the success of the industry, as traditionally reliability is evaluated by the final product quality (Safhi et al., 2019). Numerous measures can be taken to increase manufacturing reliability, such as regular maintenance and calibration of equipment, as well as diagnosing faults in components or systems.

The microscopic examination mentioned in this work is a part of the investment casting process, a process aiming to create components that can be used in turbomachinery applications, characterized by high geometrical complexity, and later subjected to demanding performance conditions. The production of such parts has multiple subprocesses and is a very sophisticated procedure with much attention to detail (Warren et al., 2021).

Most current practices in industry involve experts inspecting individually each piece produced and detecting defects manually (Jawahar et al., 2021). Particularly in the aerospace manufacturing industry, visual inspection still dominates the testing of parts including engine blades, accounting for approximately 90% of all inspections (Aust et al., 2021). With quality assessment being one of the essential steps of the process, relying solely on the ability of an inspector to detect faults could be of high risk (Aust et al., 2021). Studies have shown that during the inspection of parts, the judgment of professionals can be biased by expectations coming from contexts such as prior knowledge or experience and inspectors may be unaware when their judgments are affected (MacLean & Dror, 2021). Bias can come from different sources, either case-specific, such as data, reference materials, and contextual information, depending on the environment and experience, or cognitive architecture and human nature. Many studies have so far been carried out on using ML techniques to identify faults and improve the reliability of other processes such as fluorescent penetrant inspection

(Niccolai et al., 2021) (Shipway et al., 2019), or X-ray inspection (Jiang et al., 2021), (García Pérez et al., 2022), but little has been done on the microscopic examination of the parts, and even less on the investment casting products.

The microscopic examination process in investment casting appears to be an excellent opportunity for the application of ML methods that could improve the reliability of fault diagnosis by assisting in decision-making. This is due to the requirement that the inspector conducting the examination detects discontinuities in materials and decides whether they could endanger the structural integrity of the produced part and its functionality. The purpose of this research work is focused on improving the reliability of the decision-making mechanism of the inspector's assessment during the microscopic examination, through the application of ML techniques. As it is essential to reduce the risk of false assessment when diagnosing faults while minimizing possible bias and increasing objectivity, an assisting ML model for the operator is proposed.

2. Methodology

2.1. Background

Investment casting is a manufacturing process that produces dimensionally accurate components and is a more cost-effective alternative to forging or machining since waste materials are reduced to a very low level (Li & Wang, 2021). During the process, molten wax is injected into a metallic mold to create a wax pattern with the desired component shape. The wax mold is repeatedly dipped into a ceramic slurry which then hardens to create a ceramic casing around the wax design. The wax is then removed from the shell by melting, leaving a cavity inside that exactly resembles the shape of the component. The casting procedure itself is carried out by filling the thus-produced ceramic shell with molten alloy after hardening the ceramic shell by heating. The shell is separated as the molten metal hardens to produce the components which will then undergo various finishing and inspection processes (Del Vecchio et al., 2019).

As one of the final inspection methods, the microscopic examination contains assessments whose results determine if a part is ready for delivery, based on the requirements of each customer. Usual requirements might be the maximum allowed percentages of a specific defect found on a part, such as porosity. The conditions of the casting process in its entirety strongly determine the occurrence of defects during the observation. The operation of microscopic examination within the factory typically relies solely upon the ability of the operator, without any assisting model. The inspection is carried out using portable equipment and conventional optical microscopy procedures. For the microscopic examination to be successful and with accurate results, the operator is required to search for and detect irregularities by visually examining the cut surface of the material, an example of which is shown in Figure 1.

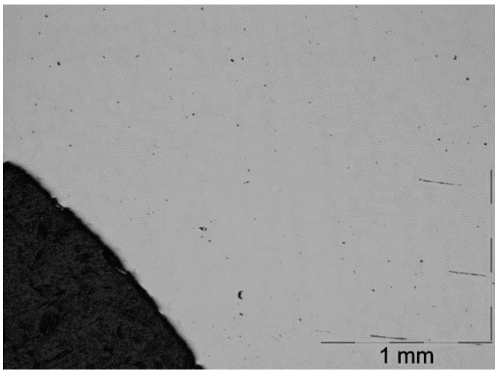

Figure 1: The cut up of a piece produced by investment casting.

When inspecting the material in the microscope, the operator comes across images that are either clean or contain a defect. It is up to the operator to decide the status of every image (faulty or non-faulty). Faults appearing on the image can be:

- Porosity (often forming as microporosity), which appears in the microscope as dark repeated streaks with smooth edges. It is known to be the most common defect found during investment casting and dramatically limits the life of aerospace components (Torroba et al., 2014). A possible porosity cause is shrinkage during solidification, where there is a shortage of molten material flow in-between the space of connected dendrites (Mozammil et al., 2020).
- Gas pockets, that are observed as dark circular shapes during the microscope examination. Similar to porosity, factors such as metal solidification time and air entrapment are due to turbulence during the pouring of the molten metal into the shell (Kaiser et al., 2011).
- Cracks, which are usually caused by internal stresses from the solidification of the metal or rapid cooling, can be identified as either hot tear cracks, appearing as noncontinuous dark

lines of variable widths, or cold state, which indicates thin continuous lines. They can also initiate forming by other defects or intermetallics (Dezecot & Brochu, 2015).

- Chemical reactions that might appear due to refractories used during the forming of the shell mold (Hao et al., 2020). They can be a result of the interaction of the metal used in investment casting and the ceramic mold where the metal is poured.

Examples of the above are shown in Figure 4. There are also fewer common cases of other defects appearing such as missruns, dross, or segregation, generated mainly during the solidification process. During the microscopic assessment, the inspector may come across one of the defects or possible combinations of them.

2.1. Approach

The method proposed in this paper aims to detect faults that can occur during the investment casting process and support the assessment of defect presence. The steps followed in this work to tackle the risk of inaccurate assessment and create an assisting model for the operator were designed as follows:

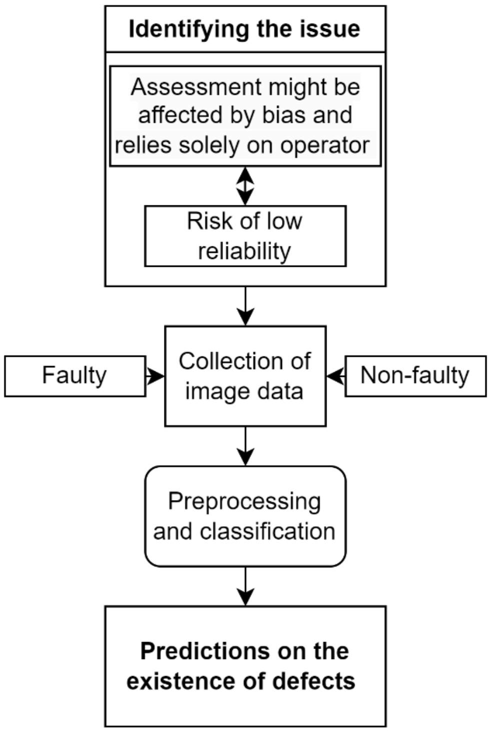

Figure 2: The approach to designing the data-driven method.

According to several researchers (Ali et al., 2012; Bertovic et al, 2013), the examination of a part requires information processing that contains signal detection and decision-making. The first decision-making at this point is not to identify the specific type of defect but to determine whether the picture of the cut material contains a defect or not. In signal detection, the aim is to recognize a signal from a background interference or noise (Swets, 1996). Therefore, the operator can give two right or wrong answers: to correctly or incorrectly accept or reject the presence of a defect (Enkvist et al., 1999; Lynn &Barrett,2014). The four possible outcomes are illustrated in Figure 3.

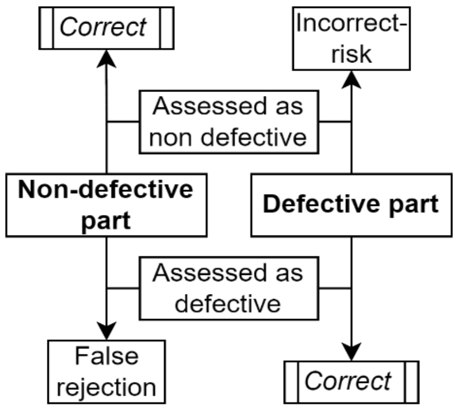

Figure 3: The possible outcomes of the assessment depend on the true state of the world, according to signal detection theory.

2.2. Data Preprocessing

The input for the model was both images that contained defects and images that did not. The images in the dataset were taken from a database of microscopic examinations and were previously used to manually inspect portions of the parts to find defects. Initially, 1787 photographs were retrieved from the database that had various kinds of defects, while 462 images had no signs of any defects. Without a form of data augmentation that would provide a wider and more balanced training dataset, it can be challenging to obtain appropriate performance because datasets from real applications (such as production) are frequently limited (Shorten & Khoshgoftaar, 2019; Xu et al., 2023).

For the initial processing of the images, data augmentation was applied. A usual form of data augmentation technique is altering the geometrical characteristics of the initial images.

The first step of augmentation consisted of using the PIL Python library to alter the dimensions of the images. PIL is widely used in Python, as a potent tool for processing images. It can alter different kinds of image formats, sizes, and orientations (Guan et al., 2019). The images were cropped to the ratio of 1:1, to facilitate the rotation process that took place later. The initial dimensions were 722*990 pixels, and the final images were 722*722 pixels, cropped regarding the defect area. To increase the number of training data, the images were flipped and subjected to rotation.

Figure 4 displays the original and altered photos as well as instances of the four categories of defects that were stated before.

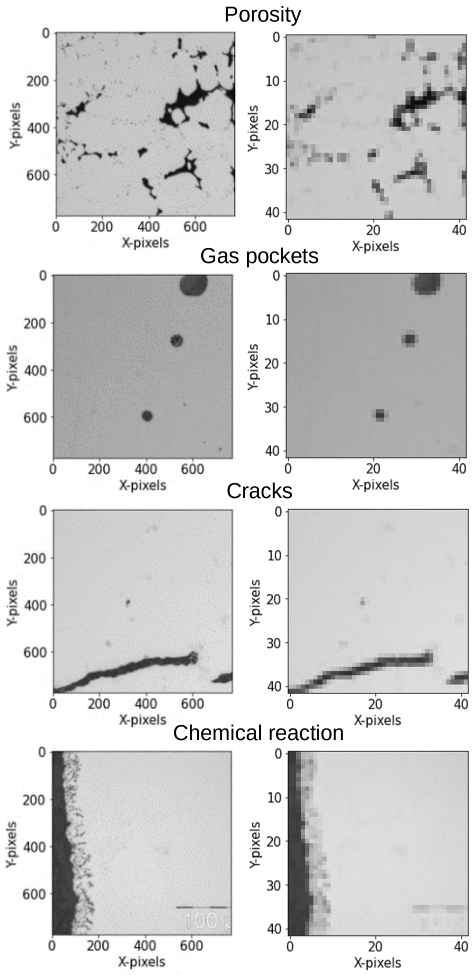

Figure 4: The original cropped images (left) of and the artificially edited ones (right) of four different types of defects (from top to bottom): porosity, gas pockets, cracks, and chemical reaction.

To enhance the computational performance of the classifier, the image pixels were reduced to 42*42 instead of 722*722. The classifier was able to better predict the existence of a defect on the image tested when the pixels were reduced to 42 per side, as shown in Figure 5, which indicates the higher accuracy levels achieved with this particular number of pixels.

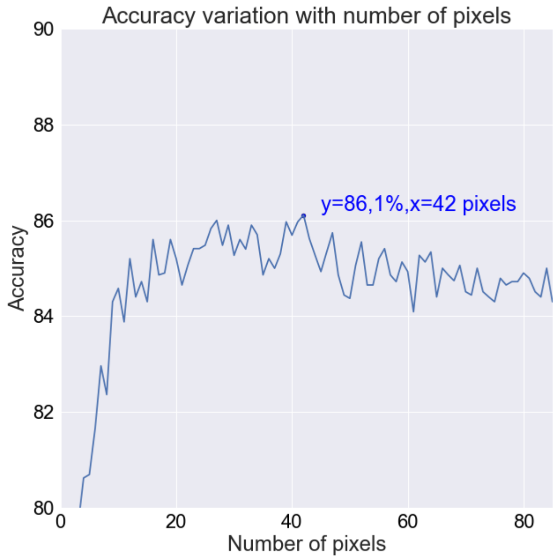

Figure 5: The accuracy score development during the repetitions with different numbers of pixels.

2.3. Classification

Considering the specific dataset's characteristics, including its size and the presence of defects, the proposed approach employs the ML classifier Random Forest (RF) to make predictions regarding the presence of defects in the input image. In applications with datasets similar to the one being utilized in this study (Khatami et al., 2019; Subudhi et al., 2020), RF shows satisfactory performance. This remains accurate for this stage of the process and is in line with the requirements of image recognition and classification between the two classes. Opting for RF over alternative methods is supported by its dependable performance in effectively tackling the challenges presented by dataset size and complexity. According to the literature, RF is often used for small data sets, similar to those from the medical field because it contributes to solving problems in industrial applications and has advantages such as ease of use, robust generalization ability, greater classification accuracy, and high functionality (Wang et al., 2023).

The RF method is considered quite a popular ensemble technique for pattern and image recognition. As an ensemble learning technique, it combines multiple decision trees to increase the predictions' accuracy. The training is accomplished for each decision tree, where all classifiers generated from different trials are collected to construct the final classifier (Azar et al., 2014). The algorithm, when used for classification, outputs the mode of the classes of the individual trees. A subset of training data and a subset of features are randomly selected by the algorithm to build each decision tree.

The limitations of an RF classifier would depend on the high dimensionality of the data, which was tackled by reducing the number of pixels during data preprocessing, as mentioned in section 2.2. For pixel-based approaches like the one in this application, and for this stage and the requirements of the process, RF can perform satisfactorily. Research on methods for pixel analysis of pictures has revealed that RF acts similar to Neural Networks (NN) in defining linear borders between classes, such as in the usage of plantation boundaries (Boston et al., 2022). When aiming to reduce time consumption and computational complexity while dealing with a small number of training samples, RF has been preferred over NN in situations with diagnostic applications comparable to this one (Han et al., 2018).

The images obtained from previous microscope examinations were pre-processed and split into training and testing datasets. One of the possible limitations in training the RF classifier would be an imbalanced data set, where the classifier might favor the minority class. Therefore, a balanced data of 3600 images from each category (faulty or non-faulty) was used to create the training and testing datasets, to better assist the training process and reduce computational complications. The data set split was 80% training and 20% testing images, which was 5760 and 1440 images respectively.

Since the data set was labeled during the preprocessing stage, comparable supervised machine learning classifiers have been employed on this dataset. These included the Decision Tree (DT), the Support Vector Machine (SVM), and the Gaussian Process (GP) Classifier. The goal of the DT classifier is to create a training model that can be used to infer learning decision rules from training data in order to predict the class or value of target variables (Charbuty & Abdulazeez, 2021). The SVM is a common pattern recognition classification technique that aims to find a central hyperplane to partition the data points. The datasets are therefore divided into different classes. Along the hyperplane that separates the classes, SVM establishes a concentrated separation boundary (Halder et al., 2023). GP classifiers offer a probability distribution over all conceivable functions that can match a given set of training points. The decision boundary then corresponds to the midpoint between the two classes as a result of the prior distribution's initial assignment of equal probability to both classes (Basha et al., 2023). On the basis of their accuracy score, the three aforementioned techniques were compared with the RF classifier.

3. Results and discussion

The RF classifier underwent testing with different numbers of estimators to determine the best configuration that would produce the most accurate outcomes. It attained an accuracy rate of 86.5%. This score was found to be higher after experimenting with several types of classifiers.

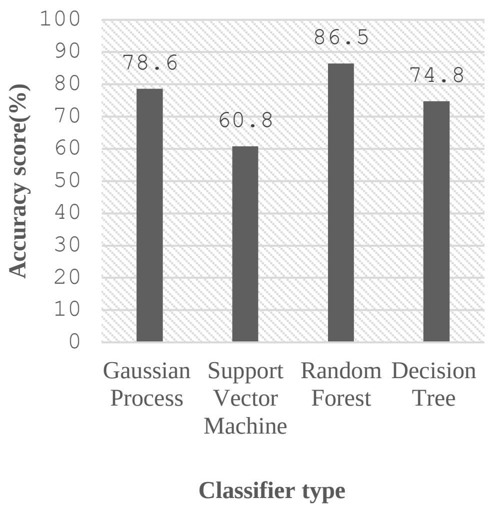

Figure 6: The accuracy score between the different classifiers.

As illustrated in Figure 6, the RF classifier outperformed other classifiers used in comparable applications, for this particular dataset with industrial images. The other types of classifiers that were tested and produced accuracy scores were the GP (78,6%), the SVM (60,8%), and finally the DT classifier (74,8%).

The number of assigned estimators, which in this application was 120 estimators, is typically used to describe the Random Forest classifier. This was obtained by several iterations of the model, each using a different set of estimators. After achieving peak accuracy at the 120 estimators (86.5%), it was seen that the computing time increased while the accuracy score did not, entering a relatively static period.

The development of the accuracy score regarding the number of estimators used is illustrated in Figure 7.

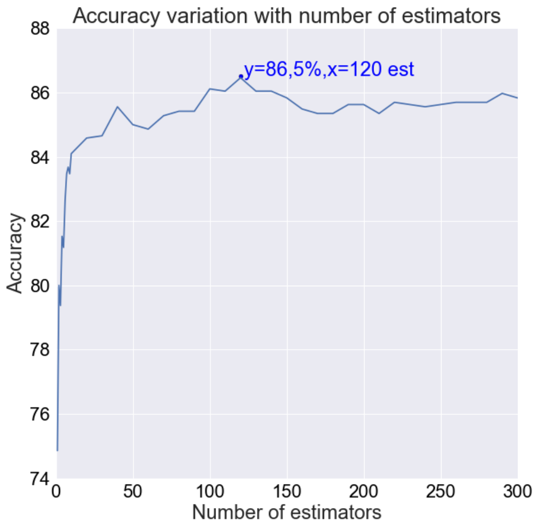

Figure 7: The accuracy score development during the repetitions with different estimator numbers.

The model produced a confusion matrix, a metric used to evaluate the accuracy of the classification. The confusion matrix contrasted the amount of accurate and inaccurate classifications made. Correct forecasts outperformed incorrect ones (false calls or misses) by a factor of five in terms of outcomes. The color gradient scale of the confusion matrix draws attention to the accurate classifications and the stark contrast between them and the inaccurate ones. The three matrices for the other classifiers were produced in addition to the confusion matrix from the RF classifier (Figure 8).

As observed in the confusion matrices for each classifier, the RF classifier demonstrates a more even distribution along the diagonal of the color scale. It achieves 1240 correct predictions (composed of 642 true positives and 548 true negatives), as opposed to 200 incorrect predictions (comprising 78 false positives and 122 false negatives). This pattern aligns with the accuracy scores, as the other classifiers show a decreased frequency of accurate predictions that match the true labels. The color-coded cells within the matrices distinctly indicate that only the SVM classifier surpasses the RF classifier in prediction count for a specific class. However, the SVM's incorrect predictions outnumber the correct ones, resulting in a lower accuracy score for this classifier. In essence, the analysis underscores that the RF classifier outperforms the others by maintaining a more balanced and accurate distribution of predictions, making it the most reliable choice among the evaluated classifiers.

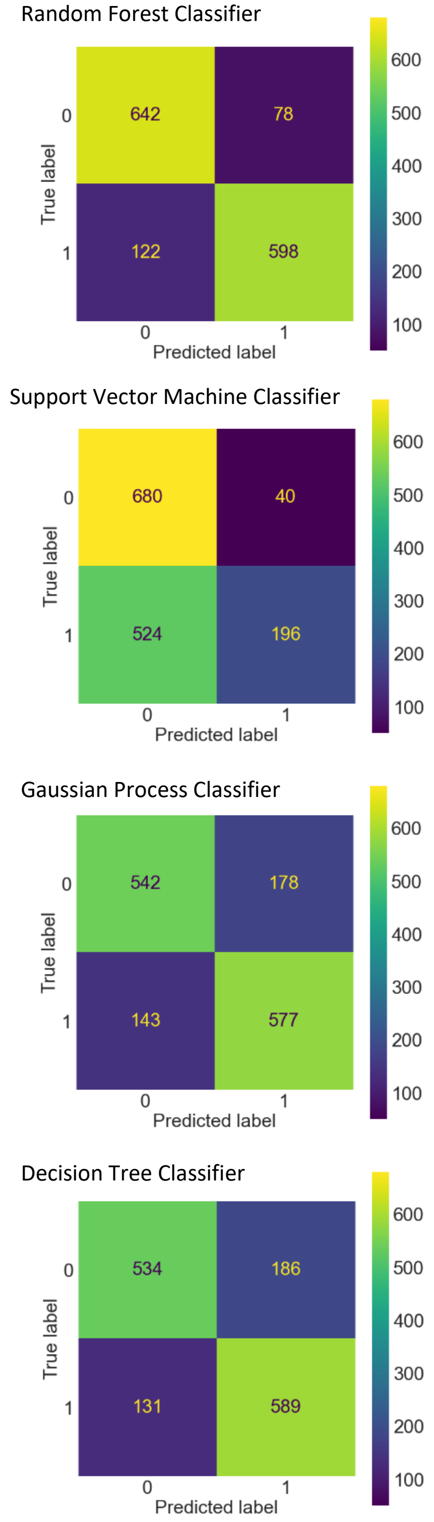

Figure 8: The Confusion Matrix for each classifier.

4. Conclusions

The present work demonstrated a data-driven approach to the investment casting microscopic examination to provide an assisting tool that supports decision-making and improves its reliability. The RF classifier that was chosen has achieved a level of prediction accuracy that is adequate given the characteristics of the dataset that was collected and preprocessed. It established higher efficiency for the selected dataset when compared to other classifiers that are employed in similar applications. Even though production data are seldom balanced, the model may also be used to predict unbalanced datasets after it has been trained. Therefore, this work contributes to developing a framework for integrating machine learning into the investment casting process, particularly in one of its subprocesses. It encourages further use of the ML classification algorithms for investment casting defects while introducing semi-automation of the investment casting microscopic examination.

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References

Ali, A. H., Balint, D., Temple, A., & Leevers, P. (2012). The reliability of defect sentencing in manual ultrasonic inspection. *NDT and E International*, *51*, 101–110. https://doi.org/10.1016/j.ndteint.2012.04.003

Aust, J., Mitrovic, A., & Pons, D. (2021). Assessment of the effect of cleanliness on the visual inspection of aircraft engine blades: An eye tracking study. *Sensors*, *21*(18). https://doi.org/10.3390/s21186135

Azar, A. T., Elshazly, H. I., Hassanien, A. E., & Elkorany, A. M. (2014). A random forest classifier for lymph diseases. *Computer Methods and Programs in Biomedicine*, *113*(2), 465–473. https://doi.org/10.1016/j.cmpb.2013.11.004

Basha, N., Kravaris, C., Nounou, H., & Nounou, M. (2023). Bayesian-optimized Gaussian process-based fault classification in industrial processes. *Computers and Chemical Engineering*, *170*. https://doi.org/10.1016/j.compchemeng.2022.108126

Boston, T., Van Dijk, A., Larraondo, P. R., & Thackway, R. (2022). Comparing CNNs and Random Forests for Landsat Image Segmentation Trained on a Large Proxy Land Cover Dataset. *Remote Sensing*, *14*(14). https://doi.org/10.3390/rs14143396

Charbuty, B., & Abdulazeez, A. (2021). Classification Based on Decision Tree Algorithm for Machine Learning. *Journal of Applied Science and Technology Trends*, *2*(01), 20–28. https://doi.org/10.38094/jastt20165

Del Vecchio, C., Fenu, G., Pellegrino, F. A., Michele, D. F., Quatrale, M., Benincasa, L., Iannuzzi, S., Acernese, A., Correra, P., & Glielmo, L. (2019). Support Vector Representation Machine for superalloy investment casting optimization. *Applied Mathematical Modelling*, *72*, 324–336. https://doi.org/10.1016/j.apm.2019.02.033

Dezecot, S., & Brochu, M. (2015). Microstructural characterization and high cycle fatigue behavior of investment cast A357 aluminum alloy. *International Journal of Fatigue*, *77*, 154–159. https://doi.org/10.1016/j.ijfatigue.2015.03.004

Enkvist, J., Edland, A., & Svenson, O. (1999). *Human Factors Aspects of Non-Destructive Testing in the Nuclear Power Context A review of Research in the Field*.

Esmaeilian, B., Behdad, S., & Wang, B. (2016). The evolution and future of manufacturing: A review. In *Journal of Manufacturing Systems* (Vol. 39, pp. 79–100). Elsevier B.V. https://doi.org/10.1016/j.jmsy.2016.03.001

García Pérez, A., Gómez Silva, M. J., & de la Escalera Hueso, A. (2022). Automated Defect Recognition of Castings Defects Using Neural Networks. *Journal of Nondestructive Evaluation*, *41*(1). https://doi.org/10.1007/s10921-021-00842-1

González Rodríguez, G., Gonzalez-Cava, J. M., & Méndez Pérez, J. A. (2020). An intelligent decision support system for production planning based on machine learning. *Journal of Intelligent Manufacturing*, *31*(5), 1257–1273. https://doi.org/10.1007/s10845-019-01510-y

Guan, Y., Zhou, F., & Zhou, J. (2019). Research and Practice of Image Processing Based on Python. *Journal of Physics: Conference Series*, *1345*(2). https://doi.org/10.1088/1742-6596/1345/2/022018

Halder, S., Das, S., & Basu, S. (2023). Use of support vector machine and cellular automata methods to evaluate impact of irrigation project on LULC. *Environmental Monitoring and Assessment*, *195*(1). https://doi.org/10.1007/s10661-022-10588-6

Han, T., Jiang, D., Zhao, Q., Wang, L., & Yin, K. (2018). Comparison of random forest, artificial neural networks and support vector machine for intelligent diagnosis of rotating machinery. *Transactions of the Institute of Measurement and Control*, *40*(8), 2681–2693. https://doi.org/10.1177/0142331217708242

Hao, Y., Liu, J., Du, J., Zhang, W., Xiao, Y., Zhang, S., & Yang, P. (2020). Effects of mold materials on the interfacial reaction between magnesium alloy and ceramic shell mold during investment casting. *Metals*, *10*(8), 1–14. https://doi.org/10.3390/met10080991

Jawahar, M., Babu, N. K. C., Vani, K., Anbarasi, L. J., & Geetha, S. (2021). Vision based inspection system for leather surface defect detection using fast convergence particle swarm optimization ensemble classifier approach. *Multimedia Tools and Applications*, *80*(3), 4203–4235. https://doi.org/10.1007/s11042-020-09727-3

Jiang, L., Wang, Y., Tang, Z., Miao, Y., & Chen, S. (2021). Casting defect detection in X-ray images using convolutional neural networks and attention-guided data augmentation. *Measurement: Journal of the International Measurement Confederation*, *170*. https://doi.org/10.1016/j.measurement.2020.108736

John A. Swets. (1996). *Book Signal Detection Theory and ROC Analysis in Psychology and Diagnostics* (1st Edition). eBook Published 21 January 2014.

Kaiser, R., Browne, D. J., & Williamson, K. (2011). Investigation of the effects of cooling rate on the microstructure of investment cast biomedical grade Co alloys. *IOP Conference Series: Materials Science and Engineering, 27*(1). https://doi.org/10.1088/1757-899X/27/1/012071

Khatami, A., Araghi, S., & Babaei, T. (2019). Evaluating the performance of different classification methods on medical X-ray images. *SN Applied Sciences*, *1*(10). https://doi.org/10.1007/s42452-019-1174-0

Li, F., & Wang, F. (2021). Preparation Process of Ceramic Shells. In *Precision Forming Technology of Large Superalloy Castings for Aircraft Engines* (pp. 101–167). Springer Singapore. https://doi.org/10.1007/978-981-33-6220-8_4

Lynn, S. K., & Barrett, L. F. (2014). "Utilizing" Signal Detection Theory. *Psychological Science*, *25*(9), 1663–1673. https://doi.org/10.1177/0956797614541991

MacLean, C. L., & Dror, I. E. (2021). The effect of contextual information on professional judgment: Reliability and biasability of expert workplace safety inspectors. *Journal of Safety Research*, *77*, 13–22. https://doi.org/10.1016/j.jsr.2021.01.002

Marija Bertovic, phil. (2013). Human Factors in Non-Destructive Testing (NDT): Risks and Challenges of Mechanised NDT. *Materials Testing*. https://doi.org/10.14279/depositonce-4685

Mohamed, M., & Saber, N. El. (2023). Intelligent Decision Support Machine Learning Based Optimizing Inventory Management. *American Journal of Business and Operations Research*, *9*(2), 41–50. https://doi.org/10.54216/AJBOR.090205

Mozammil, S., Verma, R., Karloopia, J., & Jha, P. K. (2020). Investigation and measurement of porosity in Al + 4.5Cu/6wt%TiB2 in situ composite: optimization and statistical modelling. *Journal of Materials Research and Technology*, *9*(4), 8041–8057. https://doi.org/10.1016/j.jmrt.2020.05.045

Niccolai, A., Caputo, D., Chieco, L., Grimaccia, F., & Mussetta, M. (2021). Machine learning-based detection technique for ndt in industrial manufacturing. *Mathematics*, *9*(11). https://doi.org/10.3390/math9111251

Safhi, H. M., Frikh, B., & Ouhbi, B. (2019). Assessing reliability of Big Data Knowledge Discovery process. *Procedia Computer Science*, *148*, 30–36. https://doi.org/10.1016/j.procs.2019.01.005

Shipway, N. J., Barden, T. J., Huthwaite, P., & Lowe, M. J. S. (2019). Automated defect detection for Fluorescent Penetrant Inspection using Random Forest. *NDT and E International*, *101*, 113–123. https://doi.org/10.1016/j.ndteint.2018.10.008

Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on Image Data Augmentation for Deep Learning. *Journal of Big Data*, *6*(1). https://doi.org/10.1186/s40537-019-0197-0

Subudhi, A., Dash, M., & Sabut, S. (2020). Automated segmentation and classification of brain stroke using expectation-maximization and random forest classifier. *Biocybernetics and Biomedical Engineering*, *40*(1), 277–289. https://doi.org/10.1016/j.bbe.2019.04.004

Torroba, A. J., Koeser, O., Calba, L., Maestro, L., Carreño-Morelli, E., Rahimian, M., Milenkovic, S., Sabirov, I., & LLorca, J. (2014). Investment casting of nozzle guide vanes from nickel-based superalloys: part I – thermal calibration and porosity prediction. *Integrating Materials and Manufacturing Innovation*, *3*(1), 344–368. https://doi.org/10.1186/s40192-014-0025-5

Wang, J., Rao, C., Goh, M., & Xiao, X. (2023). Risk assessment of coronary heart disease based on cloud-random forest. *Artificial Intelligence Review*, *56*(1), 203–232. https://doi.org/10.1007/s10462-022-10170-z

Warren, P., Ali, H., Ebrahimi, H., & Ghosh, R. (2021). *RAPID DEFECT DETECTION AND CLASSIFICATION IN IMAGES USING CONVOLUTIONAL NEURAL NETWORKS*.

Xu, M., Yoon, S., Fuentes, A., & Park, D. S. (2023). A Comprehensive Survey of Image Augmentation Techniques for Deep Learning. *Pattern Recognition*, *137*. https://doi.org/10.1016/j.patcog.2023.109347