

Investigate Machine Learning in Manufacturing System

Author name: Ismail Yagob

Student ID: 2239449

Module name: Advanced Industry 4.0

Module code: ACPA7000

Date of Submission: 29/09/2023

Summary:

This essay delves into the pivotal role of machine learning within the manufacturing sector, with a specific focus on its application in sheet metal operations. The exploration begins with an introduction highlighting the rapid integration of machine learning across industries and its potential to reshape manufacturing, juxtaposed against the historical backdrop of automation.

A comprehensive literature review showcases the versatility of machine learning, extending its influence beyond manufacturing into diverse domains like healthcare, education, and project management. While recognising challenges like prediction accuracy, the review emphasises the tangible benefits of machine learning, including enhanced efficiency, precision, and substantial cost savings.

The subsequent section offers a detailed overview of machine learning, dissecting its core principles and delving into three foundational techniques: supervised learning, unsupervised learning, and reinforcement learning. Practical examples illustrate their adaptability in solving intricate challenges across various sectors.

A revealing case study unveils the operations of a renowned sheet metal forming equipment manufacturer, illuminating the company's commitment to innovation, sustainability, and global reach. It highlights how machine learning optimises processes and minimises waste in the demanding sheet metal industry.

The methodology section serves as a blueprint, outlining meticulous steps for analysing and optimising sheet metal components using machine learning techniques. Processes such as data transformation, component analysis, gap optimisation, image conversion, visualisation, and pixel measurement collectively illustrate a comprehensive problem-solving approach.

In summary, this essay not only showcases the vast potential of machine learning to revolutionise the industrial landscape but also provides a holistic understanding of the subject matter. It becomes evident that machine learning is poised to play a central role in shaping the future of manufacturing by combining theoretical foundations, practical applications, and methodological insights. As companies embrace this transformative technology, the manufacturing sector stands on the precipice of an era marked by unprecedented efficiency, precision, and sustainability. Machine learning is undeniably the driving force propelling the evolution of manufacturing in the years to come.

Introduction:

Machine learning has spread quickly across industries as a result of emerging technical trends (O'Donovan et al. 2019; Mistikoglu 2021).

Machine learning has emerged as a transformative force within the manufacturing industry. As we delve into this modern technological landscape, it's worth noting that humans have a rich history of harnessing tools to automate a wide array of tasks. From the inception of machinery, the human intellect has continually innovated, streamlining various aspects of life, including transportation, industry, and computation. Within this context, machine learning exemplifies a remarkable achievement in the realm of automation (Mahesh, 2020).

Machine learning is the study that enables computers to learn on their own, without the need for explicit programming, according to Arthur Samuel, a pioneer in the subject (Samuel, Year, as referenced in Mahesh, 2020). Its foundation is the idea of directing robots to improve jobs, especially in data management, and so increase productivity. Deciphering data after exposure is one of the fundamental difficulties, a conundrum that machine learning has showed promise in resolving (Mahesh, 2020).

Furthermore, the goal of machine learning is to automatically enable computer programmes with the intention of enhancing some tasks' performance via experience. Machine learning applications in the manufacturing sector have great potential (Subramaniam, 2021). Also, the operation and growth of manufacturing businesses can be considerably enhanced by the implementation of machine learning algorithms (Sung ,2018; Xie,2020).

The application of machine learning in manufacturing has gained significant traction worldwide. Notably, McKinsey's research estimates that approximately 40% of the value generated by analytics today results from the use of technologies such as machine learning and artificial intelligence (McKinsey Report, Year). This underscores the substantial investment and impact of machine learning in the manufacturing sector, with estimates of its annual value ranging between 3.5 trillion to 5.8 trillion (Rai et al., 2021).

Machine learning techniques offer a wide range of applications that have been used in a variety of industrial industries recently. These techniques have been used in a variety of industrial sectors, including manufacturing, finance, healthcare, and transportation (Wang, 2019).

According to studies, implementing machine learning algorithms can help lower costs by 20% to 25% across banking, IT operations, infrastructure, and maintenance, as well as enhance client acquisition and retention (Accenture, 2018).

The main objective of this research is maintaining the sheet metal operation that applied in company based in Finland. This business uses sheets to make customised components and operates on a worldwide scale. Currently, it has issues handling sheet material following the required punching operations. The organisation has observed that waste sheets are commonly trapped over the worktable after punching operations because the automated grippers cannot completely grasp the waste sheets. Human operators are then required to remove the remaining waste sheets and place them in trash cans. This frequently results in a stop in production and a loss of production for the business. The main cause of this issue is the too-narrow gaps that are left between the components after the punching operation. Machine learning a technique were used to investigate the gaps between components with the aim of optimising the gaps in order to solve this problem (Mahmoodi et al. 2019).

In order to provide a thorough examination of machine learning, this essay will address important issues like examining machine learning techniques, exploring the underlying theories, presenting a case study that shows how it is applied in a manufacturing environment, and closely examining particular techniques used in the sheet metal industry. By the end of this article, readers will have learned a lot about how machine learning has the potential to revolutionise the manufacturing industry.

Literature review:

The purpose of this extended literature review is to provide a comprehensive understanding of the wide-ranging impact of machine learning across various sectors, thereby laying a solid foundation for our exploration of its role in manufacturing, specifically sheet metal operations.

Machine learning has indeed emerged as a transformative force that transcends industry boundaries, with its applications extending into numerous sectors. In the realm of healthcare, for instance, the potential of machine learning has been extensively harnessed. Nguyen et al. (2021) underscore its multifaceted success in this field, where it has been deployed for tasks ranging from disease diagnosis to drug discovery, ultimately leading to more accurate and efficient healthcare solutions.

Similarly, within the sphere of education, machine learning has proven to be a game-changer. The work of Tahmasebi et al. (2020) emphasises the remarkable potential of machine learning in this context, highlighting its ability to save significant time and enhance accuracy in tasks such as personalised learning recommendations and student performance prediction. These applications not only streamline educational processes but also contribute to better learning outcomes.

The versatility of machine learning extends beyond healthcare and education. In project management, it offers valuable tools for optimising project schedules, resource allocation, and risk assessment, thereby improving project outcomes and efficiency. This adaptability and effectiveness across sectors underline the cross-cutting nature of machine learning's impact on modern industries.

Furthermore, machine learning algorithms have proven their mettle in handling vast datasets and deriving insightful findings. The field of chemical engineering, as exemplified by Taoufik et al. (2022), has witnessed a surge of interest in leveraging machine learning to solve complex problems and enhance production quality. By analysing extensive data, machine learning models can uncover hidden patterns, optimise processes, and predict outcomes with a degree of precision that was previously unattainable.

Notably, machine learning extends its benefits beyond improved efficiency. It can also lead to substantial cost reductions, resource conservation, and waste reduction, as observed by Tsai and Chang (2018) and Weichert et al. (2019). These cost-saving measures are particularly valuable in resource-intensive industries, where optimising processes and resource allocation can translate into substantial financial savings and environmental benefits.

Machine learning's prowess is not limited to isolated tasks but is a continuous process of improvement. Through the utilization of vast datasets, the machine learning branch of artificial intelligence continually enhances task performance in the digital world, as highlighted by Carbo-Valverde et al. (2020). This iterative learning process ensures that machine learning models adapt and evolve, becoming more effective and accurate over time.

In the realm of business, the adoption of cutting-edge technology and machine learning is driving workflow improvements and promoting digitalization. Kang et al. (2020) note that many firms struggle to translate ideas into actionable results, but machine-learning algorithms have the potential to optimise corporate operations. As digitalization expands, machine learning plays a pivotal role in automating processes, making data-driven decisions, and fostering innovation.

The integration of product design and production processes has spurred the evolution of digital manufacturing, powered by digitalization. Within this landscape, machine learning emerges as a key element of artificial intelligence, crucial for making predictions and learning from data. In networked manufacturing facilities, real-time data-driven decision-making is paramount, and machine learning facilitates the optimisation of production processes and resource allocation.

However, it is essential to acknowledge the potential pitfalls of machine learning. Prediction performance, while generally remarkable, may suffer from inaccuracies, particularly in cases of sudden shifts in operational parameters. Shamsuzzoha et al. (2021) raise this concern, highlighting the need for ongoing monitoring and fine-tuning of machine learning models to ensure their reliability and accuracy.

In summary, this extended literature review underscores the transformative influence of machine learning across diverse sectors, from healthcare to manufacturing. Its ability to enhance efficiency, accuracy, and cost-effectiveness is evident in various domains. This review sets the stage for our exploration of machine learning's specific role in sheet metal operations within the manufacturing sector. It is clear that machine learning is a driving force shaping the digitalized world, and its potential to revolutionise manufacturing processes cannot be overstated.

Machine learning:

Machine learning, at its core, serves as an indispensable tool for empowering computers to navigate and conquer the ever-expanding realm of data-related challenges. It stands in stark contrast to traditional programming paradigms, where computers diligently follow explicit instructions to methodically solve problems. The distinctive essence of machine learning lies in its capacity to harness intricate models and algorithms, bestowing upon computers the remarkable ability to not just process data but to also augment their predictive prowess, uncover intricate patterns, and discern complex relationships within datasets. While Figure 1 (regrettably not included here) would have visually elucidated this distinction, we shall endeavour to paint a vivid mental picture.

In the traditional programming realm, one could envision a scenario where computers obediently accept a set of student marks as input and dutifully generate a neatly sorted list of those marks as output. This linear and deterministic approach has long been the cornerstone of computational problem-solving. However, the advent of machine learning represents a paradigm shift of profound proportions.

Machine learning, in its essence, is akin to the cultivation of an artificial intellect. It involves the intricate process of training computers not merely to execute prescribed steps but to autonomously decipher data, draw insights, and propose solutions with a degree of independence that mirrors human cognition. Mahmoodi et al. (2019) delve into the intricate tapestry of machine learning approaches, offering a nuanced understanding of how this groundbreaking technology operates at the intersection of mathematics, statistics, and computer science. Their exploration unearths the nuanced facets of machine learning, where algorithms become akin to digital apprentices, honing their skills through exposure to vast datasets, refining their predictive abilities, and adapting to evolving information.

In essence, machine learning serves as the dynamic bridge between data and decision-making. It empowers computers to not only comprehend the intricacies concealed within datasets but also to generate actionable insights and predictions, often outstripping the capabilities of traditional programming by leaps and bounds. This transformative approach has far-reaching implications across a multitude of domains, where the ability to learn and adapt from data-driven experiences empowers machines to tackle complex challenges, from image recognition to natural language processing.

In the forthcoming sections of this exploration, we shall further unpack the myriad facets of machine learning, from its foundational principles to its practical applications. Through a deeper dive into supervised learning, unsupervised learning, and reinforcement learning, we shall illuminate the diverse tools and techniques that enable computers to evolve into astute learners in their own right. This multifaceted journey will unravel the versatility of machine learning, showcasing its adaptability in solving complex problems across a broad spectrum of industries and domains.

Machine learning techniques:

1. Supervised Learning:

In supervised learning, algorithms learn from and make predictions based on labelled data. For instance, in facial recognition (shown in Figure 2), the algorithm is trained using labelled photos of faces in order to correctly detect and categorise faces (Taoufik et al, 2022).

2. Unsupervised Learning:

Unsupervised machine learning is very useful when it comes to offering descriptions of tasks, and this is because the main purpose of unsupervised machine learning is to explore the relationship between the data without providing an outcome. This kind of machine learning has a lack of response (Jiang et al., 2020). Models can find patterns in data without labels thanks to unsupervised learning. Based on data similarities, unsupervised models are shown in Figure 3 recognising geometric shapes. If the outcomes are unacceptable, the model can look for different patterns, such as grouping forms according to their surface or colour. It can tell between, for instance, forms of different hues like yellow, orange, pink, and green (Taoufik et al, 2022).

3. Reinforcement Learning (RL):

Reinforcement learning, often referred to as RL, involves an agent that learns through a series of actions in its environment. The agent receives rewards (positive marks) for positive actions and penalties (negative marks) for negative ones. By maximizing rewards and minimizing penalties, the agent autonomously discovers the optimal actions to take within its environment. Figure 4 illustrates an agent navigating a maze, where rewards or penalties are assigned based on successful navigation without hitting walls (Taoufik et al, 2022).

Overall, these machine learning techniques—supervised, unsupervised, and reinforcement learning—offer powerful tools for solving a wide range of problems. They play crucial roles in various domains, from image recognition to autonomous navigation, enabling computers to learn and make decisions independently.

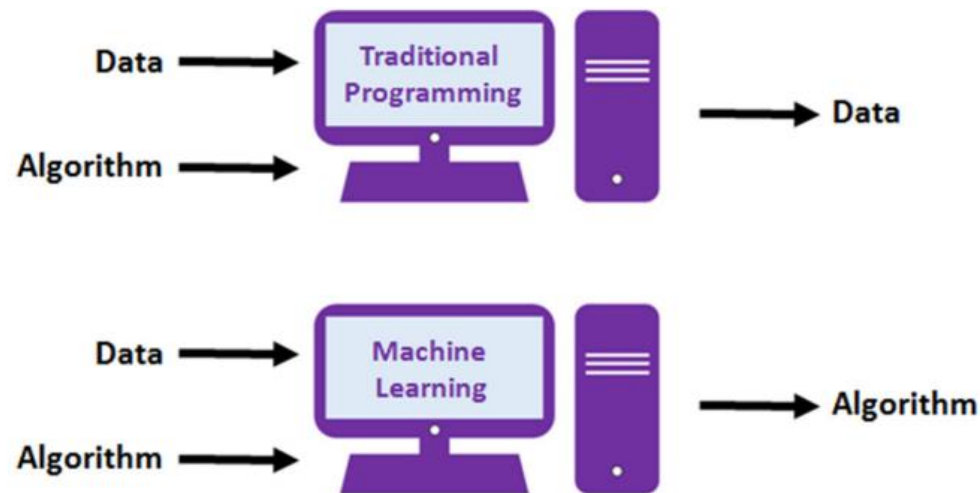


Figure. 1 shows machine learning against traditional programming (Taoufik et al, 2022).

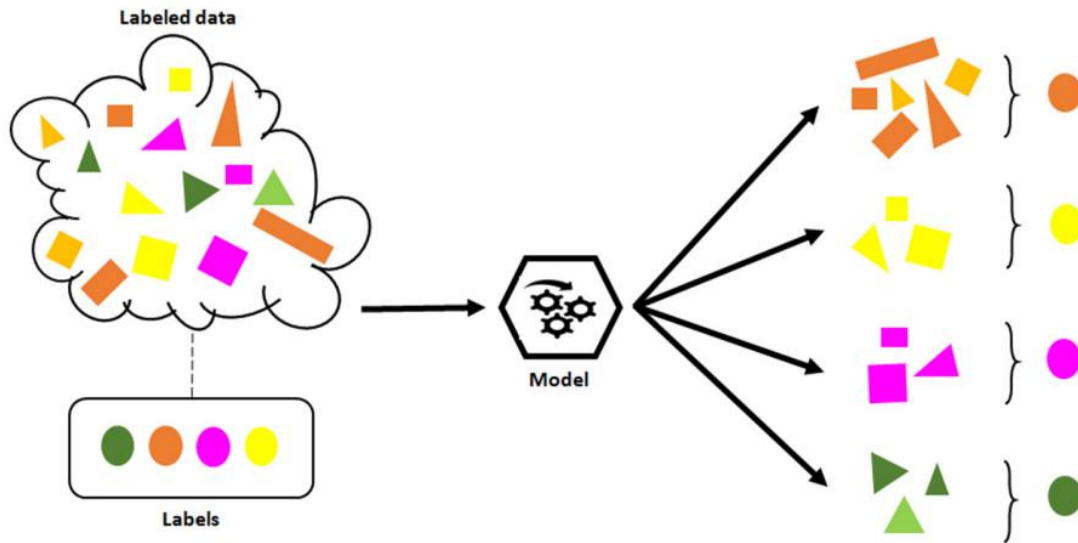


Figure. 2 explains the supervised machine learning (Taoufik et al, 2022).

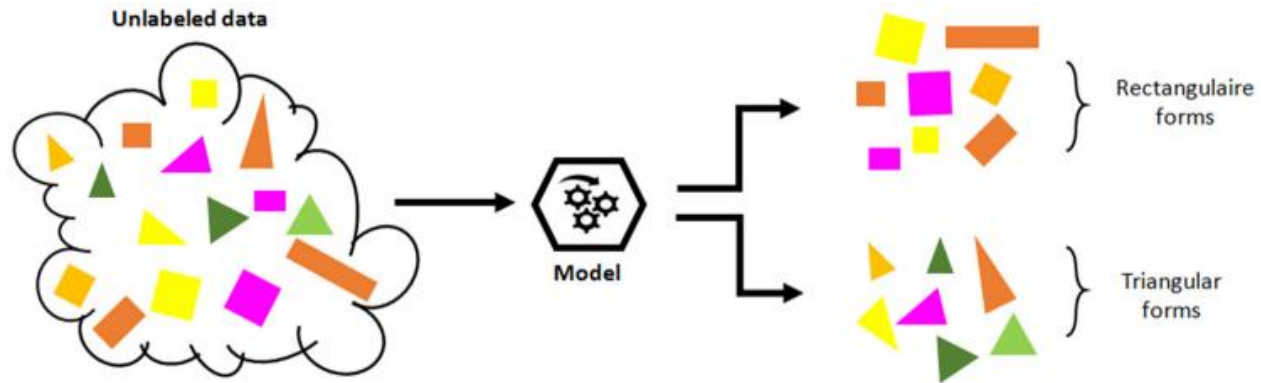


Figure. 3 explains the unsupervised machine learning (Taoufik et al, 2022).

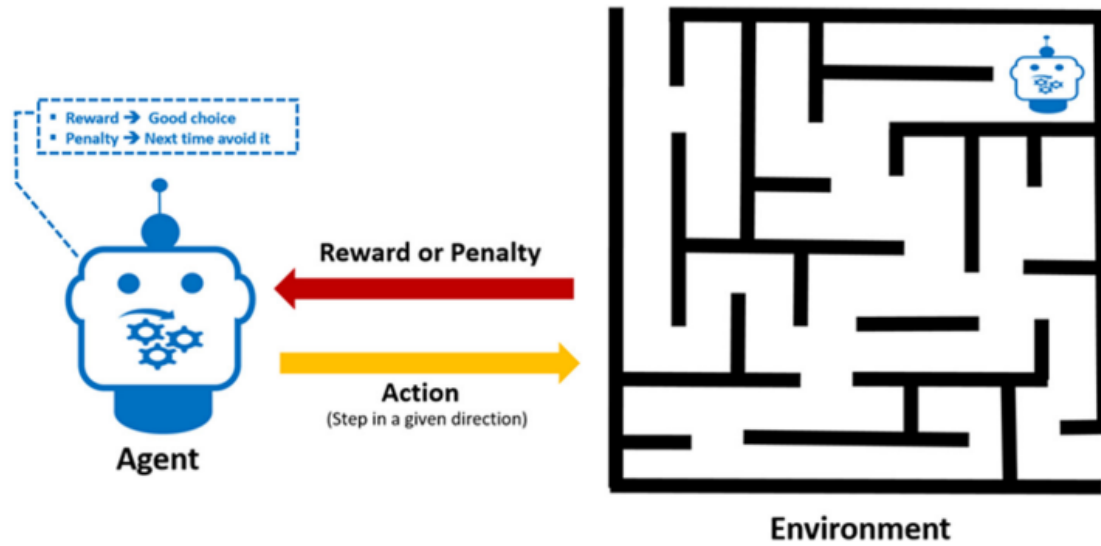


Figure.4 reinforcement learning (RL) (Taoufik et al, 2022).

Case Study:

The case business is a well-known manufacturer of high-tech sheet metal forming equipment for use in the sheet metal forming industry. The company provides a wide range of goods and services with different levels of automation. One of the most cutting-edge options is a fully automated system that needs little human involvement. The company's line of products consists of:

TheBEND: Specialized for sheet metal bending.

TheCOMBI: Multipurpose devices with laser cutting and piercing capabilities.

TheLASER: Designed for drilling and welding in addition to laser sheet metal cutting.

ThePUNCH: Concentrates on punching sheet metal.

TheSYSTEM is a modular collection of tools that combines machine operations into a single automated production line.

TheSOFTWARE: A group of extra software applications designed to improve machine performance.

The Tulus® Software Series includes tools for managing parts orders and inventories.

Numerous industries, including those that produce aviation, crops, automobiles, and household goods, employ these materials.

The case firm promotes close collaboration at many levels and is renowned for its creative approach and openness to novel approaches. The company exports machinery and systems to international markets from its numerous manufacturing locations in China, the United States, Italy, and Finland. Through direct presence or a network of specialised dealers, its sales and service network work in over 80 countries.

The business offers the most advanced servo-electric solutions for punching, bending, and integrated operations, boasting the largest product line in the world. Notably, the business places a strong emphasis on sustainability, and the complete product range is produced utilising eco-friendly techniques that give equal weight to environmental responsibility and productivity.

The sheet metal industry has complex nested applications, which is a challenge. The company's key nesting algorithm goals are waste reduction and processing optimisation for metal sheets, which are consistent with the company's dedication to efficiency and sustainability (Shamsuzzoha et al., 2021).

In conclusion, this case study focuses on a significant supplier of sheet metal forming equipment recognised for its broad and innovative product line, global reach, and dedication to efficiency and sustainability in solving the issues faced by the sheet metal industry.

Methodology:

Data transformation: To enable effective processing by machine and deep learning methods, the submitted pictures were translated into forms appropriate for analysis.

Component Analysis: To find the gaps between the components, all of the component images on the page were analysed to separate the real components from the unnecessary parts.

Gap Optimisation: Using necessary and optional components based on gap analysis, the study attempted to help the case maker optimise its operational schedule between daytime and nighttime production lines.

Image Conversion: To transform component images, including drawings and associated thresholds, into a format appropriate for analysis, a machine learning technique was applied. This technique established the permitted distance between any two components.

Visualisation: The algorithm's output consisted of the same image as the input together with extra annotations like circles designating minute gaps between components. The final image showed every conceivable little gap between components.

The software and tools: used in this study were Python 3.7.0 and the libraries specified in Table 2. These libraries played a crucial role in improving the images' visibility and resolving gap-related problems.

Pixel Measurement: To determine component distances accurately, the coordinates of these elements in a pixel image were measured. Since the input was not initially in pixel format, it was converted into a 2D matrix with m rows and n columns (Shamsuzzoha et al., 2021).

Overall, by combining data transformation, component analysis, gap optimisation, picture conversion, visualisation, and pixel measurement techniques, this methodology shows a thorough approach to analysing and optimising components within supplied photos.

Table 2. List of library files used during the study.

Serial no.	Library file	Description of the library file and its functionality
1	requirements.txt:	Contains all the needed libraries. In addition, this file is also used for installing these libraries.
2	setup.sh:	Contain the commands for setting up a virtual environment as well as installing the needed libraries.
3	run.sh:	Contains the commands for activating the virtual environment and running the application.
4	Config.py:	Contains all the default parameter values; you can modify it directly in this file.
5	Preprocessing.py:	This file is responsible for pre-processing the input images so that we can pass these as input to our application. Preprocessing.py contains some functions; each function does the specific task.
6	Component.py:	We are working with the image input. In particular, we measure the distance of any 2 of the components on this image, so it is better for us if we get the components from the image and treat them as objects. In this class Component, we define some needed attributes and methods.
7	Image.py:	This file represents the Image object. In this class, we also define some needed attributes and methods for Image object.
8	Processing.py:	This file performs the main purpose of this application. It plots the circles in every single pixel in the components, and after that these circles are responsible for measuring the distance.

Table.2 Number of library files that uses during the project (Shamsuzzoha et al., 2021).

Conclusion:

In conclusion, this essay has provided an in-depth exploration of the pivotal role that machine learning plays in the manufacturing sector, with a particular focus on its applications in sheet metal operations. The introduction served as a launchpad, shedding light on the rapid adoption of machine learning across industries and its profound potential to reshape the landscape of manufacturing. It also drew attention to the historical context of automation, underscoring how machine learning stands as the contemporary pinnacle of human ingenuity in streamlining operations and managing data.

The literature review section served as a compelling testament to the versatility and significance of machine learning. It extended its reach beyond manufacturing, showcasing its impact in diverse fields such as healthcare, education, and project management. While acknowledging the challenges, such as prediction accuracy, it underscored the tangible benefits that machine learning brings in terms of efficiency, precision, and substantial cost savings.

The comprehensive overview of machine learning in the subsequent section elucidated its core principles and delved into three fundamental techniques: supervised learning, unsupervised learning, and reinforcement learning. These techniques were brought to life through practical examples, illuminating their adaptability in tackling complex problems across industries.

The enlightening case study provided a glimpse into the operations of a renowned manufacturer of sheet metal forming equipment. This company's commitment to innovation, sustainability, and its global presence showcased how machine learning is leveraged to optimise processes and reduce waste in the demanding sheet metal industry.

Finally, the methodology section served as a valuable blueprint, elucidating the meticulous steps involved in analysing and optimising components within sheet metal operations using machine learning techniques. The processes of data transformation, component analysis, gap optimisation, image conversion, visualisation, and pixel measurement collectively demonstrated a comprehensive approach to solving real-world challenges.

In summation, this essay has not only illuminated the immense potential of machine learning in revolutionising the industrial sector but has also provided a holistic understanding of the subject matter. By delving into theory, practical applications, and methodology, it has become evident that machine learning is poised to play a central role in shaping the future of manufacturing. As companies continue to embrace and harness this transformative technology, the manufacturing sector stands on the brink of a new era marked by unprecedented efficiency, precision, and sustainability. Machine learning is undeniably the driving force that will steer the course of manufacturing evolution in the years to come.

References:

- Acceure. 2018. "Redefine Banking with Artificial Intelligence." Retrieved 2 July 2020, from https://www.accenture.com/_acnmedia/pdf-68/accenture-redefine-banking.pdf
- Carbo-Valverde, S., Cuadros-Solas, P. and Rodríguez-Fernández, F. (2020) 'A machine learning approach to the digitalization of bank customers: Evidence from random and causal forests', *PLOS ONE*, 15(10). doi:10.1371/journal.pone.0240362.
- [A machine learning approach to the digitalization of bank customers: Evidence from random and causal forests \(plos.org\)](https://doi.org/10.1371/journal.pone.0240362)
- Chiu, M.-C., C.-D. Tsai, and L. T-I T-L. 2020. "An Integrative Machine Learning Method to Improve Fault Detection and Productivity Performance in a Cyber-physical System." *Journal of Computer Information Science and Engineering* 20(2): 12. pages. <https://doi.org/10.1115/1.4045663>
- Cakir, M., M. A. Guvenc, and S. Mistikoglu. 2021. "The Experimental Application of Popular Machine Learning Algorithms on Predictive Maintenance and the Design of IIoT Based Condition Monitoring System." *Computers & Industrial Engineering* 151: 106948. doi:10.1016/j.cie.2020.106948.
- Dutta, N., P. Kaliannan, and U. Subramaniam. 2021. "Application of Machine Learning Algorithm for Anomaly Detection for Industrial Pumps." In *Machine Learning Algorithms for Industrial Applications. Studies in Computational Intelligence*, edited by S. Das, S. Das, N. Dey, and A. E. Hassanien, 237–263. Cham, 907: Springer.
- Hamouche, E. and Loukaides, E.G. (2018) 'Classification and selection of sheet forming processes with machine learning', *International Journal of Computer Integrated Manufacturing*, 31(9), pp. 921–932. doi:10.1080/0951192x.2018.1429668.
- [Classification and selection of sheet forming processes with machine learning: International Journal of Computer Integrated Manufacturing: Vol 31, No 9 \(tandfonline.com\)](https://doi.org/10.1080/0951192x.2018.1429668)
- Hamouche, E. and Loukaides, E.G. (2018) 'Classification and selection of sheet forming processes with machine learning', *International Journal of Computer Integrated Manufacturing*, 31(9), pp. 921–932. doi:10.1080/0951192x.2018.1429668.
- [Classification and selection of sheet forming processes with machine learning: International Journal of Computer Integrated Manufacturing: Vol 31, No 9 \(tandfonline.com\)](https://doi.org/10.1080/0951192x.2018.1429668)
- Jiang, T., Gradus, J.L. and Rosellini, A.J. (2020) 'Supervised machine learning: A brief primer', *Behavior Therapy*, 51(5), pp. 675–687. doi:10.1016/j.beth.2020.05.002.

Kang, Z., Catal, C. and Tekinerdogan, B. (2020) ‘Machine learning applications in production lines: A systematic literature review’, *Computers & Industrial Engineering*, 149, p. 106773. doi:10.1016/j.cie.2020.106773.

[Machine learning applications in production lines: A systematic literature review \(sciencedirectassets.com\)](https://www.sciencedirect.com/science/article/pii/S0950080420301067)

Mahmoodi, N.M. *et al.* (2019) ‘Activated carbon/metal-organic framework nanocomposite: Preparation and photocatalytic dye degradation mathematical modeling from wastewater by least squares support vector machine’, *Journal of Environmental Management*, 233, pp. 660–672. doi:10.1016/j.jenvman.2018.12.026.

[Activated carbon/metal-organic framework nanocomposite Preparation and photocatalytic dye degradation mathematical modeling from wastewater by least squares support vector machine \(sciencedirectassets.com\)](https://www.sciencedirect.com/science/article/pii/S0950080420301067)

Min, Q., Y. Lu, Z. Liu, C. Su, and B. Wang. 2019. “Machine Learning Based Digital Twin Framework for Production Optimization in Petrochemical Industry.” *International Journal of Information Management* 49: 502–519. doi:10.1016/j.ijinfomgt.2019.05.020

Mahesh, B., 2020. Machine learning algorithms-a review. *International Journal of Science and Research (IJSR)*. [Internet], 9(1), pp.381-386.
https://www.researchgate.net/profile/Batta-Mahesh/publication/344717762_Machine_Learning_Algorithms_-_A_Review/links/5f8b2365299bf1b53e2d243a/Machine-Learning-Algorithms-A-Review.pdf?eid=5082902844932096

Nguyen, X.C., Ly, Q.V., Peng, W., Nguyen, V.-H., Nguyen, D.D., Tran, Q.B., Nguyen, T.T.H., Sonne, C., Lam, S.S., Ngo, H.H., Goethals, P., Le, Q.V., 2021. Vertical flow constructed wetlands using expanded clay and biochar for wastewater remediation: a comparative study and prediction of effluents using machine learning. *J. Hazard. Mater.* 413, 125426
[1-s2.0-S004896972105631X-main.pdf](https://www.sciencedirect.com/science/article/pii/S004896972105631X-main.pdf)

O'Donovan, P., C. Gallagher, K. Leahy, and D. T. J. O'Sullivan. 2019. “A Comparison of Fog and Cloud Computing Cyber-Physical Interfaces for Industry 4.0 Real-time Embedded Machine Learning Engineering Applications.” *Computers in Industry* 110: 12–35. doi:10.1016/j.compind.2019.04.016.

Rai, R. *et al.* (2021) ‘Machine learning in manufacturing and Industry 4.0 Applications’, *International Journal of Production Research*, 59(16), pp. 4773–4778. doi:10.1080/00207543.2021.1956675.

[Machine learning in manufacturing and industry 4 0 applications.pdf](#)

Ren, Y. (2021) ‘Optimizing Predictive Maintenance With Machine Learning for Reliability Improvement’, *ASCE-ASME J Risk and Uncert in Engrg Sys Part B Mech Engrg*, 7(3). doi:10.1115/1.4049525.

[Optimizing Predictive Maintenance With Machine Learning for Reliability Improvement | ASME J. Risk Uncertainty Part B | ASME Digital Collection](#)

Stoerkle, D. D., P. Seim, L. Thyssen, and B. Kuhlenkoetter. 2016. “Machine Learning in Incremental Sheet Forming.” Proceedings of 47th International Symposium on Robotics, Munich, Germany, Germany, 667–673, 21–22 June.

Taoufik, N. *et al.* (2022) ‘The state of art on the prediction of efficiency and modeling of the processes of pollutants removal based on machine learning’, *Science of The Total Environment*, 807, p. 150554. doi:10.1016/j.scitotenv.2021.150554.

[1-s2.0-S004896972105631X-main.pdf](#)

Sung, T. K. 2018. “Industry 4.0: A Korea Perspective.” *Technology Forecasting and Social Change* 132: 40–45. doi:10.1016/j.techfore.2017.11.005.

Shamsuzzoha, A. *et al.* (2021) ‘Application of machine learning algorithm in the sheet metal industry: an exploratory case study’, *International Journal of Computer Integrated Manufacturing*, 35(2), pp. 145–164. doi:10.1080/0951192x.2021.1972469.

[Application of machine learning algorithm in the sheet metal industry an exploratory case study.pdf](#)

Tsai, S.-Y. and Chang, J.-Y. (2018) ‘Parametric study and design of deep learning on leveling system for Smart Manufacturing’, *2018 IEEE International Conference on Smart Manufacturing, Industrial & Logistics Engineering (SMILE)* [Preprint]. doi:10.1109/smile.2018.8353980.

Tsai, S.-Y., and J.-Y. Chang. 2018. “Parametric Study and Design of Deep Learning on Leveling System for Smart Manufacturing.” 2018 IEEE International Conference on Smart Manufacturing, Hsinchu, Taiwan, 8–9 February.

Weichert, D. *et al.* (2019) ‘A review of machine learning for the optimization of Production Processes’, *The International Journal of Advanced Manufacturing Technology*, 104(5–8), pp. 1889–1902. doi:10.1007/s00170-019-03988-5.

Xie, Q. 2020. “Machine learning in human resource system of intelligent manufacturing industry.” Enterprise Information Systems, Taylor and Francis, London, UK.10.1080/ 17517575.2019.1710862

Zwierzycski, M., P. Nicholas, and M. Ramsgaard Thomsen. 2018. “Localised and Learnt Applications of Machine Learning for Robotic Incremental Sheet Forming.” In: De Rycke K. *et al.* (eds) Humanizing Digital Reality. Springer, Singapore. 382,

[Localised and Learnt Applications of Machine Learning for Robotic Incremental Sheet Forming | SpringerLink](#)

Zhang, J., Wang, P. and Gao, R.X. (2019) ‘Deep learning-based tensile strength prediction in fused deposition modeling’, *Computers in Industry*, 107, pp. 11–21. doi:10.1016/j.compind.2019.01.011.

[Deep learning-based tensile strength prediction in fused deposition modeling \(sciencedirectassets.com\)](#)

