EXPLORING THE BENEFITS OF INTEGRATING MACHINE LEARNING AND TOOL CONDITION MONITORING FOR MANUFACTURING APPLICATIONS

Gokul S[1], Vigneshvar S A[1], Ashwathi Krishna R[1], Kabilan K,[1] P. Vijaya*[2]

[1] Department of Mechanical Engineering, Sri Eshwar College of Engineering, Coimbatore - 641202, Tamil Nadu, India
[2] Department of Mathematics and Computer Science, Modern College of Business and Science, Bowshar, Sultanate of Oman
pvvijaya@gmail.com*

Abstract. This review article explores the potential benefits of integrating machine learning and tool condition monitoring for manufacturing applications. It first reviews the current state of machine learning and tool condition monitoring and their respective applications in manufacturing. It then discusses the potential benefits of combining the two, including improved process control and reduced downtime, as well as the challenges associated with integrating the two technologies. Finally, the review article provides an overview of existing approaches to integrating machine learning and tool condition monitoring, examining the advantages and drawbacks of each. The article concludes with a summary of the key findings and implications for the future of integrating machine learning and tool condition monitoring in manufacturing. The article provides a comprehensive overview of the benefits and challenges associated with integrating machine learning and tool condition monitoring, as well as a review of existing approaches and future implications.

Keywords: Machine Learning, Tool Condition Monitoring, Manufacturing Applications, Process Control, Downtime, Integration

1 INTRODUCTION

Modern manufacturing applications are heavily dependent on machines to streamline production and ensure consistent quality. As such, it is essential to maintain and monitor these machines in order to detect any potential problems and avoid production downtime. Machine learning and tool condition monitoring (TCM) are two key technologies that can be used to ensure that machines are running smoothly and efficiently [1]. This review article will explore the benefits of integrating machine learning and tool condition monitoring for manufacturing applications. It will discuss the advantages and disadvantages of using machine learning and TCM in manufacturing applications, as well as the various challenges

N. Bacanin and H. Shaker (eds.), *Proceedings of the 2nd International Conference on Innovation in Information Technology and Business (ICIITB 2024)*,
Advances in Computer Science Research 113,
https://doi.org/10.2991/978-94-6463-482-2_4

associated with their integration. Furthermore, this review article will assess the current landscape of machine learning and TCM in manufacturing applications and provide an overview of future applications. The use of machine learning and TCM in manufacturing applications is an increasingly popular trend due to their ability to detect anomalies and provide predictive maintenance. These technologies allow for the detection of problems before they become serious, which can lead to significant cost savings due to reduced production downtime. Additionally, machine learning and TCM can be used to optimize production processes and maximize efficiency. Furthermore, the integration of machine learning and TCM in manufacturing applications can provide valuable insights into the performance of the machines and provide real-time feedback on the production process. This can be used to make informed decisions about how to optimize the manufacturing process and identify areas for improvement. Overall, the integration of machine learning and TCM in manufacturing applications can provide numerous benefits and can help manufacturers reduce costs, maximize efficiency, and improve production processes. This review article will discuss the advantages and disadvantages of using machine learning and TCM in manufacturing applications, the various challenges associated with their integration, and the current landscape of machine learning and TCM in manufacturing applications. Finally, it will provide an overview of future applications.

2 OVERVIEW OF MACHINE LEARNING FOR MANUFACTURING APPLICATIONS

Machine mastering for manufacturing applications has end up increasingly more famous in recent years, due to its potential to enhance productivity, reduce charges and growth performance. Machine studying algorithms can be used to optimize manufacturing methods, automate decision-making, and broaden predictive models for various production responsibilities. In this assessment, we can discuss the numerous gadget learning techniques used for numerous manufacturing procedures and applications. We will offer a top level view of the important thing principles and procedures utilized by the numerous algorithms and provide an explanation for how they can be implemented to improve the efficiency of manufacturing procedures. We will also speak the demanding situations related to applying system getting to know in manufacturing methods and the capacity solutions to those challenges. The first step in applying machine studying to production programs is to expand a dataset that as it should be displays the production surroundings. Figure 1 illustrates a flow chart for an integrated system of Machine Learning (ML) and Traditional Chinese Medicine (TCM). [30]

This is generally performed by means of accumulating information from various assets inclusive of sensors, machines, and manufacturing logs. Once the dataset is developed, the device getting to know algorithm may be skilled at the facts to broaden an accurate version. The forms of algorithms utilized in machine gaining knowledge of for production applications variety from super-

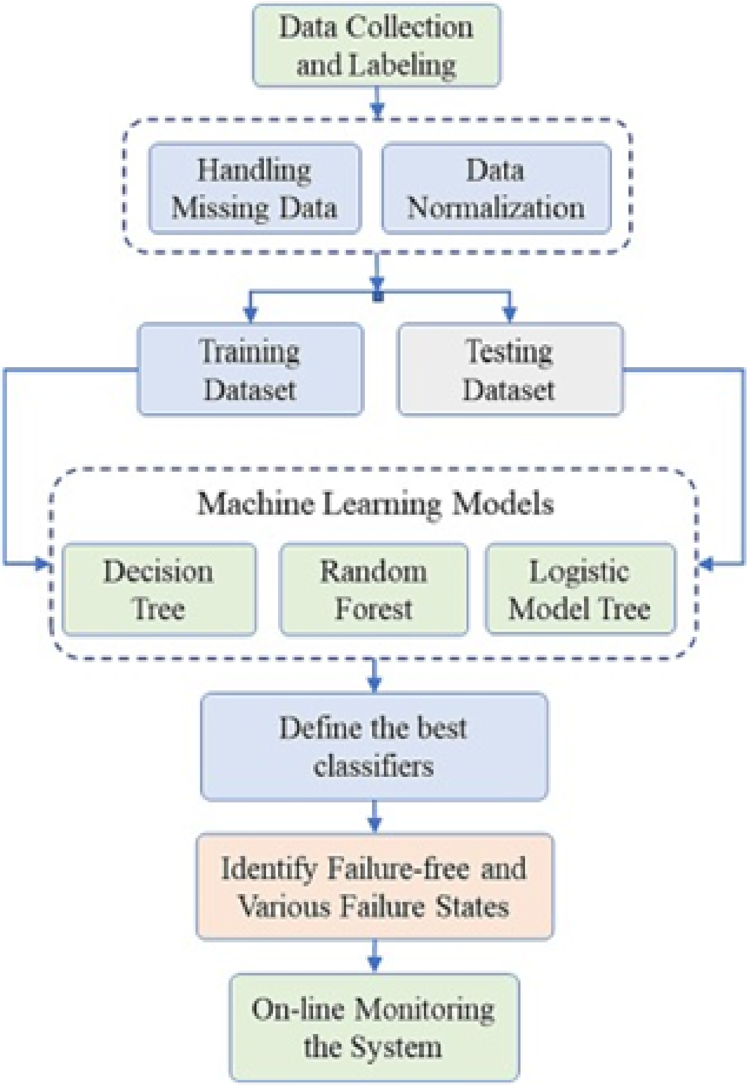

Fig. 1. Flow chart – Integrated System of ML & TCM

vised algorithms along with Random Forest and Support Vector Machines, to deep getting to know networks along with Convolutional Neural Networks and Recurrent Neural Networks. Each of those algorithms has its own particular properties and is nicely desirable to one-of-a-kind sorts of responsibilities [2]. For instance, deep mastering networks are appropriate for duties which include item recognition, while supervised algorithms are better suitable for responsibilities inclusive of predicting the output of a process. Once the version is skilled, it is able to be used to automate selection-making and optimize the manufacturing technique. This is carried out by means of using the version to make predictions approximately destiny consequences and then using those predictions to inform selections about production procedures [3].

This can result in stepped forward efficiency and reduced fees. Furthermore, system mastering algorithms can be used to broaden predictive fashions to discover capability problems in the manufacturing method. This can help producers stumble on and address troubles such as device breakdowns or low manufacturing yields earlier than they emerge as severe problems. Overall, device learning for production programs has the ability to revolutionize the producing industry. With the right algorithms and data, machine learning may be used to optimize tactics, automate selection-making, and expand predictive fashions to perceive potential issues. While there are nonetheless a few demanding situations associated with making use of machine getting to know in manufacturing programs, the ability advantages make it an attractive choice for plenty producers [4].

3 ADVANTAGES OF INTEGRATING MACHINE LEARNING AND TOOL CONDITION MONITORING

Integrating gadget mastering and tool circumstance monitoring (TCM) is becoming an increasing number of popular in a wide variety of industries, from production to healthcare. By combining the two technology, agencies can gain insights into their operations and discover ability troubles earlier than they motive pricey disruptions or delays [5]. This type of proactive technique can assist companies enhance their performance, lessen downtime, and enhance protection. Machine studying is a effective tool for analysing massive quantities of records and figuring out patterns and tendencies in that facts. By leveraging this technology, agencies can gain insights into their operations and pick out capability problems earlier than they reason steeply-priced disruptions or delays [6]. For instance, gadget getting to know can be used to stumble on anomalies in manufacturing approaches, alerting personnel to take corrective action before the trouble turns into too expensive. Meanwhile, tool situation monitoring is a method that facilitates corporations reveal and preserve the performance of their tools. This technique includes frequently inspecting and trying out gear to identify any capacity troubles, which include wear and tear, that could motive them to malfunction. By combining gadget studying and tool situation monitoring, groups can gain a better know-how in their equipment and how they're being used, permitting them to take preventive measures to keep away from high-priced troubles inside the destiny [7]. The benefits of combining gadget mastering and tool situation tracking are severe. For starters, it allows groups come to be greater proactive of their approach to renovation, as they may be able to come across capability issues before they turn out to be critical problems. This allows companies save cash on maintenance and downtime, as they may be capable of take corrective movement earlier than the trouble becomes too luxurious. Additionally, integrating the 2 technologies permits groups to fast discover and cope with any issues that can stand up, which further facilitates to lessen downtime and improve performance. Another advantage is that system gaining knowledge of and tool situation monitoring can be included into current systems, allowing companies to advantage from both technologies without having to invest in new hardware or software program. This makes it easier for corporations to implement the technology and start to gain the benefits proper away [8]. Finally, integrating device mastering and device condition monitoring can assist corporations improve safety. By the use of the era to screen tools and methods, organizations can speedy identify any potential problems that could lead to injuries or accidents, permitting them to take corrective motion earlier than any harm is done. In conclusion, integrating device gaining knowledge of and device condition monitoring can help groups gain insights into their operations, reduce downtime, and enhance safety. By leveraging the power of these technology, organizations can turn out to be greater proactive in their approach to maintenance, saving cash on maintenance and downtime, and enhancing performance [9].

4 CHALLENGES OF IMPLEMENTING MACHINE LEARNING AND TOOL CONDITION MONITORING

Machine Learning (ML) and Tool Condition Monitoring (TCM) are two of the most effective and hastily evolving technology which have the capacity to revolutionize the manufacturing enterprise. ML and TCM permit for the automation of tactics, the optimization of manufacturing tactics, and the optimization of resources. The implementation of ML and TCM can bring about a greater efficient, fee-powerful, and secure manufacturing environment. However, there are various demanding situations related to the implementation of ML and TCM that should be addressed [10]. One of the number one challenges of ML and TCM implementation is the problem of acquiring correct statistics. Data is a critical element of ML and TCM, as it is used to inform the algorithms and permit them to make selections. However, obtaining accurate data may be hard and time consuming, mainly in commercial settings with big amounts of machinery and complex production strategies. Additionally, the facts need to be accumulated on a regular basis in order for the ML and TCM algorithms to stay up to date. Another task associated with the implementation of ML and TCM is the complexity of the algorithms [11]. The algorithms need to be capable of perceive styles and traits within the information for you to generate accurate predictions and choices. This calls for an intensive expertise of the facts and the underlying strategies, in addition to an know-how of the algorithms and techniques used to interpret the statistics. Additionally, the algorithms ought to be continuously up to date to ensure that they remain effective inside the face of changing situations or statistics. A 0.33 task is the cost associated with the implementation of ML and TCM. The fee of the hardware, software program, and personnel required for the implementation can be prohibitively costly for plenty organizations. Additionally, the price of schooling employees to function and maintain the device can be large. Finally, the implementation of ML and TCM may be hindered by the dearth of technical information available in some agencies. Organizations won't have the vital personnel with the abilities and know-how required to successfully put in force ML and TCM [12]. This can result in mistakes and inefficiencies, in addition to a loss of confidence within the device. In conclusion, while the implementation of ML and TCM can result in vast value savings, extended efficiency, and stepped forward safety, the challenges related to implementation have to be considered. It is crucial for groups to make certain that they've the necessary technical information and monetary sources to put in force and hold ML and TCM systems, or else they'll be not able to gain the whole advantages of those powerful technologies [13].

5 CURRENT APPLICATIONS OF MACHINE LEARNING AND TOOL CONDITION MONITORING

ML is a rapidly growing area of synthetic intelligence (AI) that has been carried out to a extensive range of industries and programs. Its capability to revolutionize how businesses perform, how decisions are made, and how products and services are designed and introduced, has positioned it at the leading edge of the AI revolution [14]. One of the most interesting programs of ML is in tool situation monitoring (TCM). TCM is a method of tracking the circumstance of tools and machines in real-time, with the purpose of predicting potential breakdowns earlier than they arise. By leveraging ML, corporations at the moment are in a position to investigate huge volumes of information and detect signs and symptoms of wear and tear and tear in gear and machines earlier than they cause catastrophic disasters, as a consequence reducing the chance of high priced maintenance. The application of ML in TCM has a wide range of advantages. By monitoring the situation of tools and machines, agencies can perceive areas wherein renovation and restore are wanted and take suitable measures to lessen the threat of breakdowns. Additionally, via making use of ML to research the information amassed from equipment and machines, groups can gain insights at the overall performance in their tools and machines and make informed selections on a way to optimize their operations. In order to take advantage of the blessings of ML in TCM, corporations ought to first set up a facts-collection method [15]. This includes amassing relevant data from the gear and machines and storing it in a centralized database. Once the facts have been accumulated, organizations can leverage ML algorithms to perceive styles within the records and come across symptoms of potential breakdowns. In addition to the usage of ML for TCM, companies can also leverage ML to improve the performance in their gear and machines. By analysing the data gathered from the equipment and machines, organizations can identify regions in which improvements may be made and optimize their tools and machines to operate greater efficiently. Overall, the application of ML in TCM has the capacity to revolutionize how groups manage and preserve their gear and machines. By utilising ML to locate signs and symptoms of capacity breakdowns, organizations can lessen the risk of high-priced maintenance and optimize the performance of their equipment and machines. By leveraging ML, groups can advantage valuable insights on the overall performance in their equipment and machines and make informed decisions on a way to optimize their operations. As the era maintains to evolve, groups can assume to peer extra programs of ML in TCM, which will in addition improve how organizations manipulate and keep their tools and machines [16].

6 FUTURE OPPORTUNITIES FOR MACHINE LEARNING AND TOOL CONDITION MONITORING

The potential benefits of machine learning and tool condition monitoring have been demonstrated in numerous industries, and their use is only increasing. The future of this technology holds great promise, as new applications and ideas continue to be developed. In this article, we review some of the exciting opportunities for machine learning and tool condition monitoring in the future. First and foremost, machine learning and tool condition monitoring could be used to improve the accuracy of predictive maintenance. Predictive maintenance is the practice of using machine learning algorithms and models to predict when an asset will need maintenance, thus avoiding unexpected downtime and costs. With machine learning and tool condition monitoring, it is possible to detect small changes in the condition of a tool before it develops into a major issue [17]. This could allow companies to predict and address problems before they become too expensive or cause significant downtime. Another potential application of machine learning and tool condition monitoring is in the process of asset tracking. By using machine learning algorithms, companies could predict and detect when an asset has been lost or stolen. This could help reduce the financial losses associated with asset theft, as companies could take preventive measures to prevent it from occurring in the first place. Additionally, asset tracking could be used to monitor the usage of an asset, allowing companies to better understand how their assets are being utilized. In addition, machine learning and tool condition monitoring could help improve the quality of products and services. By monitoring the condition of tools and machines, companies could detect problems before they occur, and take steps to prevent them. This could lead to increased customer satisfaction and improved product quality. Finally, machine learning and tool condition monitoring could be used to improve the efficiency of production processes [18]. By monitoring the condition of tools and machines, companies could detect problems before they become costly and time-consuming. In addition, machine learning algorithms could be used to optimize the production process, ensuring that resources are used in the most efficient way possible [19]. Overall, the future of machine learning and tool condition monitoring looks very promising. As new applications and ideas continue to be developed, the potential benefits of this technology will only continue to increase. By leveraging the power of machine learning and tool condition monitoring, companies could significantly reduce costs, improve customer satisfaction, and optimize production processes [20].

7 EMERGING TECHNIQUES IN FEATURE ENGINEERING AND INTERPRETABILITY FOR MACHINE LEARNING-POWERED TOOL CONDITION MONITORING

Moving beyond traditional feature engineering techniques that rely on domain expertise to handcraft features from sensor data, recent advancements highlight the potential of deep learning architectures for feature extraction in tool condition monitoring (TCM) applications. Deep learning models, particularly autoencoders, can learn informative representations from raw sensor data automatically. This eliminates the need for manual feature selection, potentially leading to superior model performance and generalizability. Autoencoders are a class of neural networks trained to reconstruct their input data at the output layer. During this reconstruction process, the autoencoder learns a compressed representation of the input data, capturing the most salient features essential for TCM tasks. Figure 2 shows the training and testing accuracy of a convolutional neural network (CNN) model for three different image datasets: (a), (b), and (c). Figure 3 shows the training and testing loss of a convolutional neural network (CNN) model for three different image datasets: (a), (b), and (c). [27]

Interpretability remains a challenge for machine learning models, despite their ability to achieve high accuracy in TCM. A major hurdle in adopting ML models for real-world applications is the lack of understanding of how these models arrive at their predictions. This is where Explainable Artificial Intelligence (XAI) techniques come into play. XAI methods can unpack the decision-making process of an ML model, providing insights into the features and data points that most influence its predictions. In the context of TCM, XAI can help identify the sensor readings and data patterns that correlate most strongly with different stages of tool wear or potential tool failures. This interpretability is crucial for building trust in the system and for flagging potential biases in the data or the model itself. By leveraging XAI techniques, manufacturers can gain deeper insights from their ML-powered TCM systems and make more informed decisions about maintenance schedules and process optimization.

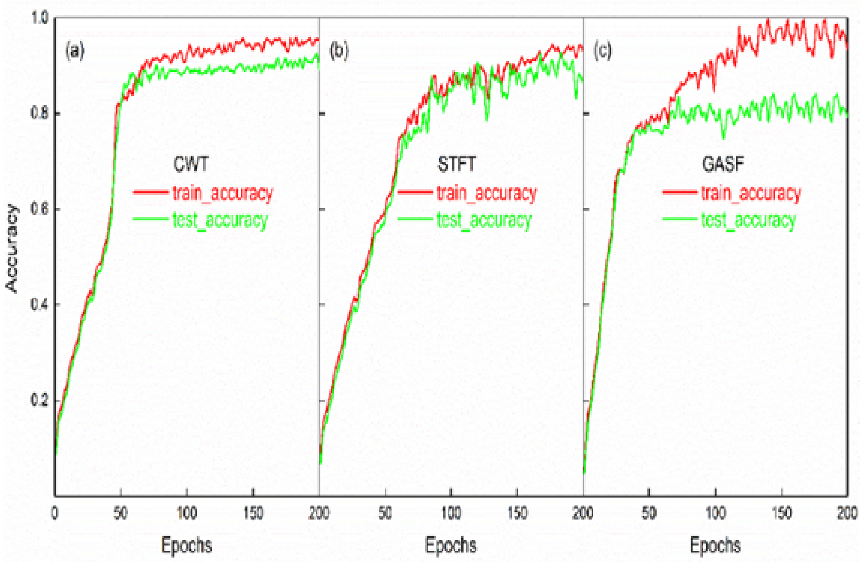

Fig. 2. CNN model accuracy, (a), (b) and (c) represent the image datasets

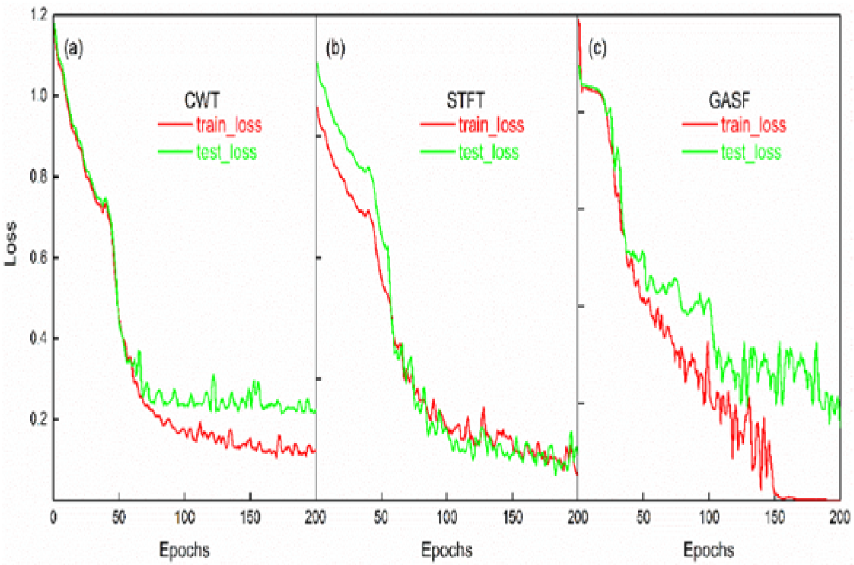

Fig. 3. CNN model loss item, (a), (b) and (c) represent the image datasets

8 INTEGRATION WITH CLOUD COMPUTING AND INDUSTRIAL IOT (IIOT) FOR ENHANCED MACHINE LEARNING-BASED TOOL CONDITION MONITORING

The integration of machine learning with cloud computing and Industrial IoT (IIoT) holds immense promise for revolutionizing tool condition monitoring (TCM) in manufacturing environments. Cloud-based platforms offer scalability and flexibility for deploying and managing ML models. Manufacturers can leverage cloud-based resources to train and deploy their ML models without significant upfront investments in hardware infrastructure. Additionally, cloud platforms facilitate data storage and sharing across geographically distributed manufacturing facilities. This enables centralized model training on data collected from various production lines, potentially leading to more robust and generalizable models. Furthermore, cloud-based architectures allow for real-time processing of large datasets generated by sensors on machines and tools. This real-time processing capability is essential for timely predictions and proactive maintenance interventions. Figure 4 shows the Condition Monitoring Value[29]

Fig. 4. Condition Monitoring Value

Industrial IoT (IIoT) plays a critical role in seamlessly acquiring data for ML-powered TCM systems. IIoT encompasses a network of connected sensors, machines, and devices that communicate with each other and cloud platforms. Sensors attached to tools and machines can continuously collect data on various parameters, such as vibration, temperature, and power consumption. IIoT protocols enable seamless communication between these sensors and the cloud platform, providing a real-time, high-fidelity data stream for ML models. This continuous flow of data allows ML models to continuously learn and adapt, improving their accuracy in predicting tool health and potential failures.

9 CYBERSECURITY CONSIDERATIONS FOR SECURE MACHINE LEARNING-POWERED TOOL CONDITION MONITORING

The growing interconnectivity of machines and devices in manufacturing environments, driven by ML-powered TCM systems, necessitates robust cybersecurity measures. As data becomes the lifeblood of manufacturing operations, securing its transmission, storage, and processing is paramount. Here, we discuss critical considerations for ensuring the security of ML-based TCM systems:

9.1 Securing Data Transmission and Storage

Protecting data in transit between sensors, machines, and the cloud platform is crucial. Manufacturers should implement encryption protocols like TLS/SSL to safeguard data confidentiality and integrity during transmission. At rest, data stored in the cloud requires robust access controls and encryption measures to prevent unauthorized access or manipulation. Regular security audits and penetration testing can identify vulnerabilities in the system and mitigate potential security risks.

9.2 Mitigating AI Model Vulnerabilities

Machine learning models themselves can be susceptible to adversarial attacks. These attacks involve manipulating the input data to deceive the model and generate false predictions. In the context of TCM, an adversary could potentially manipulate sensor data to mask tool wear or induce the model to predict a healthy state for a failing tool. To mitigate such risks, implementing techniques like adversarial training can enhance the robustness of ML models against adversarial attacks. Additionally, regular monitoring of model performance and data quality can help identify anomalous patterns that might indicate attempted manipulation.

10 ECONOMIC IMPACT AND COST-BENEFIT ANALYSIS FOR MACHINE LEARNING-POWERED TOOL CONDITION MONITORING

While the benefits of ML-powered TCM are substantial, quantifying the economic impact on manufacturing operations is crucial for wider adoption. Here, we explore methods for evaluating the return on investment (ROI) associated with implementing ML-based TCM systems:

10.1 Quantifying Return on Investment (ROI)

Calculating the ROI of ML-powered TCM systems involves considering both the costs and the benefits. Benefits include reduced downtime due to predictive maintenance, improved product quality through early detection of tool wear, and optimized maintenance schedules that minimize unnecessary repairs. Costs include investments in hardware, software, data storage, and personnel expertise required to develop, deploy, and maintain the ML system. By carefully evaluating these factors and demonstrating a positive ROI, manufacturers can build a strong business case for investing in ML-based TCM.

10.2 Cost-Effectiveness for Small and Medium-sized Enterprises (SMEs)

The initial costs associated with implementing ML-powered TCM systems can be a barrier for smaller manufacturers. However, several approaches can make ML-based TCM more cost-effective for SMEs. One approach involves utilizing pre-trained ML models developed for specific TCM tasks. These pre-trained models can be adapted to the specific needs of an SME with less customization effort, reducing development costs. Another approach leverages cloud-based platforms that offer pay-as-you-go subscriptions for ML model deployment and management. This eliminates the need for significant upfront investments in hardware infrastructure and makes ML-powered TCM more accessible for SMEs.

11 FUTURE DIRECTIONS AND CHALLENGES IN MACHINE LEARNING-POWERED TOOL CONDITION MONITORING

While machine learning (ML) offers immense potential for revolutionizing tool condition monitoring (TCM) in manufacturing, several challenges and future directions necessitate exploration:

11.1 Multimodal Data Fusion

Manufacturing processes generate a rich tapestry of data beyond traditional sensor readings. This data can include acoustic emissions, machine vision data, and even process log information. Future research should explore effective methods for fusing multimodal data sources within ML models for TCM. By incorporating diverse data types, models can potentially gain a more holistic understanding of tool health and predict failures with greater accuracy.

11.2 Explainable AI for Continuous Learning

As ML models for TCM continuously learn and adapt from real-time data streams, the need for explainable AI (XAI) becomes even more critical. Future work should focus on developing XAI techniques specifically tailored for continuously learning models. This will enable manufacturers to maintain trust in the system and understand how the models evolve over time, ensuring reliability and transparency.

11.3 Integration with Digital Twin Technology:

Digital twins are virtual representations of physical machines and processes. Integrating ML-powered TCM systems with digital twins holds great promise. Real-time data from TCM can be fed into the digital twin to continuously update its state and predict potential issues. This synergy between technologies can facilitate proactive maintenance strategies and optimize manufacturing processes for peak performance.

11.4 Standardization and Interoperability:

The widespread adoption of ML-powered TCM hinges on standardization and interoperability. Standardized data formats and communication protocols are essential for seamless integration of ML models with different sensor systems and manufacturing platforms. This will enable manufacturers to leverage pre-trained models and cloud-based solutions more easily, accelerating the adoption of ML-based TCM across the manufacturing industry.

11.5 Addressing Ethical Considerations:

The increasing reliance on ML in manufacturing raises ethical considerations that need to be addressed. Issues such as bias in training data and the potential for job displacement due to automation must be carefully considered. Developing fair and responsible AI practices for ML-powered TCM is essential for building trust and ensuring the ethical implementation of this technology.

By focusing on these future directions and addressing the associated challenges, researchers and practitioners can usher in a new era of intelligent manufacturing powered by advanced machine learning techniques for tool condition monitoring.

12 CONCLUSION

In conclusion, this review article provides an insightful overview of the potential benefits of integrating Machine Learning and Tool Condition Monitoring for Manufacturing Applications. It highlights the ways in which Machine Learning can provide improved diagnostics and predictive maintenance capabilities, as well as optimize processes. Furthermore, it highlights the need for further research to investigate the effectiveness of Machine Learning in this field and to identify the best strategies to effectively use it in manufacturing applications. Ultimately, this review article provides a great starting point for anyone interested in exploring the potential of Machine Learning in this domain. the integration of Machine Learning and Tool Condition Monitoring for manufacturing applications is proving to be beneficial in a number of ways. It is allowing for improved monitoring, better predictions of tool failure, and the ability to make informed decisions regarding maintenance, resulting in improved efficiency, cost savings, and improved product quality. The use of machine learning for tool condition monitoring is still in its early stages and many challenges remain. However, with continued research and development, and the implementation of the various strategies presented in this review, the potential for this technology to provide great value to the manufacturing industry is immense.

References

1. Pimenov, D.Y., Bustillo, A., Wojciechowski, S., Sharma, V.S., Gupta, M.K. and Kuntoğlu, M., 2022. Artificial intelligence systems for tool condition monitoring in machining: Analysis and critical review. Journal of Intelligent Manufacturing, pp.1-43.
2. Russell, M. and Wang, P., 2022. Physics-informed deep learning for signal compression and reconstruction of big data in industrial condition monitoring. Mechanical Systems and Signal Processing, 168, p.108709.
3. Malekloo, A., Ozer, E., AlHamaydeh, M. and Girolami, M., 2022. Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights. Structural Health Monitoring, 21(4), pp.1906-1955.
4. Baduge, S.K., Thilakarathna, S., Perera, J.S., Arashpour, M., Sharafi, P., Teodosio, B., Shringi, A. and Mendis, P., 2022. Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. Automation in Construction, 141, p.104440.
5. Zhou, Y., Zhi, G., Chen, W., Qian, Q., He, D., Sun, B. and Sun, W., 2022. A new tool wear condition monitoring method based on deep learning under small samples. Measurement, 189, p.110622.
6. Zhu, K., 2022. Big data oriented smart tool condition monitoring system. In Smart Machining Systems (pp. 361-381). Springer, Cham.
7. Liu, Y., Guo, L., Gao, H., You, Z., Ye, Y. and Zhang, B., 2022. Machine vision based condition monitoring and fault diagnosis of machine tools using information from machined surface texture: A review. Mechanical Systems and Signal Processing, 164, p.108068.
8. Yang, X., Gao, Y., Fang, C., Zheng, Y. and Wang, W., 2022. Deep learning-based bolt loosening detection for wind turbine towers. Structural Control and Health Monitoring, 29(6), p.e2943.
9. Kumar, S.D., Development of CAPP System using CATIA feature extraction for Job shop environment. International Journal of Applied Engineering Research, 10(19), p.2015.
10. Guo, S., Agarwal, M., Cooper, C., Tian, Q., Gao, R.X., Grace, W.G. and Guo, Y.B., 2022. Machine learning for metal additive manufacturing: Towards a physics-informed data-driven paradigm. Journal of Manufacturing Systems, 62, pp.145-163.
11. Sun, I., Cheng, R.C. and Chen, K.S., 2022. Evaluation of transducer signature selections on machine learning performance in cutting tool wear prognosis. The International Journal of Advanced Manufacturing Technology, 119(9), pp.6451-6468.

12. Liu, K., Wei, Z., Zhang, C., Shang, Y., Teodorescu, R. and Han, Q.L., 2022. Towards long lifetime battery: AI-based manufacturing and management. IEEE/CAA Journal of Automatica Sinica.
13. Naveenkumar, M., 2021. Experimental and numerical investigation in the series arrangement square cyclone separator. Powder Technology, 383, pp.93-103.
14. Ganeshkumar, S., Thirunavukkarasu, V., Sureshkumar, R., Venkatesh, S. and Ramakrishnan, T., 2019. Investigation of wear behaviour of silicon carbide tool inserts and titanium nitride coated tool inserts in machining of en8 steel. International Journal of Mechanical Engineering and Technology, 10(01), pp.1862-1873.
15. Ganeshkumar, S., Sureshkumar, R., Sureshbabu, Y. and Balasubramani, S., 2020. A review on cutting tool measurement in turning tools by cloud computing systems in industry 4.0 and IoT. GIS science journal, 7(8), pp.1-7.
16. Kumar, S.S., Kumar, S.D. and Magarajan, U., 2020. Investigation of mechanical and wear behaviour of graphene reinforced aluminium alloy 6061 metal matrix composite. Kovove Materialy-Metallic Materials, 58(5), pp.341-349.
17. Ganeshkumar, S., Sureshkumar, R., Sureshbabu, Y. and Balasubramani, S., 2019. A numerical approach to cutting tool stress in CNC turning of EN8 steel with silicon carbide tool insert. International Journal of Scientific & Technology Research, 8(12), pp.3227-3231.
18. Kumar, S.G. and Thirunavukkarasu, V., 2016. Investigation of tool wear and optimization of process parameters in turning of EN8 and EN 36 steels. Asian Journal of Research in Social Sciences and Humanities, 6(11), pp.237-243.
19. Gokilakrishnan, G., Ganeshkumar, S., Anandakumar, H. and Vigneshkumar, M., 2021, March. A Critical Review of Production Distribution Planning Models. In 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 2047-2051). IEEE.
20. Magarajan, U., Arvind, D., Kannan, N. and Hemanandan, P., 2018. A comparative study on the static mechanical properties of glass fibre vs glass-jute fibre polymer composite. Materials Today: Proceedings, 5(2), pp.6711-6716.
21. Kumar, S.D. and Kumar, S.S., 2019. Investigation of mechanical behavior of friction stir welded joints of AA6063 with AA5083 aluminum alloys. Mechanics and Mechanical Engineering, 23(1), pp.59-63.
22. Ganeshkumar, S., Kumar, S.D., Magarajan, U., Rajkumar, S., Arulmurugan, B., Sharma, S., Li, C., Ilyas, R.A. and Badran, M.F., 2022. Investigation of tensile properties of different infill pattern structures of 3D-printed PLA polymers: analysis and validation using finite element analysis in ANSYS. Materials, 15(15), p.5142.
23. Ganeshkumar, S. and Venkatesh, S., 2022. Manufacturing Techniques and Applications of Multifunctional Metal Matrix Composites. Functional Composite Materials: Manufacturing Technology and Experimental Application, p.157.
24. Kumar, S.D., Kumar, S.S. and Kumar, K.A., 2018. Investigation of forced frequency in a commercial vehicle suspension system. Mechanics and Mechanical Engineering, 22(4), pp.967-974.
25. S, G., T, D., & Haldorai, A. (2022). A Supervised Machine Learning Model for Tool Condition Monitoring in Smart Manufacturing. Defence Science Journal, 72(5), 712-720. https://doi.org/10.14429/dsj.72.17533
26. S. Ganeshkumar, S. Venkatesh, P. Paranthaman, R. Arulmurugan, J. Arunprakash, M. Manickam, S. Venkatesh, G. Rajendiran, "Performance of Multilayered Nanocoated Cutting Tools in High-Speed Machining: A Review", International Journal of Photoenergy, vol. 2022, Article ID 5996061, 8 pages, 2022. https://doi.org/10.1155/2022/5996061

27. Zhang, Yaping, Xiaozhi Qi, Tao Wang, and Yuanhang He. "Tool wear condition monitoring method based on deep learning with force signals." Sensors 23, no. 10 (2023): 4595. https://www.mdpi.com/1424-8220/23/10/4595
28. Tran, Minh-Quang, Hoang-Phuong Doan, Viet Q. Vu, and Lien T. Vu. "Machine learning and IoT-based approach for tool condition monitoring: A review and future prospects." Measurement 207 (2023): 112351. https://www.sciencedirect.com/science/article/abs/pii/S0263224122015470
29. https://www.te.com/usa-en/industries/automation-control/applications/industrial-condition-monitoring-sensors.html
30. Tran, Minh-Quang, Hoang-Phuong Doan, Viet Q. Vu, and Lien T. Vu. "Machine learning and IoT-based approach for tool condition monitoring: A review and future prospects." Measurement 207 (2023): 112351. https://www.sciencedirect.com/science/article/abs/pii/S0263224122015470