Integration of Artificial Intelligence And Industrial IoT For Defect-Free Machining And Reduced Rework

Manigandan S[1], Sreeharan B N[2], Rajasekaran N[3], Guna D[4]
[1]Dept of Textile Engineering
[2]Assistant Professor, Dept of Mechanical Engineering
[3]Divisional Manager, Ashok Leyland Limited, Unit 1, Hosur 635109, Tamil Nadu, India
[4]Forge, FORT (SIPCOT Industrial Innovation Centre), Hosur 635109, Tamil Nadu, India
[1, 2] Anna University Regional Campus Coimbatore

Abstract- *The challenges faced in an engine machining shop, specifically focusing on unfinished operations in the oil pump surface machining process due to human errors. The study recognizes that these errors result in rework, extended time consumption, and resource depletion, consequently impacting overall productivity and resource utilization. The research employs a multifaceted approach, incorporating process analysis, human factors assessment, and technological interventions to identify, quantify, and mitigate the root causes of human errors in the oil pump surface machining operations. By leveraging advanced machining technologies, automation, and implementing targeted training programs, the solution proposes a comprehensive strategy to reduce the occurrence of unfinished operations and enhance the efficiency of the machining process. The anticipated outcomes of this research include a significant reduction in rework instances, minimized time consumption, and optimized resource utilization in the engine machining shop. The proposed interventions aim to improve the machining operations' overall productivity and contribute to a more sustainable and resource-efficient manufacturing environment. The findings of this solution can be valuable for practitioners, researchers, and industry stakeholders seeking innovative solutions to enhance precision machining processes and mitigate the impact of human errors on production outcomes.*

Keywords- Machining Operation, Artificial Intelligence, Machine Learning, Manufacturing, IIOT,AI Vision sensor, Unfinished Operations

I. INTRODUCTION

In the engine machining shop, the oil pump surface machining station encounters challenges stemming from human errors, resulting in unfinished operations. These errors contribute to a domino effect of consequences, necessitating rework, amplifying time consumption, and depleting valuable resources. The repercussions reverberate across productivity metrics and resource utilization efficiency, creating a bottleneck in the machining workflow. The occurrence of unfinished operations in the oil pump surface machine not only demands additional labor for rectification but also extends the overall production timeline. This impediment not only disrupts the seamless workflow within the machining shop but also places strain on the workforce and resources. Addressing these human errors becomes paramount for streamlining operations, enhancing productivity, and optimizing resource allocation in the engine machining process. Implementing corrective measures, such as employee training and process refinement, becomes pivotal in mitigating these challenges and fostering a more efficient and effective machining environment.

II. LITERATURE REVIEW

Rosenfeld, A. (1985): Introduction to Machine Vision: This seminal book by Rosenfeld laid the groundwork for the field of machine vision. It established the core concepts and techniques that are still fundamental to modern machine vision systems today. These concepts include image formation, image processing (filtering, segmentation, etc.), and pattern recognition. Rosenfeld's work provides a crucial theoretical foundation for the development and application of AI-powered defect detection systems in machining, as proposed by Manigandan et al.

Teoh, E. K., Mital, D. P., Lee, B. W., and Wee, H. S. (1992): An intelligent vision system for inspection of SMDs :This paper by Teoh et al. demonstrates the practical effectiveness of machine vision in industrial quality control. They developed a system specifically for inspecting surface-mount devices (SMDs) for defects. Their work is highly relevant to the proposed research by Manigandan et al.as it showcases how machine vision can be used to automate visual inspection tasks, leading to improved product quality and potentially reducing rework caused by human error.

Khleif, A. A. (2018): Vision system aided 3D object reconstruction and machining using CNC milling machine: Khleif's work explores the potential of machine vision for complex manufacturing processes beyond simple inspection. They propose a system that utilizes a vision system to reconstruct 3D models of objects and then guide a CNC milling machine for automated machining tasks. This research highlights the versatility of machine vision and its potential integration with other aspects of the manufacturing process, paving the way for more intelligent and automated production lines.

Gopan, V., Ragavanantham, S., and Sampathkumar, S. (2012): Condition monitoring of grinding process through machine vision system: Gopan et al. demonstrate how machine vision can be used for real-time process monitoring. Their research focuses on monitoring the condition of a grinding process through a machine vision system. This type of real-time monitoring allows for early detection of potential issues and helps to optimize the grinding process, ultimately leading to improved efficiency and reduced production costs. The proposed research by Manigandan et al. can potentially benefit from similar real-time monitoring capabilities to identify potential machining errors before they lead to unfinished operations.

Sako, H. (2007): Recognition strategies in machine vision applications: Sako's work delves into the critical aspect of object recognition within machine vision applications. They discuss various recognition strategies that can be employed depending on the specific task and object characteristics. This is particularly important for the proposed research by Manigandan et al. as the AI model will need an effective recognition strategy to accurately identify unfinished operations in the oil pump surface machining process.

Wei, L., and Jiao, Z. (2008): Visual location system for placement machine based on machine vision: Wei and Jiao's research showcases machine vision application for precise positioning tasks in automated manufacturing. They developed a vision-based location system for a placement machine. This research aligns with the potential future integration of AI and machine vision in Manigandan et al.'s proposed solution. Beyond defect detection, the system could potentially be expanded to guide automated systems within the machining process for improved precision and efficiency.

III. METHODOLOGY

It can be classified into

1. Data Collection
2. Intervention Strategies
3. Root cause Analysis
4. Solution Identification

3.1. Data Collection

Data collection should focus on key metrics like defect rate, time wastage, productivity loss, power wastage, and cost savings. This Summary of it shown below;

Table 3.1.1 –Data collection based on significance.

Denotation	Description	UOM	Weekly [Tentative]	Monthly [Tentative]	Yearly [Tentative]	Cost/Annum [Rs]
Lower the Better	Defect Frequency	Qty	3	12	144	-1,44,000
	Time Wastage [Based on Cycle Time]	Mins	45	180	2160	-4,32,000
	Productivity (Blocks)	Qty	9	36	432	
	Time Can be saved	Mins	45	180	2160	
	Power Can be saved	kwh	23	90	1080	-38,880
		Mins	115	450	5400	
Total Savings/Annum	***Rs 6,15,000***					

3.2. Data Intervention Strategies

Technological Implementations: Fully integrating Industry 2.0 machinery with advanced technologies presents challenges. Limited processing power and outdated communication protocols in these machines hinder seamless integration. Fortunately, alternative approaches exist! Retrofitting sensors onto legacy equipment provides basic data on machine health, allowing for rudimentary monitoring. Standalone data acquisition systems offer a way to collect this sensor data and transmit it for analysis. In some instances, upgrading communication ports might even enable connection to newer monitoring software. These workarounds bridge the gap for legacy equipment, paving the way for data-driven improvements in Industry 2.0 environments.

Improved Work Instructions and Standard Operating Procedures (SOPs): Even with clear Standard Operating Procedures (SOPs) and a completed Failure Mode and Effects Analysis (FMEA), human error can persist. SOPs can't account for every situation, and FMEAs might miss unforeseen issues.

Targeted Training Programs: Persistent errors despite targeted training and employee awareness campaigns suggest deeper root causes. The complexity of tasks, inadequate feedback mechanisms, or even design flaws in the machinery itself could be contributing factors that need investigation

3.3. Root Cause Analysis

Problem Statement: High occurrence of unfinished operations due to human error in the oil pump surface machining process.

Action: A cross-departmental brainstorming session was conducted utilizing Fishbone diagrams to identify potential root causes.

Root Cause Identified: Limitations of aging machinery.

Analysis:The outdated machinery struggles to maintain consistent performance under the pressure of increased production rates.This strain on the equipment translates to a higher workload for operators.The limitations of the technology combined with the inherent margin for human error create a situation where even minor mistakes can lead to producing defective parts.

Impact: Increased rework rates and production delays. Resource depletion due to wasted materials and labor. Potential quality issues with finished products.

3.4. Solution Identification

A thorough analysis of all factors, combined with a brainstorming session with project and department leads, pinpointed a solution for unfinished operations. This collaborative effort examined every aspect of the machining process, maximizing the effectiveness of the identified fix.The specific Solution selection matrix is shown below;

Project Selected: Auto Detection system to Detect the Unfinished operations

Table3.4.1 – Solution Selection Matrix

Criteria (Weight)	Description	Probe based system measure the Thickness of machining using IOT	Laser based system measure the Thickness of machining using IOT	Image Based System using AI to detect the operation
Potential to Meet Goal (10)	How well does the solution address the project goal?	9	6	8
Positive Customer Impact (8)	How beneficial is the solution for the customer?	8	8	8
Cost to Implement (7)	What is the estimated cost of implementing the solution?	4	4	6
Stakeholder Buy-in (5)	How likely are stakeholders to support this solution?	3	2	4
Time to Implement (5)	How long will it take to implement the solution?	4	5	5
Total Score	Sum of the weighted ratings for each criterion	28	25	31
Implement? (Yes/No)	Based on the analysis, should this solution be implemented?	No	No	Yes

IV. RESULTS AND DISCUSSIONS

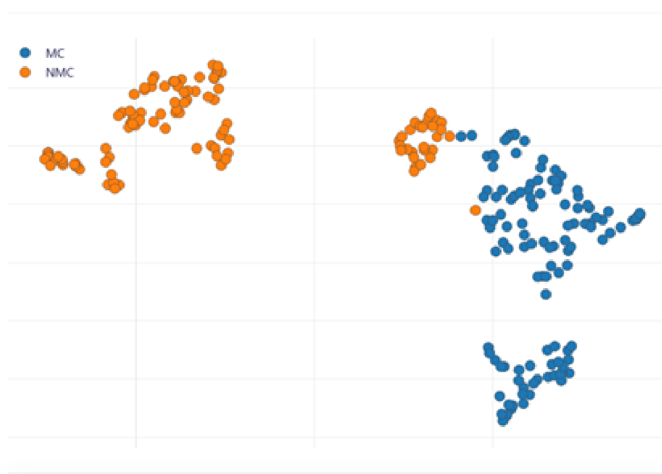
4.1 How will you build AI Model?

- We can hardcode the AI model in Python using specific libraries and parameters. However, this approach can be time-consuming and require significant effort for perfection

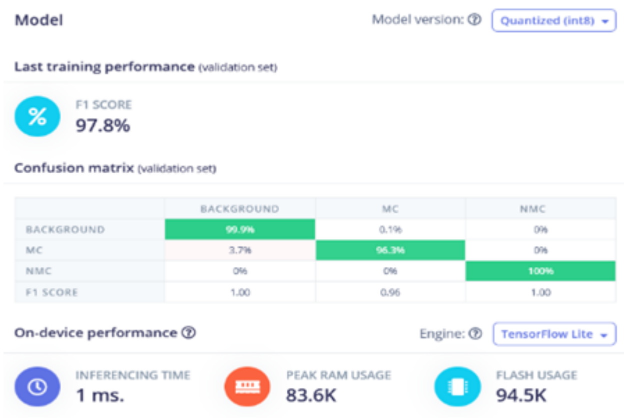
- While building an AI model from scratch by hardcoding in Python offers the most control and flexibility, it can be a time-consuming process requiring significant expertise for both development and fine-tuning. AI builder platforms, on the other hand, provide a faster and more user-friendly approach, but may not be suitable for complex needs and often require extensive customization, potentially increasing the overall difficulty of the project. The Platforms are; Teachable Machine,

  - Amazon SageMaker,
  - Azure Machine Learning,
  - Google Cloud AI Platform,
  - Papers With Code,
  - Edge Impulse

4.2 Building an AI Model based and Optimizing the Model F1 Score in Edge Impulse



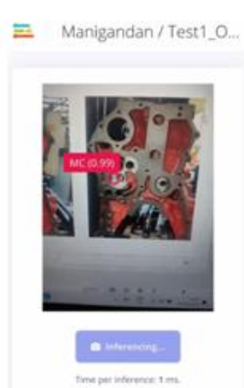
Model Clustering



F1 Score

F1 SCORE:F1 Score in AI balances precision and recall. Precision reflects how many true positives the model identified (avoiding false positives), while recall measures how well the model catches all actual positive cases (avoiding false negatives). By taking the harmonic mean of these two metrics, the F1 Score provides a more comprehensive picture of a model's performance, preventing a high score in one from hiding a weakness in the other.

Non-Machined- NMC



Machined - MC

4.3 How will you Integrate with Solution with mechanical Components?

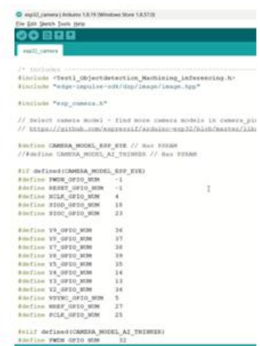
After deploying the Edge Impulse library to your Arduino, you can customize it for advanced control. While the library handles core communication, you can directly control the P298N motor driver and DC motor for fine-tuned actuation. Here's the breakdown:

Understand the Library: Explore the library code to see how Edge Impulse interacts with your Arduino. This foundation helps you understand how model predictions are currently being used.

Hardcode the P298N Driver: Identify the sections in the library responsible for generic motor control. By studying this code, you can write custom logic to directly interact with the P298N driver for precise control over the DC motor.

DC Motor Actuation: Write code specifically for the P298N driver, referencing its datasheet for proper pin configurations and control signals. This custom code will leverage the library's model predictions but implement the actuation logic yourself using the P298N for tailored motor control.

Deployment from Arduino



Hardcode in Arduino IDE

V. CONCLUSION

This study investigates the impact of human error on oil pump surface machining, leading to unfinished parts and inefficiencies. It proposes a multi-pronged approach using advanced technologies to address these issues. After evaluating various solutions, an AI-powered auto-detection system for unfinished operations emerged as the most viable option. This system would leverage image recognition to objectively identify defects, removing human error from the process. Faster defect detection allows for prompt corrective actions, minimizing rework and production delays. Additionally, early identification of defects improves overall quality control. However, challenges remain. Training the AI model requires a substantial collection of machined and unmachined surface samples. The system's effectiveness depends heavily on the quality of this data and the image capture setup, including lighting and camera positioning. Moreover, integrating the AI system with existing machinery might require hardware modifications or additional sensors. Despite these hurdles, the potential benefits of reduced rework, enhanced quality control, and increased productivity make this a promising approach for the engine machining shop. Future research should focus on developing a data collection plan, exploring suitable AI model architectures, investigating integration feasibility, and conducting a cost-benefit analysis. By refining this approach, researchers and industry professionals can pave the way for AI-powered solutions to streamline machining processes and minimize human error in production environments

REFERENCES

[1] Rosenfeld, A. (1985). Introduction to machine vision. IEEE Transactions on Systems, Man, and Cybernetics, SMC-15(2), 236-266. doi: 10.1109/MCS.1985.1104954

[2] Teoh, E.K., Mital, D. P., Lee, B. W., & Wee, H. S. (1992). An intelligent vision system for inspection of SMDs. In 1992 5th IEEE International Conference on Factory Automation (ETFA'92) (pp. 184-189). IEEE. doi: 10.1109/etfa.1992.683322

[3] Khleif, A. A. (2018). Vision system aided 3D object reconstruction and machining using CNC milling machine. In 2018 International Conference on Automation, Signal Processing, Communications and Computers (ICASEA) (pp. 1-6). IEEE. doi: 10.1109/icasea.2018.8370990

[4] Gopan, V., Ragavanantham, S., & Sampathkumar, S. (2012). Condition monitoring of grinding process through machine vision system. In 2012 4th IEEE International Conference on Machine Vision (MViP) (pp. 244-249). IEEE. doi: 10.1109/mvip.2012.6428789

[5] Sako, H. (2007). Recognition strategies in machine vision applications. In 15th International Conference on Image Processing (ICIP 2007) (Vol. 5, pp. 305-308). IEEE. doi: 10.1109/IMVIP.2007.45

[6] Wei, L., & Jiao, Z. (2008). Visual location system for placement machine based on machine vision. In 2008 2nd International Symposium on Electronic Computer Technology (SECT) (pp. 244-247). IEEE. doi: 10.1109/sec.2008.41

[7] Bostrom,N. (2014). Superintelligence: Paths, dangers, strategies. Oxford University Press.

[8] Russell, S. J., & Norvig, P. (2009). Artificial intelligence: A modern approach (3rd ed.). Pearson Education Limited.

[9] Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who’s the fairest in the land? On the relationships between people and machines. Journal of Business Ethics, 156(1), 59-78.

[10] Brynjolfsson, E., & McAfee, A. (2016). Race against the machine: The impact of artificial intelligence on jobs, wages, and growth. Penguin Random House.

[11] Bostrom, N. (2014). Ethical issues in advanced artificial intelligence. Science, 346(6208), 1230216.

[12] Müller, V. C. (2016). Fairness and accountability in algorithmic decision-making. Philos. Trans. R. Soc. A, 374(2083), 20160084.

[13] Jobin,A., Ienca, M., &Vayena, E. (2019). The global landscape of AI ethics guidelines. The Alan Turing Institute

[14] .Brysam, D. (2016). Explainable artificial intelligence (XAI). Communications of the ACM, 59(6), 54-60.

[15] Lipton, Z. C. (2018). The flip side of fairness in machine learning. Fairness, Accountability, and Transparency in Machine Learning (FATML), 81(1), 81-96.

[16] Hutson, M. (2018). Artificial intelligence explainability: A review. arXiv preprint arXiv:1802.07208

[17] Mitchell, T. M. (1997). Machine learning. McGraw-Hill. (Classic text on machine learning fundamentals)

[18] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT press. (Comprehensive guide to deep learning techniques)

[19] Ng, A. (2018). Deep learning specialization. https://www.deeplearning.ai/ (Online course offering a practical introduction to deep learning)

[20] Jurafsky, D., & Martin, J. H. (2020). Speech and language processing (3rd ed.). Pearson Education Limited. (In-depth exploration of NLP concepts and applications)

[21] Collobert, R., & Weston, J. (2008). A unified architecture for natural language processing. Proceedings of the National Academy of Sciences, 103(36), 13642-13647. (Influential paper on neural network architectures for NLP)

[22] Bird, S., Klein, E., & Loper, E. (2009). Natural language processing with Python. O'Reilly Media, Inc. (Practical guide to implementing NLP tasks in Python)

[23] Forsyth, D. A., & Ponce, J. (2012). Computer vision: A modern approach. Pearson Education Limited. (Comprehensive textbook on computer vision algorithms and techniques)

[24] Szeliski, R. (2011). Computer vision: Algorithms and applications. Springer Science & Business Media. (Another comprehensive resource for computer vision)

[25] OpenCV Team. (2015). OpenCV 3.x computer vision library documentation. https://opencv.org/ (Open-source library with extensive functionalities for computer vision tasks)