Library Progress International
Vol.44 No. 3, Jul-Dec 2024: P. 11406-11423

Print version ISSN 0970 1052
Online version ISSN 2320 317X

Original Article

Available online at www.bpasjournals.com

Predictive Maintenance for Smart Manufacturing: An AI and IoT-Based Approach

Shopan Dey[1], Prof. (Dr) Preeti Sharma[2]

[1]Research Scholar, School of Management, University of Engineering & Management, Jaipur,shopan.dey@uem.edu.in

[2]Associate Dean, School of Management, University of Engineering & Management, Jaipur,preeti.sharma@uem.edu.in

How to cite this article: Shopan Dey, Preeti Sharma (2024) Predictive Maintenance for Smart Manufacturing: An AI and IoT-Based Approach. *Library Progress International,* 44(3), 11406-11423.

ABSTRACT

In this era of AI, Edge AI is getting popular day by day. The main advantage of Edge AI over conventional AI is that it requires very small processing power to perform its task. And this can be easily deployed on a microcontroller and mobile processor. On the other hand, permanent damage of an industrial machine increases maintenance cost and reduces productivity. This paper presents a new predictive maintenance system for smart manufacturing, using AI and IoT technologies. The developed device uses the inertia measurement unit (IMU) sensors and deep learning to detect machinery faults. We use six channel of accelerometer data to analysis the horizontal and vertical vibration of machine. The proposed system analyzes the data locally to reduce latency and transmits the results to the cloud server for further processing. So during the development, a special dataset was prepared with the possible fault conditions of machines to train the neural model. Deep learning-based algorithms identify any kind of anomaly in the machine and alert the user to an impending failure, thus improving timeliness in their intervention. This will reduce downtime and chances of major machine damage. This approach will be very useful in the proactive maintenance domain, with higher performance of machinery, to help the user schedule a timely maintenance visit before the permanent damage of the machine.

Keyword: Edge AI, Internet of Things (IoT), Predictive Maintenance (PdM), Deep Learning (DL), Convolutional Neural Network (CNN).

Introduction:

The paper investigates an in-depth framework of predictive maintenance in smart manufacturing with the application of AI and IoT. The proposed system makes use of advanced sensors that can sense potential faults in machinery through vibration, accelerometer, and microphone sensors. Edge AI processing allows data to be analyzed close to the source to reduce latency and improve real-time decision-making. The results are then directed to a cloud server for further analysis and storage. The developed device, in this context, offers a multisensor application with nine axes for vibration analysis, two axes for sound analysis, and one axis for current monitoring; thus, twelve axes of data are available. The vibration and sound sensors together provide a holistic view of the health of the machine, registering subtle anomalies that may mean an impending fault. This is further built upon with the addition of current monitoring for a greater level of insight into the machine's operational status. The system, with a combination of sensors and Edge AI, tries to move from preventive maintenance to predictive maintenance, hence averting problems before they turn out to be full-fledged critical failures. The collected information is analyzed through the use of machine learning algorithms that are able to detect patterns related to upcoming failures. In this way, at the time of the occurrence of an anomaly, the device immediately raises a flag for the user, who can intervene in time without accumulating too many delays. This work contributes to predictive maintenance strategies in advance, providing a very much scalable and effective solution in the smart manufacturing environment. The combination of AI and IoT technologies provides a higher level of overall reliability and effectiveness in the predictive maintenance system to optimize machinery performance with minimal operational disruptions in an industrial setup. In the context of smart manufacturing, the application of Artificial Intelligence (AI) fused with the Internet of Things (IoT) has been quite revolutionary for predictive maintenance strategies. The work goes a step further to predictive maintenance by incorporating a Convolutional Neural Network for predictive analysis. The aim is to integrate AI and IIoT through a framework that adopts the computing power of an STM32H7-based microcontroller. With a dual-core architecture that has an Arm Cortex-M7 and an Arm Cortex-M4 processor, these microcontrollers allow the running of efficient analyses for predictions which are very low on reliance on the network bandwidth and local data processing. Selection of an STM32H7-series microcontroller is based on high processing speed and low power consumption so that complex AI algorithms can run at the edge. The hierarchical feature extraction of the CNN model, formed by convolutional and pooling layers, further strengthens the discriminative capability of the system toward subtle patterns within the sensor data, which are significant for predictive maintenance. With Edge AI, the requirement for continuous large data communication to a center server is significantly reduced, leading to improved demand on network bandwidth and reduced latency. Local processing on the microcontroller allows real-time decision-making, therefore ensuring timely response to changing operational conditions. This edge AI framework deploys with the efficient processing of vibration, accelerometer, and microphone sensor data on-site. It is also important to focus on improving communication with the use of MQTT implementation using ESP6266 SoC. It is a very lightweight protocol meant for effective and efficient communication between the microcontroller and cloud servers for enhancement of data transmission effectiveness. Such a lightweight protocol will suit the constrained IoT device environments in order to ensure the most reliable, lowest-latency communication. The microcontroller supports advanced algorithms and operates with low power consumption, in line with the needs of industry. The prediction analyses are carried out locally; for communication within the framework, it relies on MQTT. The overall dependency on network functioning is thus significantly reduced, reducing chances of work getting interrupted due to network issues. The approach, backed by AIoT (AI of Things), has the potential to detect faults proactively in such a manner as to reduce downtime, and optimize machinery efficiency through timely interventions.

1. Related Work:

Alberto Boretti1, (2024), [1] In his article "A narrative review of AI-driven predictive maintenance in medical 3D printing", he discussed how the utilization of AI-driven Predictive Maintenance can offer a substantial improvement in operation efficiency and reliability of machines operating in medical 3D printing. Traditional techniques are unable to adequately optimize machine uptime and provide cost savings. Simultaneously AI and ML techniques enable proactive maintenance through the prediction of failures. It integrates digital twins, collaborative robots, blockchain, and IIoT for better fault detection and to establish transparency. The result is minimalized downtime, cost economies, engendering improved reliability of equipment to set a new standard in 3D printing operations within the healthcare segment while providing a differentiated competitive advantage.

In the context of a smart plant, Ayoub Chakroun et al. (2024), [2] proposed a predictive maintenance model using ML in the article "A predictive maintenance model for health assessment of an assembly robot based on machine learning in the context of smart plant", in regard to the health of assembly robots. The case study highlighted the degradation prediction in power transmitters for two brass accessory robots working under extreme conditions. A DBF model outperforms the NBF approach in predicting machinery deterioration. Given that DBF can enable a more precise maintenance schedule, it would empower operators to make their decisions more effectively, hence improving operational efficiency. Real testing on robots was used to validate these findings and improved the company's maintenance strategies.

Salama Mohamed Almazrouei et al. (2024), [3 in their article "A review on the advancements and challenges of artificial intelligence-based models for predictive maintenance of water injection pumps in the oil and gas industry", performed a critical review that related to AI-based models for the prediction of maintenance among water-injected pumps within the oil and gas industries. Algorithm selection, data requirements, and optimization strategies were discussed as methods that could be put to use to improve performance in WIPs and predict their respective maintenance schedules. Much emphasis is given to data quality and interpretability as core drivers for efficient AI integration. The paper provides several key insights to OGI professionals regarding how to improve techniques of performing maintenance and further reduce levels of downtime, and how to inform future studies with theoretical and practical perspectives. This resource aids researchers, practitioners, and decision-makers in the sector of OGI.

Lakshmana Phaneendra Maguluri et al. (2024), [4] proposed the "AI-enhanced predictive maintenance in hybrid roll-to-roll manufacturing integrating multi-sensor data and self-supervised learning" with the development of an AI-assisted Predictive Maintenance framework for hybrid R2R manufacturing, with multi-sensor data and self-supervised learning. The developed framework involves Contrastive Predictive Coding that can predict failure with good accuracy and detect anomalies with 96.2% accuracy in failure prediction. It was then tested on the R2R-Chemical Vapour Deposition reactor, where the failure was predicted by as far as 12 minutes, hence optimizing the maintenance schedules and reducing a lot of downtime. This approach enhances efficiency in robotic manufacturing that can be expanded to all other R2R applications, therefore improving production and reducing the cost of maintenance.

Abubakar Bala et al. (2024), [5] during the article "Artificial intelligence and edge computing for machine maintenance-review", discuss how these technologies of IIoT and Edge Computing will affect the concept of machine health diagnostics. Though centralized computing is used in practice, sending sensor data to a remote data centre for AI-based analysis, there are several challenges such as privacy, latency, and availability. This is addressed by edge computing, which can provide faster AI inferences by doing the processing of data closer to the source. The paper reviews some of the research works related to edge-based diagnostics and prognostics of industrial machines that indicate the trends, data processing locations, and future research directions in the field.

Sudhi Sinha et al. (2024), [6], within the paper "Challenges with developing and deploying AI models and applications in industrial systems", illustrate some aspects of AI integration in industrial classes that are of great importance because of prognosis for some elements of improvement such as productivity, quality, and innovation. Still, this paper underlines how complex it is to take the concept of artificial intelligence into a real application and technical-ethical-regulatory challenges. It provides insight into the challenges of data collection, construction of AI models, and how to ensure proper and responsible deployment in industrial settings. The paper provides strategic recommendations for ethics consideration and compliance with regulations-in full avail of benefits from AI while minimizing risks in industrial applications.

Samuel Fidelis et al. (2024), [7], under the article "Improving edge AI for industrial IoT applications using distributed learning with consensus", made it known that there is a need to have an industrial IoT application considering real-time machine learning processing in a distributed architecture. The need is to ensure high accuracy with low latency. The paper has segregated data storage and processing across mist, fog, and cloud layers, where, at the edge, the nodes perform ML inferences. Each edge node applies different ML techniques or uses varying training datasets, and a consensus algorithm integrates these results to improve accuracy. Long-term data is stored and reported at the cloud layer. This architecture has shown better accuracy of the ML model with almost no impact on the response time.

Ambarish Gajendra Mohapatra et al. (2024), [8] In the article "IoT-Enabled Predictive Maintenance and Analytic Hierarchy Process Based Prioritization of Real-Time Parameters in a Diesel Generator: An Industry 4.0 Case Study", discussed how IoT-enabled CMS will replace traditional RM for DG units in the context of Industry 4.0. Attention in the paper will be paid to the performance analysis, which has been done with the help of the 4G enabled IoT node, capable of tracking engine speed, voltage, power factor, coolant, and fuel levels. Furthermore, in this paper, the Analytic Hierarchy Process has been applied to rank the relative importance of these indicators in helping top decision-makers identify which ones to focus on while finding effective ways of enhancing DG system efficiency through predictive maintenance.

Chenfeng Zhu et al. (2024), [9] The authors surrogate a novel AI-based preventive maintenance in the manuscript entitled "Optoelectronic sensor fault detection based predictive maintenance smart industry 4.0 using machine learning techniques" that detects defects in optoelectronic sensors applied in Smart Industry 4.0. It includes noise reduction and normalization; afterward, machine learning techniques can be applied to sensor data features, including a moath quantile convolutional neural network and extreme encoder learning based on spatial clustering. The methodology will find the abnormal error in data features effectively. The experimental results prove high performance for high prediction accuracy, precision, recall, F1 score, and robustness of the approach for different predictive classes and datasets.

The following authors, Franciskus Antonius Alijoyo et al. (2024), [10] have proposed a machine learning-driven approach for fault prediction models to predict the Zigbee-enabled networks of smart home networks to enhance service scheduling and reduce breakdown costs. It proposes the adoption of a framework combined with Firefly Optimization and XGBoost algorithms that will have the potential capability to detect system faults by showing hidden insightful relationships in sensor data readings to improve prediction accuracy. Preprocessed data is then analyzed to predict imminent faults and thus permits proactive maintenance. The developed approach was implemented in Python with an accuracy score of 98%, effectively extending the life and reliability of smart home devices through timely maintenance interventions.

Gan Huang et al. (2024), [11], in their paper "Predictive mobility and cost-aware flow placement in SDN-based IoT networks: a Q-learning approach", propose a mobility-aware adaptive flow entry placement scheme for the SDN-based IoT environment so as to handle network dynamics and thereby mobility challenges. It uses Q-learning for predicting the location of end devices and AdaBoost for high-traffic flow selection. Thus, efficient flow rules are implemented dynamically, reducing consumption caused by table misses of resources. Detailed simulations show that this method drastically improves the match probability and prediction accuracy against existing schemes, improving overall performance in SDN-based IoT systems.

Wei Dang et al. (2024), [12] within an article entitled "The impact of economic and IoT technologies on air pollution: an AI-based simulation equation model using support vector machines", discusses the interoperability of AI and IoT technologies to achieve solutions for environmental and economic issues. In this study, a Support Vector Machine algorithm is used for analysing complex nonlinear relationships of different economic indicators with air pollution. It incorporates IoT sensor data with economic factors to offer a simultaneous equation model that estimates the contribution of pollution to healthcare systems. The SVM model has an accuracy of 84.5%, outperforming other methods such as K-Nearest Neighbors and XGBoost; thus, it's relatively effective in modeling the complex dynamics between economic development and air pollution.

N. Rajkumar et al., (2024), [13] In their article, "The power of AI, IoT and advanced quantum-based optical systems in smart cities", the authors look ahead to the study in integration of Quantum computing combined with AI, IoT and Advanced Optical systems into Smart City Development. Introduction of "optical IoT" is made that employs high-resolution optical for real time urban monitoring hence enhancing decision making process rather conventional methods. It accesses quantum-enhanced sensors and AI for unprecedented accuracies with respect to traffic management, environmental quality, and emergencies. In so doing, ASCA therefore promises the furtherance of Smart City Development by 91.98%, hence arguably indicating the efficiency and resilience of this methodology.

Amirhossein Jamarani et al. (2024), [14] in their article entitled "Big data and predictive analytics: A systematic review of applications", reviewed Big Data Predictive Analytics (BDPA) with a comprehensive overview from 2014 to 2023. This study shall be based on predictive analytics using big data mining techniques, having carried out an SLR review methodology on 109 articles. In this paper, a taxonomy that encompasses seven broad categories includes Industrial, e-commerce, smart healthcare, smart agriculture, smart city, ICT, and weather. It also deals with the pros and disadvantages of each approach, raises many open issues, and offers a few future research avenues. It emphasizes how, with improvements in important metrics like timeliness, accuracy, and scalability, progress is made possible in predictive analytics.

Vincenzo Varriale et al. (2024), [15] in his work "Critical analysis of the impact of artificial intelligence integration with cutting-edge technologies for production systems", made a systematic review of the integration of AI with emerging technologies and their impacts on business performance. The fragmented literature concerning this topic is dealt with here by categorizing case studies and applications into well-defined taxonomies. It introduces the co-occurrence ratio as one of the indicators that will help in finding the significant technology combinations and their contexts. The research highly interconnects AI with other cutting-edge technologies, highlighting that the integration of those is promising to improve the market and organizational performance in given production systems.

Byung-Sub Kim et al. (2024), [16] explores data-driven health diagnosis methods in dry vacuum pumps using machine learning for anomaly detection in the article "Development of a Real-Time Anomaly Detection System for Dry Vacuum Pumps Using Low-Cost IoT Devices and Machine Learning". The investigation brings into focus two major findings: first, related to generalizing machine learning algorithms beyond training data; usually, it is challenging, and secondly, it considers a range of different anomaly detection algorithms. It is noticed from this research that the LSTM-autoencoder with DWT input signals outperforms others in learning normal state characteristics. This approach leverages loss indicators to precisely evaluate deterioration in machine health and succeeds in demonstrating real-time monitoring on low-cost IoT Raspberry Pi 4, and Arduino Mega 2560 boards. The work of Huishuang Su et al. in (2024), [17], under the title "Innovation mechanism of AI empowering manufacturing enterprises: case study of an industrial internet platform", studied AI-driven innovation with a manufacturing case on Haier COSMOPLAT. It systematically illustrates the evolution of AI-enabled manufacturing enterprise innovation, including early development, growth, and maturity. It explains how industrial internet platforms support resource patchwork to ecological symbiosis at the innovation level, enabling value creation to be economic, network, and ecological, with a focus on these three dimensions. The paper enriches the understanding of AI's function in manufacturing innovation and supplements some experience for accelerating intelligent transformation processes in the industry.

In the "Digital twin and predictive quality solution for insulated glass line" article, such authors as Gülcan Aydin et al. (2024) [18], presented how digital twins have been applied to insulating glass manufacturing. The study puts forward the real-time monitoring and analysis of the gas filling process, being one of the most critical factors for the production of high-quality energy-efficient glass. The study will, therefore, seek to enhance the quality of products by reducing defects through the inclusion of predictive solutions for quality that will be able to show the potential of such technologies in enhancing production standards for global sustainability.

Saurabh Pratapa et al. (2024), [19] in his paper "Optimising IoT and big data-embedded smart supply chains for sustainable performance", had presented a review in the realm of sustainable and resilient supply chain management and Industry 4.0. The paper discussed various challenges, starting from forecasting and inventory management up to environmental impact issues, laying stress on the integration of IoT and big data, which becomes so crucial for supply chain modernization. It has included 19 papers related to applications of IoT, big data, and blockchain in supply chain optimization within the special issue. The authors have thus emphasized the need for future research on smart supply chains for sustainable performance that will help develop evidence-based frameworks and solutions to further improve industrial and societal benefits.

Accordingly, Malik Abdul Sami et al., in the year (2023), [20] present "Forecasting failure rate of IoT devices: A deep learning way to predictive maintenance", a deep learning technique-based proactive maintenance strategy that can forecast failures for IoT-based smart home applications. The system improves serviceability through the analysis of device logs and the calculation of the failure rate, hence providing timely decision-making. The paper presents the performance of Bi-directional Long Short-Term Memory and Gated Recurrent Unit models. From the results obtained, GRU outperforms Bi-LSTM in terms of device failure prediction. They have presented the Mean Squared Error, root mean square error, and mean absolute error metrics of both models. This proposed system enhances the reliability of IoT systems with early alerts regarding any action that may be essential or required.

Himanshu Gauttam et al. (2023), [21] introduced his article entitled "An efficient DNN splitting scheme for edge-AI enabled smart manufacturing", a Task Aware DNN Splitting (TADS) scheme that was intended for the optimization of multi-task deep neural networks (DNNs) in the execution of smart manufacturing. The choice of DNN splitting policies at TADS must be supported in making decisions based on task types, computing, and communication resources. It is designed to minimize average task execution time. It outperforms the state-of-the-art methods, including ECN-only, ES-only, and Greedy-based approaches, in both simulation and hardware-based tests, including a vision-based product quality inspection use case. These results show TADS in real-time multi-task scenarios and illustrate its utility in Edge-AI solutions for smart manufacturing.

Xiaoqiao Wang et al. (2023), [22], within their article "Data-driven and Knowledge-based predictive maintenance method for industrial robots for the production stability of intelligent manufacturing", indicated a predictive maintenance method for IRs considering data and knowledge. The method is designed with an LSTM model, which recognizes future running states from historical and real-time data to predict faults by designating a KNN algorithm. Predictions feed into the KG for reasoning and the automatic formulation of PdM strategies. Herein, the performance of the proposed system is tested on welding robots in auto workshops to assess its effectiveness with respect to the improvement of production stability in intelligent manufacturing.

Chengxi Li et al. (2023) In the paper "Deep reinforcement learning in smart manufacturing: A review and prospects" [23], the status of DRL in smart manufacturing is reviewed. By analyzing 261 related publications up to October 2022, the research investigates the development and application of DRL in different parts of the manufacturing lifecycle: design, manufacturing, distribution, and maintenance. This review elaborates how DRL can make adaptive and fast decisions in complicated environments by incorporating DNN and RL. In addition, current challenges and future directions of DRL, with a focus on improving the cognitive capability and efficiency of smart manufacturing systems, are discussed.

The review of Minh-Quang Tran et al. (2023), [24] entitled "Machine learning and IoT-based approach for tool condition monitoring: A review and future prospects" provided an overview of recent development in the systems of tool condition monitoring in professional manufacturing. The review has highlighted the novelties in the fields of fusion sensors, DAQ systems, virtual machining, and lightweight TCM models combined with AI and IoT. These technologies detect tool failures and predict remaining tool life, hence improving machining efficiency. Challenges are also pointed out, such as handling big data, model generalization, or latency in cloud computing, while solutions by cloud migration and shared knowledge bases are suggested. Future prospects for intelligent TCM systems in smart manufacturing are discussed.

Recently, ongoing research by Abdul Matin et al. in (2023), [25] In their article entitled, "AIoT for sustainable manufacturing: Overview, challenges, and opportunities", they comprehensively reviewed the integration of Artificial Intelligence of Things in manufacturing, with a focus on how it might contribute toward Industry 4.0 sustainability. AIoT has thus enhanced human-machine interaction, big data analytics, and operational efficiency in regards to automation, process optimization, and making informed decisions. It also enumerates the benefits of AIoT, including reduced waste, improved safety, and better productivity. In addition, this review surveys the existing research on manufacturing using the approaches of AIoT, discusses various challenges, and pinpoints some future research prospects concerning sustainable manufacturing by leveraging AIoT technologies.

Bernar Tascl et al. (2023), [26], in the work entitled "Remaining useful lifetime prediction for predictive maintenance in manufacturing", proposed predictive maintenance coupled with a machine learning approach, able to predict the RUL of the production lines in manufacturing. By using IoT sensor data from an actual factory, this study aims to forecast equipment failures on the assembly line in advance of any actual occurrence. The authors developed different models: Random Forest, XGBoost, Multilayer Perceptron, and Support Vector Regression, and compared their performance. RF outperformed other models with a very good performance, with a 42% reduction in actual production line failures, hence proving the efficiency of the approach.

Gabriel Avelino Sampedro et al. (2023), [27], in their article "Industrial Internet of Things-Based Fault Mitigation for Smart Additive Manufacturing Using Multi-Flow BiLSTM," proposed an IIoT-based setup for enhancing predictive maintenance in 3D printers. The study introduces a failure prediction algorithm using Multi-Flow BiLSTM, which integrates a multi-learning flow process and residual connections. This approach achieved a mean absolute error of 2.95 and an R^2 value of 0.9121, outperforming other methods and improving productivity in manufacturing plants.

Karim Haricha et al. (2023), [28], in their article "Recent Technological Progress to Empower Smart Manufacturing: Review and Potential Guidelines," conducted a systematic review of current trends in Smart Manufacturing, focusing on how advanced technologies such as AI and IoT enhance manufacturing systems' flexibility and complexity. The study provides a comprehensive overview of existing research and highlights the benefits and open issues that need further exploration to advance smart manufacturing.

Wenjin Yu et al. (2023), [29], in their article "Edge Computing-Assisted IoT Framework With an Autoencoder for Fault Detection in Manufacturing Predictive Maintenance," introduced a comprehensive IIoT framework for predictive maintenance in smart manufacturing. This framework integrates IoT, Big Data, AI, and cloud computing into a three-layer architecture, consisting of edge, cloud, and application layers. Edge computing improves real-time response and privacy, with tasks effectively distributed between the cloud and edge. An edge-assisted autoencoder enhances performance and efficiency, and the article provides an API implementation guideline. A real industrial case study demonstrates the system's reliability, scalability, and performance improvements for predictive maintenance.

Kyung Sung Lee et al. (2023), [30], in their article "Enhanced Anomaly Detection in Manufacturing Processes Through Hybrid Deep Learning Techniques," presented a hybrid deep learning-based anomaly detection model for smart factories. Designed to prevent equipment downtime without labeled data, this model reconstructs sequential data patterns, outperforming other detection algorithms. Experimental results demonstrate its effectiveness in predicting downtime and improving production efficiency. The research also introduces a real-time anomaly detection system, enhancing smart factory operations from data collection to deployment. This work contributes to both academic literature and practical applications, helping to reduce downtime and improve product quality.

Vishal Gupta et al. (2023), [31], in their article "Predictive Maintenance of Baggage Handling Conveyors Using IoT," proposed a scalable predictive maintenance solution for airport baggage handling systems. The study introduces an algorithm to clean noisy IoT data and distinguishes between anomaly and outlier detection, preventing breakdowns. The paper also presents an automated machine learning pipeline to process industrial data, comparing algorithm performance and suggesting future research directions.

Among them, Etienne Valette et al., (2023), [32] performed a Systematic Literature Review on Industry 4.0 concerning the place of humans in IoT- and CPS-based industrial systems in the paper "Industry 5.0 and its technologies: A systematic literature review upon the human place into IoT- and CPS-based industrial systems". This paper assesses how recent industrial research has taken into consideration society and human components beyond pure technological releases. The study will underline the advance in the understanding of industrial systems as complex socio-technical entities and explore the evolution of research for the introduction of human and societal dimensions by analyzing literatures through frameworks of Industry 5.0 enabling technologies and systemic grounding concepts.

Onat Gungor et al. (2022), [33], in their article "DOWELL: Diversity-Induced Optimally Weighted Ensemble Learner for Predictive Maintenance of Industrial Internet of Things Devices," introduced an ensemble learning framework for predicting the remaining useful life (RUL) in predictive maintenance systems within the IIoT. The framework selects diverse and accurate base learners from 20 state-of-the-art deep learning models, optimizing their weights for accuracy and retraining speed. This approach reduces retraining time by 39.2% compared to traditional accuracy-based ensembles, with only a 3.4% decrease in accuracy. The method accounts for performance variability across different datasets and system parameters.

Ayan Chatterjee et al. (2022), [34] in the review article entitled "IoT Anomaly Detection Methods and Applications: A Survey," discussed the trends and gaps present in IoT anomaly detection applications. Their review encompasses 64 papers, from January 2019 to July 2021, covering major application areas such as network security, smart homes, and smart cities. This paper presents a structured overview of the IoT anomaly detection algorithms and discusses various challenges regarding sensor integration, data drifts, and sparsity of Ground Truth data. They also call for further research to bridge these gaps, especially in areas like system integration and data augmentation toward robust IoT anomaly detection.

Snehasis Sahoo et al. (2022), [35] in the article "Smart manufacturing powered by recent technological advancements: A review", did a comprehensive review about the role of smart manufacturing in enhancing Industry 4.0. The authors reviewed the evolution of industrial revolutions, describing how these five major manufacturing countries-Germany, the U.S.A., Japan, China, and Taiwan-develop and adopt various strategies toward smart manufacturing. This paper underlines some key technologies to watch out for in AI, Virtual Reality, and the Internet of Things-or simply IoT-effectively applied to quality checks, maintenance, and sustainability for greater production. Far from that, it goes into challenges in implementing such an AI-based inspection system, future prospectives on global smart manufacturing, and shared case studies showing real-world applications.

Recently, Tiep M. Hoang et al. (2022), [36], in their article "RIS-Aided Smart Manufacturing: Information Transmission and Machine Health Monitoring," proposed a novel IIoT framework for monitoring machine health in smart factories. This framework uses a reconfigurable intelligent surface (RIS) to resolve signal blockage issues, incorporating a power mapping scheme and autoencoder for efficient machine health condition (MHC) transmission and classification. The study evaluates ergodic capacity (primary information) and MHC accuracy (secondary information) based on RIS size and transmit power. Results show stable MHC detection accuracy across various RIS sizes and power levels, enabling parallel transmission of primary data and MHC alerts.

Imran Ahmed et al. (2022), [37], in their article "From Artificial Intelligence to Explainable Artificial Intelligence in Industry 4.0: A Survey on What, How, and Where," presented a comprehensive survey of AI and explainable AI (XAI) methods within Industry 4.0. They explore various technologies driving Industry 4.0, focusing on AI and XAI techniques for tasks such as self-monitoring, diagnosis, and predictive maintenance. The survey highlights opportunities and challenges for future research, especially in developing responsible and human-centric AI systems for high-stakes industrial applications, aiming to guide advancements in intelligent and transparent AI technologies.

Tuan-Anh Tran et al. (2022), [38], in their article "Retrofitting-Based Development of Brownfield Industry 4.0 and Industry 5.0 Solutions," presented an overview of retrofitting legacy manufacturing systems with IoT capabilities to improve production efficiency. The study addresses the challenges of scalability, digitization, and technical requirements in retrofitting, providing guidelines for transforming existing factories into smart spaces and preparing for Industry 5.0.

Serkan Ayvaz et al. (2021), [39], in their article "Predictive Maintenance System for Production Lines in Manufacturing: A Machine Learning Approach Using IoT Data in Real-Time," presented a data-driven predictive maintenance system for manufacturing production lines. Using real-time IoT sensor data, the system employs machine learning to detect potential failures, allowing operators to take preventive actions. Comparative analysis shows that Random Forest and XGBoost models outperformed other algorithms and were integrated into the factory's production system to improve maintenance effectiveness.

Amin Khalil et al. (2021), [40], in their paper "Deep Learning in the Industrial Internet of Things: Potentials, Challenges, and Emerging Applications," explore the potential of deep learning (DL) in the industrial Internet of Things (IIoT) and its applications in smart manufacturing, networking, and accident prevention. The roles of key DL techniques, such as convolutional neural networks, autoencoders, and recurrent neural networks, are reviewed across various industries. The article presents use cases, including smart metering and smart agriculture, and addresses the research challenges in designing and implementing DL for IIoT systems. It also suggests future research directions to encourage advancements in the field.

Vignesh V. Shanbhag et al. (2021), [41] presented an overview of condition monitoring methods for hydraulic cylinders in their article "Failure Monitoring and Predictive Maintenance of Hydraulic Cylinder—State-of-the-Art Review." These methods are crucial for preventing fluid leakage and equipment failure. The techniques reviewed include those based on fluid properties, pressure, vibration, and acoustic emission, with a focus on detecting various failure modes. The article highlights advances in sensor-based condition monitoring and identifies challenges, providing guidance for new researchers. The authors emphasize the importance of these methods for improving reliability and reducing maintenance costs in industries such as construction, manufacturing, and aerospace.

Alan Bastos et al. (2021), [42], in their article "Industry 4.0 Readiness Assessment Method Based on RAMI 4.0 Standards," explored the Industry 4.0 concept, emphasizing its potential to enhance efficiency in smart factories through cleaner energy sources and digital transformation. The research assesses the current technological status of operational plants and offers a roadmap for stakeholders to transition into Industry 4.0 using the Rami 4.0 Reference Architecture Model.

Parjanay Sharma et al. (2021), [43] in their review article entitled "Role of machine learning and deep learning in securing 5G-driven industrial IoT applications", discuss the security-related aspects of Industrial IoT devices considering emerging technologies such as 5G and blockchain amongst others. The emphasis of the paper is that the main challenges facing privacy and security issues are encryption, authentication, access control, and communication security. It assesses the present security implementation and probes into the contribution of ML/DL in I-IoT security. With the view to establishing security in smart environments, this review also discusses the advantages and limitations of security algorithms within fog architecture and their potential.

Wenjin Yu et al. (2020), [44], in their article "A Global Manufacturing Big Data Ecosystem for Fault Detection in Predictive Maintenance," describe a big data ecosystem for fault detection and diagnosis in predictive maintenance, using real industrial data from global manufacturing plants. This paper outlines an Industry 4.0-driven smart manufacturing architecture that incorporates real-time analytics while addressing challenges in data ingestion, integration, transformation, and storage. Real-time fault detection also leverages technologies such as data lakes, NoSQL databases, Apache Spark, and MapReduce-based distributed PCA. The system, developed in a real industrial environment, successfully provided early fault warnings, with a 2014 test case predicting outages several days in advance.

Aniekan Essien (2020), [45], in his article "A Deep Learning Model for Smart Manufacturing Using Convolutional LSTM Neural Network Autoencoders," proposed a deep learning model for multistep machine speed prediction in smart factories. This model, based on a convolutional LSTM encoder-decoder architecture, forecasts machine speed to optimize production processes and energy usage. Empirical analyses using real-world data from a UK metal packaging plant show that the model outperforms existing predictive models in handling complex, noisy industrial data and capturing temporal and spatial distributions for accurate forecasting.

Shohin Aheleroffa et al., in the year (2020), [46] presented in their article "IoT-enabled smart appliances under industry 4.0: A case study" how conventional home appliances are now changing to meet the IoE requirements of Industry 4.0 using IoT-enabled smart systems. They mention how IoT is much beneficial in regard to cost reductions, efficiency enhancement, and predictive maintenance by using smart sensors and real-time data integration. The paper discusses the problem of how traditional factories update their legacy production line. This work aims to present an industry-driven case study that involves, for the first time, the transformation of traditional appliances into SPSs by utilizing new Industry 4.0 advanced technologies, towards more customer satisfaction and energy efficiency.

Prasanna Kumar Illa et al. (2018), [47], in their article "Practical Guide to Smart Factory Transition Using IoT, Big Data and Edge Analytics," presented a guide for transforming legacy manufacturing units into smart factories compliant with Industry 4.0 principles. The paper emphasizes the importance of an "integrated approach" for implementing IoT-based solutions, detailing benefits, challenges, and providing a reference architecture to assist organizations in balancing faster time-to-market with long-term digital transformation goals.

Yu-Chuan Lin et al. (2017), [48], in their article "Development of Advanced Manufacturing Cloud of Things (AMCoT)—A Smart Manufacturing Platform," described a five-stage approach to enhancing production yield in semiconductor manufacturing. They designed and implemented the AMCoT platform, integrating IoT, cloud computing, big data analytics, cyber-physical systems, and predictive technologies. Applied to a bumping process at a Taiwanese semiconductor company, AMCoT conducts total production inspections, provides predictive maintenance, and manages big production data, showing potential for achieving zero defects in manufacturing processes.

Qinglin Qi et al. (2017), [49], in "Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison," discuss the roles of big data and digital twin technologies in smart manufacturing. They explore how these technologies contribute to product design, production planning, manufacturing, and predictive maintenance. The article emphasizes the complementary nature of big data and digital twins and discusses how their integration can address challenges in cyber-physical integration, driving the transformation of global manufacturing towards smart, data-driven processes.

Yyi Kai Teoh et al. (2013), [50], in "IoT and Fog-Computing-Based Predictive Maintenance Model for Effective Asset Management in Industry 4.0 Using Machine Learning," proposed a predictive maintenance model based on a genetic algorithm (GA) and machine learning, applied in fog computing for Industry 4.0. The study focuses on optimizing task distribution and predictive maintenance using real-time IIoT data. The GA-based scheduling algorithm outperforms traditional algorithms such as MinMin, MaxMin, FCFS, and RoundRobin in execution time, cost, and energy efficiency. The predictive maintenance model, developed using two-class logistic regression, achieved 95.1% training accuracy and 94.5% testing accuracy, demonstrating significant improvements in cost (5.43% lower) and energy usage (28.10% lower).

Yuehua Liu et al. (2013), [51], in their article "An Evaluative Study on IoT Ecosystem for Smart Predictive Maintenance (IoT-SPM) in Manufacturing: Multiview Requirements and Data Quality," presented an overview of IoT-based smart predictive maintenance (IoT-SPM) within the context of digital twins and Industry 4.0. The article proposes a reference framework for IoT-SPM, outlining its architecture, platforms, and components. It identifies key technologies such as IoT, cyber-physical systems, big data platforms, advanced computing, and machine learning. The study addresses IoT data quality challenges and provides a qualitative evaluation of existing solutions, highlighting open research issues and future directions to advance IoT-SPM in industrial applications.

2. Methodology

a) Dataset Preparation:

To develop the predictive maintenance system, we collected vibration data from a mini-CNC machine using two MEMS Inertial Measurement Unit (IMU) sensors. The dataset comprises six axes of vibration data, which include both horizontal and vertical components, captured under different machine statuses. The defined statuses are as follows which will be considered as classes in neural model:

1. Standby: The CNC machine is idle, with no operations in progress.
2. Running: The spindle motor is active, while other functions remain off.
3. Moving: The CNC cutter moves along the x and y axes with the spindle motor turned off.
4. Blocked: The movement of the CNC cutter along the x and y axes is obstructed by an external object.
5. Overload: The cutter is stopped due to an obstacle during operation, indicating an overload condition.

These status labels represent various operating conditions of the CNC machine, ensuring comprehensive data collection for training purposes. The collected vibration data serves as a foundation for building a custom dataset, which is crucial for training the deep learning algorithm to accurately detect and classify potential machine anomalies.

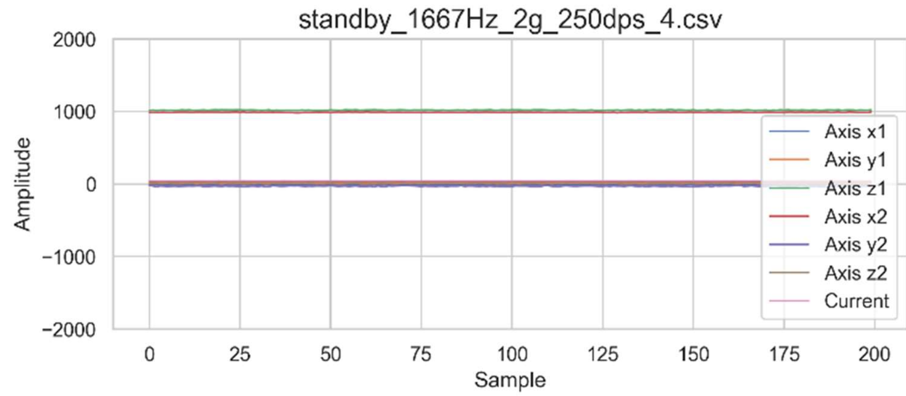


Fig 1: Randomly selected sample data frame from standby class.

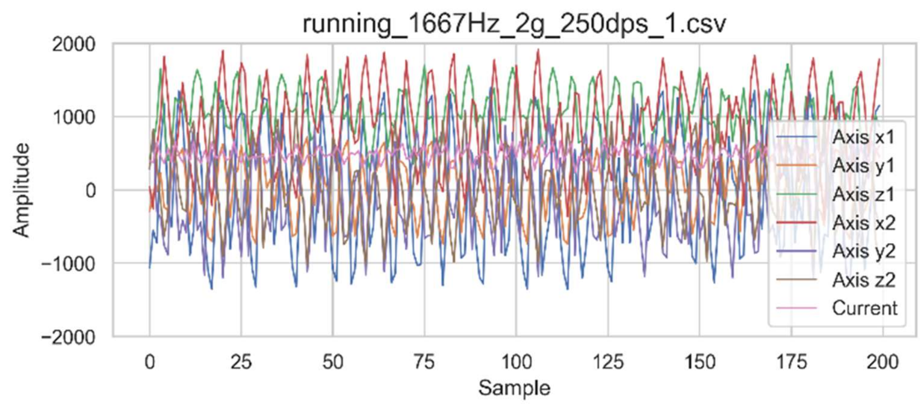


Fig 2: Randomly selected sample data frame from running class.

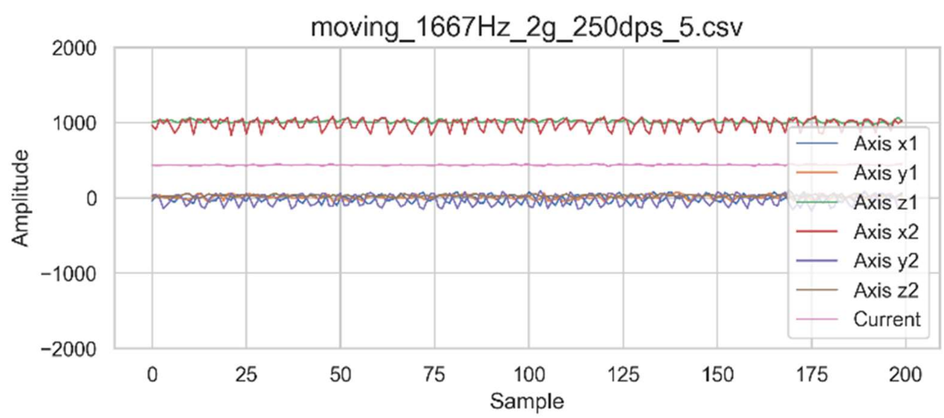


Fig 3: Randomly selected sample data frame from moving class.

Fig 4: Randomly selected sample data frame from blocked class.

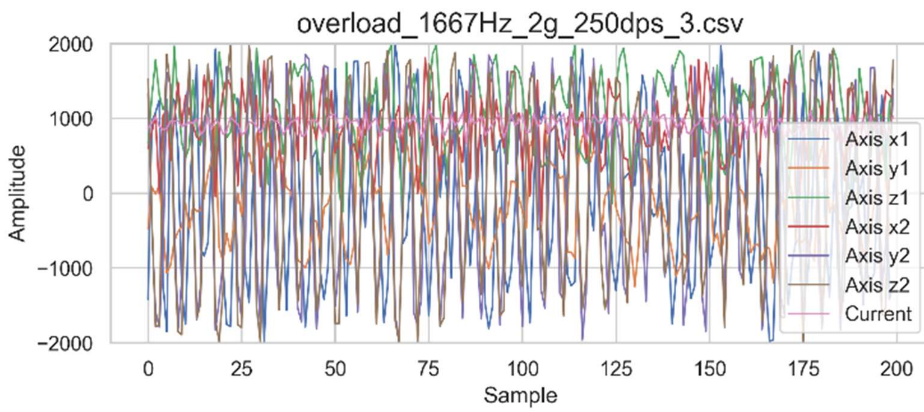


Fig 5: Randomly selected sample data frame from overload class.

b) Deep learning model:

Model Architecture: To detect machine faults, a Long Short-Term Memory (LSTM) based model was developed with a combination of convolutional and LSTM layers. The architecture begins with two 1D convolutional layers; the first consists of 32 filters with a kernel size of 3, followed by a second convolutional layer with 64 filters, yielding a total of 6,912 trainable parameters. A max-pooling layer is applied to reduce the dimensionality of the feature maps, followed by a dropout layer to prevent overfitting. The sequential model then incorporates two LSTM layers, each with 64 units, designed to capture the temporal dependencies in the vibration data. The first LSTM layer has 33,024 parameters, and the second LSTM layer adds another 33,024 parameters. After the LSTM layers, a fully connected dense layer with 128 units is introduced, contributing 8,320 trainable parameters, followed by another dropout layer. The final output layer is a dense layer with 5 units, corresponding to the five machine statuses: "standby," "running," "moving," "blocked," and "overload." This layer adds 645 trainable parameters. The overall model contains 81,925 trainable parameters, and it is designed to process both spatial and temporal patterns from the six axes of vibration data, enabling accurate detection and classification of machine faults.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	20
1	1.00	1.00	1.00	27
2	1.00	1.00	1.00	22
3	1.00	1.00	1.00	28
4	1.00	1.00	1.00	31
accuracy			1.00	128
macro avg	1.00	1.00	1.00	128
weighted avg	1.00	1.00	1.00	128

Fig 6: Training result of neural LSTM model.

c) Analysis of neural model:

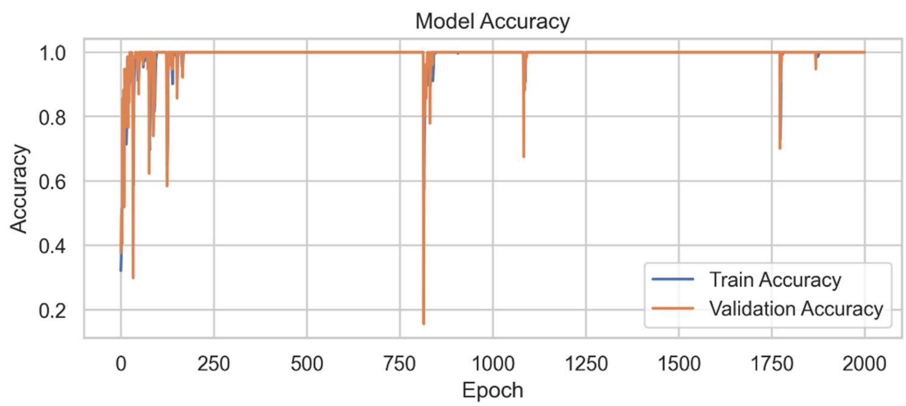


Fig 7: LSTM model accuracy during the training.

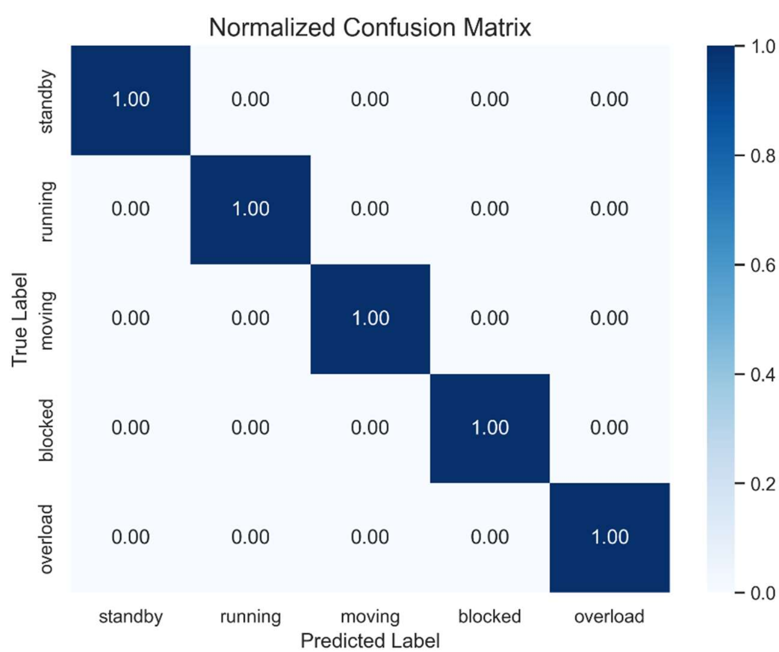


Fig 8: Confusion matrix for LSTM model.

The developed LSTM model was analyzed using several performance metrics, including precision, recall (sensitivity), specificity, and the F1 score for each class. Additionally, the overall accuracy and geometric mean were evaluated to assess the model's robustness. The results showed that the model achieved a perfect score of 1.0 across all metrics, demonstrating exceptional performance in detecting machine faults for each class. This indicates that the model was able to accurately classify the machine statuses ("standby," "running," "moving," "blocked," and "overload") with 100% precision, sensitivity, and specificity, while maintaining a balanced F1 score and overall accuracy.

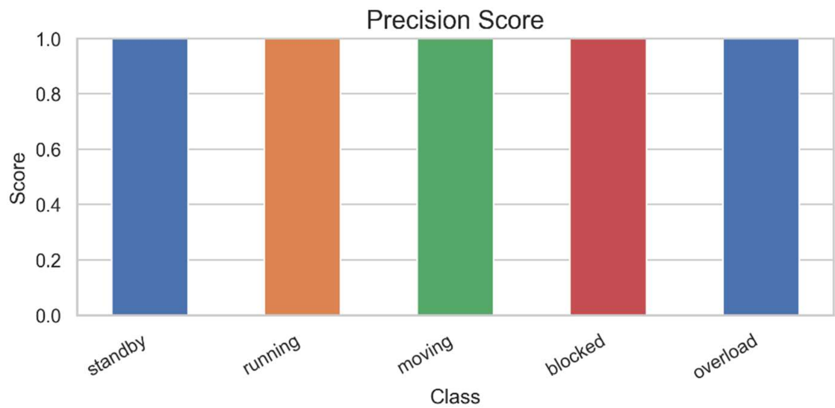


Fig 9: Precision score for LSTM model.

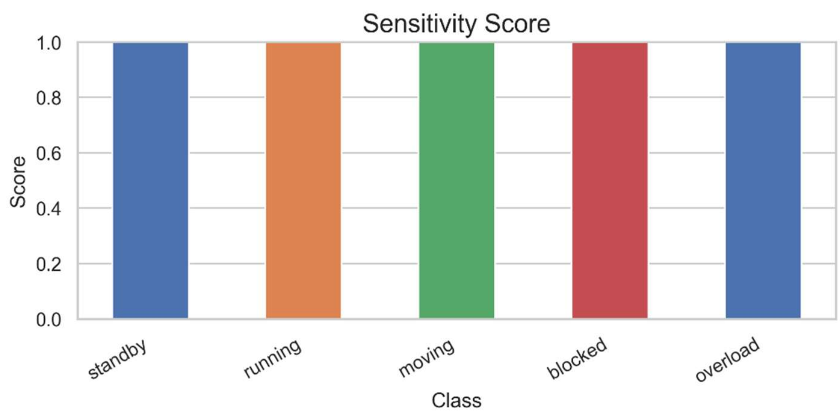


Fig 10: Sensitivity score for LSTM model.

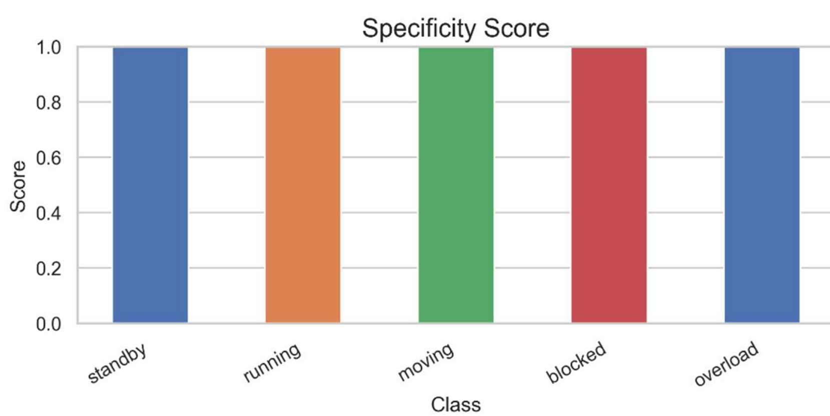


Fig 11: Specificity score for LSTM model.

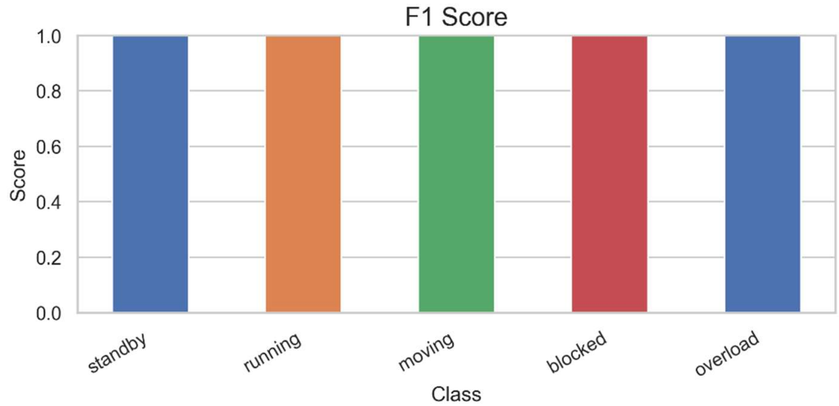
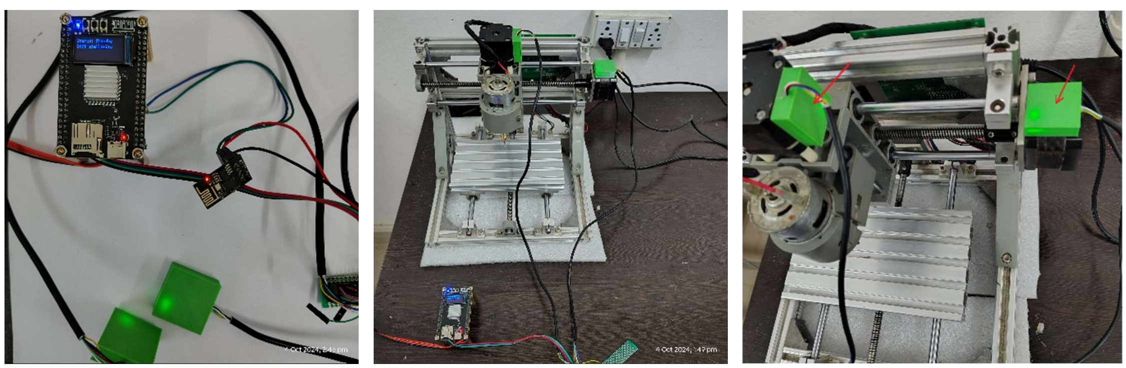


Fig 12: F1 score for LSTM model.

d) Hardware Testing for Proof of Concept:

For proof of concept, the LSTM model was deployed on a mini CNC machine to perform field testing. During testing, the model successfully recognized the operational status of the mini CNC, accurately identifying conditions such as "standby," "running," "moving," "blocked," and "overload." The model's results were transmitted in real-time to the user's mobile phone via MQTT (Message Queuing Telemetry Transport) protocol, demonstrating the system's capability to detect machine statuses and provide instant feedback to users. This field testing validated the model's effectiveness in a real-world environment, confirming its potential for practical predictive maintenance applications.



(a) (b) (c)

Fig 13: (a) Prototype of proposed hardware, (b) Hardware setup for prototype testing , (c) attachment of vibration sensor with motor.

3. Results & observations

The developed predictive maintenance system undergoes testing with the help of a mini CNC machine, in which six-axis vibration data under different machine conditions have served for training the proposed LSTM model. Predictive, proactive, and preventive maintenance strategies are integrated within the system to monitor and maintain machine health.

Predictive maintenance can also be done to forecast a machine failure for enabling timely interventions. Our system was able to do this by employing a deep learning model that processed real-time data in order to predict with great precision faulty operation in machines. All the performance metrics-measure of precision, recall sensitivity, specificity, F1 score, overall accuracy, and geometric mean-all reached the perfect score of 1.0, pointing at the high reliability of the system in anomaly detection and prediction on machines.

Proactive maintenance involves activities that are conducted to prevent failures, based on knowledge gained through continuous monitoring of data. The MQTT protocol updated in real time the status of machines to the model integrated with IoT sent on the user's mobile device. Thus, the status of the machine could easily be determined and necessary steps initiated, so that operation disruption can be stopped and overall manufacturing process efficiency increased.

The system allowed for constant monitoring of machine status for timely warnings in programmed maintenance before a failure of a critical nature would occur. Thus, conditions like "blocked" or "overload" could be spotted so that in this way, operators could take small issues that might have turned out to be major problems in the later stage and help extend useful life with less costlier repairs.

Real-world testing revealed that the system was highly effective at recognizing machine statuses in real time and transmitting the results back to the user. The fusion of accelerometers, gyroscopes, vibration, sound, and current sensors provided a complete amount of data input, while the custom dataset of machine faults assured robust model training. The high performance of the system confirms that it is perfectly suitable for predictive, proactive, and preventive maintenance in smart manufacturing environments. A study conducted on the same has returned positive results, showing that such AI-driven maintenance systems can reduce downtime, rationalize the schedule of maintenance, and improve machine reliability. The scalability and cost-efficiency of the system make it a promising solution for small- to large-scale manufacturing operations, boosting productivity with lower maintenance costs-sustainable methodology in machine management, therefore.

Overall, the results demonstrate the feasibility and efficiency of AI-powered predictive maintenance systems in industrial settings, paving the way for future enhancements and broader deployment within smart manufacturing ecosystems.

4. Conclusion:

This paper successfully demonstrates the development of an AI-powered predictive maintenance system for smart manufacturing, integrating sensor fusion techniques with MEMS sensors and leveraging a deep learning LSTM model. The system efficiently monitors the health of industrial machines, detecting anomalies in real-time by processing six axes of vibration data. Through comprehensive field testing on a mini-CNC, the model accurately identified various machine statuses and provided timely alerts via MQTT to a mobile device. With high performance across all evaluation metrics, including precision, recall, specificity, and F1 score, the system shows great promise for reducing machine downtime, preventing costly failures, and enhancing overall operational efficiency. The successful deployment and testing of this system validate its potential for practical application in predictive and preventive maintenance, paving the way for its use in broader industrial settings.

References:

[1]. Boretti, A. A narrative review of AI-driven predictive maintenance in medical 3D printing. Int J Adv Manuf Technol 134, 3013–3024 (2024). https://doi.org/10.1007/s00170-024-14305-0

[2]. Chakroun, A., Hani, Y., Elmhamedi, A. et al. A predictive maintenance model for health assessment of an assembly robot based on machine learning in the context of smart plant. J Intell Manuf (2024). https://doi.org/10.1007/s10845-023-02281-3

[3]. Mohamed Almazrouei, S., Dweiri, F., Aydin, R. et al. A review on the advancements and challenges of artificial intelligence based models for predictive maintenance of water injection pumps in the oil and gas industry. SN Appl. Sci. 5, 391 (2023). https://doi.org/10.1007/s42452-023-05618-y

[4]. Maguluri, L.P., Suganthi, D., Dhote, G.M. et al. AI-enhanced predictive maintenance in hybrid roll-to-roll manufacturing integrating multi-sensor data and self-supervised learning. Int J Adv Manuf Technol (2024). https://doi.org/10.1007/s00170-024-14263-7

[5]. Bala, A., Rashid, R.Z.J.A., Ismail, I. et al. Artificial intelligence and edge computing for machine maintenance-review. Artif Intell Rev 57, 119 (2024). https://doi.org/10.1007/s10462-024-10748-9

[6]. Sinha, S., Lee, Y.M. Challenges with developing and deploying AI models and applications in industrial systems. Discov Artif Intell 4, 55 (2024). https://doi.org/10.1007/s44163-024-00151-2

[7]. Fidelis, S., Castro, M. & Siqueira, F. Improving edge AI for industrial IoT applications with distributed learning using consensus. Des Autom Embed Syst 28, 67–89 (2024). https://doi.org/10.1007/s10617-024-09284-0
[8]. Mohapatra, A.G., Mohanty, A. & Tripathy, P.K. IoT-Enabled Predictive Maintenance and Analytic Hierarchy Process Based Prioritization of Real-Time Parameters in a Diesel Generator: An Industry 4.0 Case Study. SN COMPUT. SCI. 5, 145 (2024). https://doi.org/10.1007/s42979-023-02508-3
[9]. Zhu, C., Shao, S. RETRACTED ARTICLE: Optoelectronic sensor fault detection based predictive maintenance smart industry 4.0 using machine learning techniques. Opt Quant Electron 55, 1134 (2023). https://doi.org/10.1007/s11082-023-05410-7
[10]. Alijoyo, F.A., Pradhan, R., Nalini, N. et al. Predictive Maintenance Optimization in Zigbee-Enabled Smart Home Networks: A Machine Learning-Driven Approach Utilizing Fault Prediction Models. Wireless Pers Commun (2024). https://doi.org/10.1007/s11277-024-11233-w
[11]. Huang, G., Ullah, I., Huang, H. et al. Predictive mobility and cost-aware flow placement in SDN-based IoT networks: a Q-learning approach. J Cloud Comp 13, 26 (2024). https://doi.org/10.1186/s13677-024-00589-w
[12]. Dang, W., Kim, S., Park, S. et al. The impact of economic and IoT technologies on air pollution: an AI-based simulation equation model using support vector machines. Soft Comput 28, 3591–3611 (2024). https://doi.org/10.1007/s00500-023-09622-7
[13]. Rajkumar, N., Viji, C., Latha, P.M. et al. The power of AI, IoT, and advanced quantum based optical systems in smart cities. Opt Quant Electron 56, 450 (2024). https://doi.org/10.1007/s11082-023-06065-0
[14]. Jamarani, A., Haddadi, S., Sarvizadeh, R. et al. Big data and predictive analytics: A systematic review of applications. Artif Intell Rev 57, 176 (2024). https://doi.org/10.1007/s10462-024-10811-5
[15]. Varriale, V., Cammarano, A., Michelino, F. et al. Critical analysis of the impact of artificial intelligence integration with cutting-edge technologies for production systems. J Intell Manuf (2023). https://doi.org/10.1007/s10845-023-02244-8
[16]. Kim, BS., Ro, SK. Development of a Real-Time Anomaly Detection System for Dry Vacuum Pumps Using Low-Cost IoT Devices and Machine Learning. Int. J. Precis. Eng. Manuf. (2024). https://doi.org/10.1007/s12541-024-01039-y
[17]. Su, H., Li, L., Tian, S. et al. Innovation mechanism of AI empowering manufacturing enterprises: case study of an industrial internet platform. Inf Technol Manag (2024). https://doi.org/10.1007/s10799-024-00423-4
[18]. Aydin, G., Tezcan, M., Ozgen, B. et al. Digital twin and predictive quality solution for insulated glass line. J Intell Manuf (2024). https://doi.org/10.1007/s10845-024-02426-y
[19]. S.h Pratap, S. K. Jauhar, A. Gunasekaran, S. S. Kamble, Optimizing the IoT and big data embedded smart supply chains for sustainable performance, Computers & Industrial Engineering, Volume 187, 2024. https://doi.org/10.1016/j.cie.2023.109828.
[20]. Malik Abdul Sami, Tamim Ahmed Khan, Forecasting failure rate of IoT devices: A deep learning way to predictive maintenance, Computers and Electrical Engineering, Volume 110, 2023, https://doi.org/10.1016/j.compeleceng.2023.108829.
[21]. Himanshu Gauttam, K.K. Pattanaik, Saumya Bhadauria, Garima Nain, Putta Bhanu Prakash, An efficient DNN splitting scheme for edge-AI enabled smart manufacturing, Journal of Industrial Information Integration, Volume 34, 2023, https://doi.org/10.1016/j.jii.2023.100481.
[22]. Xiaoqiao Wang, Mingzhou Liu, Conghu Liu, Lin Ling, Xi Zhang, Data-driven and Knowledge-based predictive maintenance method for industrial robots for the production stability of intelligent manufacturing, Expert Systems with Applications, Volume 234, 2023, https://doi.org/10.1016/j.eswa.2023.121136.
[23]. Chengxi Li, Pai Zheng, Yue Yin, Baicun Wang, Lihui Wang, Deep reinforcement learning in smart manufacturing: A review and prospects, CIRP Journal of Manufacturing Science and Technology, Volume 40, 2023, https://doi.org/10.1016/j.cirpj.2022.11.003.

[24]. Minh-Quang Tran, Hoang-Phuong Doan, Viet Q. Vu, Lien T. Vu, Machine learning and IoT-based approach for tool condition monitoring: A review and future prospects, Measurement, Volume 207, 2023, https://doi.org/10.1016/j.measurement.2022.112351.

[25]. Abdul Matin, Md Rafiqul Islam, Xianzhi Wang, Huan Huo, Guandong Xu, AIoT for sustainable manufacturing: Overview, challenges, and opportunities, Internet of Things, Volume 24, 2023, https://doi.org/10.1016/j.iot.2023.100901.

[26]. Bernar Taşcı, Ammar Omar, Serkan Ayvaz, Remaining useful lifetime prediction for predictive maintenance in manufacturing, Computers & Industrial Engineering, Volume 184, 2023, https://doi.org/10.1016/j.cie.2023.109566.

[27]. G. A. Sampedro, M. A. P. Putra, J. -M. Lee and D. -S. Kim, "Industrial Internet of Things-Based Fault Mitigation for Smart Additive Manufacturing Using Multi-Flow BiLSTM," in IEEE Access, vol. 11, pp. 99130-99142, 2023, doi: 10.1109/ACCESS.2023.3312724.

[28]. K. Haricha, A. Khiat, Y. Issaoui, A. Bahnasse and H. Ouajji, "Recent Technological Progress to Empower Smart Manufacturing: Review and Potential Guidelines," in IEEE Access, vol. 11, pp. 77929-77951, 2023, doi: 10.1109/ACCESS.2023.3246029.

[29]. W. Yu, Y. Liu, T. Dillon and W. Rahayu, "Edge Computing-Assisted IoT Framework With an Autoencoder for Fault Detection in Manufacturing Predictive Maintenance," in IEEE Transactions on Industrial Informatics, vol. 19, no. 4, pp. 5701-5710, April 2023, doi: 10.1109/TII.2022.3178732.

[30]. K. S. Lee, S. B. Kim and H. -W. Kim, "Enhanced Anomaly Detection in Manufacturing Processes Through Hybrid Deep Learning Techniques," in IEEE Access, vol. 11, pp. 93368-93380, 2023, doi: 10.1109/ACCESS.2023.3308698.

[31]. Vishal Gupta, Rony Mitra, Frank Koenig, Maneesh Kumar, Manoj Kumar Tiwari, Predictive maintenance of baggage handling conveyors using IoT, Computers & Industrial Engineering, Volume 177, 2023, https://doi.org/10.1016/j.cie.2023.109033.

[32]. Etienne Valette, Hind Bril El-Haouzi, Guillaume Demesure, Industry 5.0 and its technologies: A systematic literature review upon the human place into IoT- and CPS-based industrial systems, Computers & Industrial Engineering, Volume 184, 2023, https://doi.org/10.1016/j.cie.2023.109426.

[33]. O. Gungor, T. S. Rosing and B. Aksanli, "DOWELL: Diversity-Induced Optimally Weighted Ensemble Learner for Predictive Maintenance of Industrial Internet of Things Devices," in IEEE Internet of Things Journal, vol. 9, no. 4, pp. 3125-3134, 15 Feb.15, 2022, doi: 10.1109/JIOT.2021.3097269.

[34]. Ayan Chatterjee, Bestoun S. Ahmed, IoT anomaly detection methods and applications: A survey, Internet of Things, Volume 19, 2022, https://doi.org/10.1016/j.iot.2022.100568.

[35]. Snehasis Sahoo, Cheng-Yao Lo, Smart manufacturing powered by recent technological advancements: A review, Journal of Manufacturing Systems, Volume 64, 2022, Pages 236-250, https://doi.org/10.1016/j.jmsy.2022.06.008.

[36]. T. M. Hoang, S. Dinh-Van, B. Barn, R. Trestian and H. X. Nguyen, "RIS-Aided Smart Manufacturing: Information Transmission and Machine Health Monitoring," in IEEE Internet of Things Journal, vol. 9, no. 22, pp. 22930-22943, 15 Nov.15, 2022, doi: 10.1109/JIOT.2022.3187189.

[37]. Ahmed, G. Jeon and F. Piccialli, "From Artificial Intelligence to Explainable Artificial Intelligence in Industry 4.0: A Survey on What, How, and Where," in IEEE Transactions on Industrial Informatics, vol. 18, no. 8, pp. 5031-5042, Aug. 2022, doi: 10.1109/TII.2022.3146552.

[38]. T. -A. Tran, T. Ruppert, G. Eigner and J. Abonyi, "Retrofitting-Based Development of Brownfield Industry 4.0 and Industry 5.0 Solutions," in IEEE Access, vol. 10, pp. 64348-64374, 2022, doi: 10.1109/ACCESS.2022.3182491.

[39]. Serkan Ayvaz, Koray Alpay, Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time, Expert Systems with Applications, Volume 173, 2021, https://doi.org/10.1016/j.eswa.2021.114598.

[40]. R. A. Khalil, N. Saeed, M. Masood, Y. M. Fard, M. -S. Alouini and T. Y. Al-Naffouri, "Deep Learning in the Industrial Internet of Things: Potentials, Challenges, and Emerging Applications," in IEEE Internet of Things Journal, vol. 8, no. 14, pp. 11016-11040, 15 July15, 2021, doi: 10.1109/JIOT.2021.3051414.

[41]. V. V. Shanbhag, T. J. J. Meyer, L. W. Caspers and R. Schlanbusch, "Failure Monitoring and Predictive Maintenance of Hydraulic Cylinder—State-of-the-Art Review," in IEEE/ASME Transactions on Mechatronics, vol. 26, no. 6, pp. 3087-3103, Dec. 2021, doi: 10.1109/TMECH.2021.3053173.

[42]. A. Bastos, M. L. Sguario Coelho De Andrade, R. T. Yoshino and M. M. D. Santos, "Industry 4.0 Readiness Assessment Method Based on RAMI 4.0 Standards," in IEEE Access, vol. 9, pp. 119778-119799, 2021, doi: 10.1109/ACCESS.2021.3105456.

[43]. Parjanay Sharma, Siddhant Jain, Shashank Gupta, Vinay Chamola, Role of machine learning and deep learning in securing 5G-driven industrial IoT applications, Ad Hoc Networks, Volume 123, 2021, https://doi.org/10.1016/j.adhoc.2021.102685.

[44]. W. Yu, T. Dillon, F. Mostafa, W. Rahayu and Y. Liu, "A Global Manufacturing Big Data Ecosystem for Fault Detection in Predictive Maintenance," in IEEE Transactions on Industrial Informatics, vol. 16, no. 1, pp. 183-192, Jan. 2020, doi: 10.1109/TII.2019.2915846.

[45]. Essien and C. Giannetti, "A Deep Learning Model for Smart Manufacturing Using Convolutional LSTM Neural Network Autoencoders," in IEEE Transactions on Industrial Informatics, vol. 16, no. 9, pp. 6069-6078, Sept. 2020, doi: 10.1109/TII.2020.2967556.

[46]. Shohin Aheleroff, Xun Xu, Yuqian Lu, Mauricio Aristizabal, Juan Pablo Velásquez, Benjamin Joa, Yesid Valencia, IoT-enabled smart appliances under industry 4.0: A case study, Advanced Engineering Informatics, Volume 43, 2020, https://doi.org/10.1016/j.aei.2020.101043.

[47]. P. K. Illa and N. Padhi, "Practical Guide to Smart Factory Transition Using IoT, Big Data and Edge Analytics," in IEEE Access, vol. 6, pp. 55162-55170, 2018, doi: 10.1109/ACCESS.2018.2872799.

[48]. Y. -C. Lin et al., "Development of Advanced Manufacturing Cloud of Things (AMCoT)—A Smart Manufacturing Platform," in IEEE Robotics and Automation Letters, vol. 2, no. 3, pp. 1809-1816, July 2017, doi: 10.1109/LRA.2017.2706859.

[49]. Q. Qi and F. Tao, "Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison," in IEEE Access, vol. 6, pp. 3585-3593, 2018, doi: 10.1109/ACCESS.2018.2793265.

[50]. Y. K. Teoh, S. S. Gill and A. K. Parlikad, "IoT and Fog-Computing-Based Predictive Maintenance Model for Effective Asset Management in Industry 4.0 Using Machine Learning," in IEEE Internet of Things Journal, vol. 10, no. 3, pp. 2087-2094, 1 Feb.1, 2023, doi: 10.1109/JIOT.2021.3050441.

[51]. Y. Liu, W. Yu, W. Rahayu and T. Dillon, "An Evaluative Study on IoT Ecosystem for Smart Predictive Maintenance (IoT-SPM) in Manufacturing: Multiview Requirements and Data Quality," in IEEE Internet of Things Journal, vol. 10, no. 13, pp. 11160-11184, 1 July1, 2023, doi: 10.1109/JIOT.2023.3246100.