Development of Predictive Models for Downtime Prevention in Industrial Equipment Using Machine Learning

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Abstract

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Dedication and acknowledgements

Here goes the dedication.

Author's declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and that it has not been submitted for any other academic award. Except where indicated by specific references in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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Chapter 1

Introduction

The advent of Industry 4.0 heralds a transformative era in manufacturing, characterized by the integration of digital technologies, IoT, and data-driven decision-making. As manufacturing facilities evolve, they increasingly rely on IoT sensors to monitor equipment and optimize operational processes. This shift underscores the need for advanced machine learning models that are not only effective but also open source and transparent.

Current proprietary solutions often limit flexibility and raise concerns regarding data privacy and on-premise deployment. In contrast, an open source approach ensures that the underlying algorithms and methodologies are accessible and auditable, fostering trust and enabling customization to meet specific industrial requirements. This research aims to develop a transparent machine learning model that harnesses sensor data from manufacturing facilities, thereby aligning with the core principles of Industry 4.0 and paving the way for smarter, more secure, and efficient manufacturing environments.

Chapter 2

Definitions

Python Python is a high-level, interpreted programming language widely used for data science, machine learning, and scientific computing due to its simplicity and extensive ecosystem of libraries.

CUDA Compute Unified Device Architecture (CUDA) is a parallel computing platform and programming model developed by NVIDIA. It allows developers to utilize GPU acceleration for deep learning, numerical simulations, and large-scale computations.

Linux Linux is an open-source operating system kernel known for its stability, security, and flexibility. It is widely used in server environments, high-performance computing, and embedded systems.

Jupyter Jupyter is an application that allows to write Python code alongside Markdown documentations. It works with Python environments out of the box and decreases complexity of the code base.

TensorFlow TensorFlow is an open-source machine learning framework developed by Google. It provides tools for building and deploying deep learning models efficiently, supporting both CPU and GPU acceleration.

Keras Keras is a high-level deep learning API that runs on top of TensorFlow. It simplifies the process of building and training neural networks by providing an intuitive and user-friendly interface.

Matplotlib Matplotlib is a Python library for creating static, animated, and interactive visualizations. It is commonly used for plotting data in scientific computing and machine learning.

Scikit-learn Scikit-learn is an open-source Python library for machine learning. It provides simple and efficient tools for data mining and analysis, including classification, regression, clustering, and dimensionality reduction.

Pandas Pandas is a Python library used for data manipulation and analysis. It offers powerful data structures like DataFrames and Series, facilitating efficient data handling and preprocessing.

NumPy NumPy is a fundamental library for numerical computing in Python. It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these data structures.

Chapter 3

Aim and Objectives

3.0.1 Aim

To develop a model that uses machine learning to analyze data from equipment sensors in manufacturing facilities, enabling anomaly detection and downtime prediction.

3.0.2 Objectives

- Analyze common issues and inefficiencies in manufacturing caused by current equipment monitoring systems.
- Gather and preprocess sensor data from manufacturing equipment.
- Research and select appropriate machine learning algorithms for predictive analysis.
- Design and train a machine learning model capable of detecting anomalies and predicting failures.
- Validate the model's performance using real or simulated sensor data.
- Create a deployment-ready framework for use in manufacturing environments.

3.0.3 Significance of Study

- The proposed model will enable manufacturing facilities to transition from reactive to predictive maintenance.

- It can reduce downtime, optimize resource allocation, and extend equipment life, leading to cost savings and increased operational efficiency.
- The setup time and labor costs of the current system can be reduced, optimizing the deployment process.

Chapter 4

Literature Review

The integration of advanced technologies in manufacturing, commonly referred to as Industry 4.0, is revolutionizing industrial processes. This review explores the development of models for equipment sensors in manufacturing facilities using machine learning, drawing upon the provided literature. The discussion is structured around key themes including Industry 4.0 and smart manufacturing, equipment sensors, machine learning applications, time series data processing, predictive maintenance, and the challenges and ethical considerations in industrial AI deployment.

1. Industry 4.0 and Smart Manufacturing

Industry 4.0 represents a paradigm shift in manufacturing, characterized by the integration of cyber-physical systems, the Internet of Things (IoT), and advanced data analytics [1]. Zhang et al. [1] provide a comprehensive review of Industry 4.0 and its implementation, highlighting its potential to enhance efficiency and productivity in manufacturing. The concept of smart manufacturing, a key component of Industry 4.0, leverages interconnected systems and data-driven decision-making to optimize production processes. Liu et al. [2] delve into the IoT ecosystem for smart predictive maintenance (IoT-SPM) in manufacturing, emphasizing the multiview requirements and data quality crucial for effective implementation. Their evaluative study underscores the importance of a robust IoT infrastructure for realizing predictive maintenance capabilities.

Digital twins, virtual representations of physical assets, are also integral to smart manufacturing. Lattanzi et al. [3] review the concepts of digital twins in the context of smart manufacturing, exploring their practical industrial implementation. Digital twins facilitate real-time monitoring and simulation, enabling proactive maintenance and process optimization. Furthermore, the principles of Industry 4.0 extend to sustainability in manufacturing. Awasthi et al. [4] discuss sustainable and smart metal forming manufacturing processes, indicating the broader impact of these technological advancements on environmental and economic aspects of production.

2. Equipment Sensors in Manufacturing Facilities

Equipment sensors are fundamental to acquiring real-time data in manufacturing environments, enabling monitoring, control, and optimization of industrial processes. Jiang et al. [5] present a review on soft sensors, which are inferential sensors that utilize readily available process measurements to estimate difficult-to-measure variables. These sensors are crucial for enhancing process visibility and control. For effective condition monitoring, robust data acquisition systems are essential. Toscani et al. [6] introduce a novel scalable digital data acquisition system designed for industrial condition monitoring, highlighting its potential for real-time data collection and analysis.

The data collected from equipment sensors, often in the form of multivariate time-series data, plays a critical role in detecting anomalies and predicting equipment failures. Nizam et al. [7] propose a real-time deep anomaly detection framework specifically for multivariate time-series data in industrial IoT settings. Their work demonstrates the application of deep learning for timely anomaly detection, which is crucial for preventing downtime and ensuring operational continuity. Pech et al. [8] further emphasize the role of predictive maintenance and intelligent sensors in the smart factory, providing a review of how these technologies converge to create more efficient and resilient manufacturing systems.

3. Machine Learning in Industrial Applications

Machine learning (ML) is at the core of analyzing sensor data and developing predictive models for industrial applications. Amer et al. [9] discuss the application of machine learning methods for predictive maintenance, showcasing how ML algorithms can be trained to predict equipment failures based on sensor data. Anomaly detection, a key application of ML in manufacturing, is further explored by Liu et al. [10]. They propose an anomaly detection method on attributed networks using contrastive self-supervised learning, which can be adapted for identifying unusual patterns in sensor networks.

In the context of industrial soft sensors, Ou et al. [11] introduce quality-driven regularization for deep learning networks. Their work focuses on enhancing the reliability and accuracy of soft sensors through advanced deep learning techniques. Addressing the challenge of limited data in industrial settings, Zhou et al. [12] present a time series prediction method based on transfer learning. This approach is particularly relevant in manufacturing environments where historical failure data might be scarce, enabling more effective predictive modeling even with limited datasets.

4. Time Series Data Processing for Equipment Monitoring

The data generated by equipment sensors is typically time-series data, requiring specialized processing techniques for effective analysis and prediction. Islam et al. [13] introduce a novel probabilistic feature engineering approach, RKnD, for understanding time-series data, although their specific application is in driver behavior understanding, the principles of feature engineering are transferable to manufacturing sensor data. Makridakis et al. [14] provide a comprehensive comparison of statistical, machine learning, and deep learning forecasting methods for time series data. Their review offers insights into the strengths and weaknesses of different methods, guiding the selection of appropriate techniques for equipment monitoring.

Preprocessing sensor data to remove noise and enhance signal quality is crucial for accurate analysis. Alami and Belmajdoub [15] discuss noise reduction techniques in sensor data management, although focused on ADAS sensors, the comparative analysis of methods is relevant for industrial sensor data as well. Furthermore, understanding the context of the manufacturing process is important. Taskinen and Lindberg [16] highlight the challenges facing non-ferrous metal production, providing a domain-specific perspective that can inform the development of sensor-based monitoring systems in metal smelting factories.

5. Predictive Maintenance in Metal Smelting Factories

Predictive maintenance is a critical application of sensor-based monitoring and machine learning in industries like metal smelting. Olesen and Shaker [17] present a state-of-the-art review of predictive maintenance for pump systems and thermal power plants, outlining trends and challenges that are also pertinent to metal smelting factories which often involve similar equipment. Leukel et al. [18] systematically review the adoption of machine learning technology for failure prediction in industrial maintenance. Their findings are valuable for understanding the practical implementation and benefits of ML-based predictive maintenance strategies.

The economic evaluation of implementing artificial intelligence in manufacturing, including predictive maintenance, is also a key consideration. Chen et al. [19] discuss the economic evaluation of energy efficiency and renewable energy technologies using artificial intelligence, providing a framework for assessing the financial viability of AI-driven solutions in industrial settings.

6. Challenges and Ethical Considerations in Industrial AI Deployment

Deploying AI and machine learning models in industrial environments is not without challenges and ethical considerations. Khowaja et al. [20] propose a two-tier framework for data and model security in industrial private AI, addressing the critical aspect of data privacy and security in interconnected manufacturing systems. Paleyes et al. [21] provide a survey of case studies highlighting the challenges in deploying machine learning in real-world applications, emphasizing the practical hurdles that need to be overcome. Landers and Behrend [22] discuss the ethical dimension, specifically focusing on auditing AI auditors and evaluating fairness and bias in high-stakes AI predictive models, raising important questions about the responsible and ethical deployment of AI in manufacturing.

Chapter 5

Analysis of Existing Systems

5.0.1 Traditional Rule-Based Systems

Traditional Rule-Based Systems have been a cornerstone in industrial automation for decades. These systems rely on predefined rules to monitor and control processes, but they often lack the flexibility and adaptability required for modern manufacturing demands. Moreover, many traditional rule-based implementations are proprietary, not open source, and typically do not support on-premise deployment. This results in data being managed off-site, which raises significant concerns regarding data privacy and confidentiality.

5.0.2 AWS Industrial Solutions

AWS Industrial Solutions provide a broad array of cloud-based services designed for industrial applications, including real-time monitoring and predictive maintenance. Despite their advanced capabilities, these solutions are proprietary and not open source. Additionally, they are designed exclusively for cloud deployment, which limits the option for on-premise installations. This reliance on external cloud environments can compromise data privacy and confidentiality, as sensitive operational data must be transferred to and stored within third-party data centers.

5.0.3 SAP Leonardo

SAP Leonardo integrates innovative technologies such as IoT, machine learning, and big data analytics to enable smart manufacturing solutions. However, SAP Leonardo is a proprietary system and does not offer an open source alternative or on-premise deployment. This dependency on cloud-based services raises issues related to data security, privacy, and the confidentiality of sensitive information, as all data processing occurs off-premise.

5.0.4 Google Cloud MDE & Connect

Google Cloud MDE & Connect is designed to enhance industrial operations through cloud-based connectivity and data management solutions. Like other cloud-centric platforms, it is not open source and lacks support for on-premise deployment. The necessity to store and process data in Google's cloud infrastructure can pose risks to data privacy and confidentiality, as the control over sensitive data is relinquished to a third-party provider.

5.0.5 Nvidia Omniverse

Nvidia Omniverse is a collaborative platform that facilitates real-time simulation and visualization for industrial applications. Although it offers state-of-the-art tools for digital transformation, Nvidia Omniverse is not an open source solution and does not support on-premise deployment. This reliance on a cloud-based environment means that proprietary data and simulation models are managed externally, potentially leading to concerns over data privacy and confidentiality.

Chapter 6

Data collection

The dataset utilized in this study originates from a ferrous alloy smelting facility in Kazakhstan, which has chosen to remain anonymous to protect its proprietary information. Data from equipment sensors was collected using AVEVA Historian, a robust system designed for industrial data acquisition. Subsequently, SQL Server was employed to query and export the sensor data, resulting in a comprehensive dataset for further analysis.

Chapter 7

Methodology

7.0.1 Development Environment

The development environment for this research is centered on Python, selected for its extensive ecosystem of libraries and strong support for machine learning and data analysis. The experiments and model development are carried out on a Linux-based system, which offers a robust and secure platform ideal for computational research.

Interactive coding and rapid prototyping are facilitated using Jupyter Notebook, enabling a seamless integration of code, visualizations, and documentation. Additionally, Python virtual environments are employed to manage project dependencies efficiently, ensuring an isolated and reproducible setup throughout the research process.

7.0.2 Machine Learning

The machine learning pipeline in this research is developed primarily using TensorFlow, an open-source framework that facilitates the creation and deployment of complex neural network models. By leveraging the CUDA toolkit, TensorFlow is optimized to run on the NVIDIA RTX 4060 GPU, enabling efficient acceleration of both training and inference processes. This integration significantly reduces computational time, allowing for more rapid iterations during model development.

Keras is employed as a high-level API built on top of TensorFlow. It provides a user-friendly interface that simplifies the construction, training, and evaluation of neural networks. Keras abstracts much of the underlying complexity, enabling quick prototyping and flexible model experimentation, which is essential for refining the predictive models used in this study.

Together, these tools form a robust ecosystem that supports the development of sophisticated machine learning models, tailored to analyze industrial sensor data for predictive maintenance and other applications in smart manufacturing.

7.0.3 Python Utilities

Several Python utilities are leveraged to streamline data processing, visualization, and feature engineering within this research.

Matplotlib is employed to visualize key performance metrics, including training loss, validation loss graphs, and histograms of the Mean Absolute Error (MAE). It also aids in the comparative analysis of true versus predicted values, providing crucial insights during model evaluation.

Scikit-learn is used primarily for its `MinMaxScaler`, which scales features to a defined range. This normalization ensures that all features contribute equally to the model training process.

Pandas facilitates data handling by importing datasets and performing initial filtering and manipulation. This utility simplifies the preprocessing steps required before feeding the data into the machine learning pipeline.

NumPy is instrumental in numerical computations, especially for creating time-series sequences tailored for the Convolutional Layers of the model. Its efficient array operations enable the transformation of raw data into a structured format suitable for deep learning.

7.0.4 Hardware

The computational resources used for this research include a machine with the following technical specifications:

- **CPU:** Intel(R) Core(TM) i5-13450HX – a high-performance processor with multiple cores optimized for demanding computational tasks.
- **GPU:** NVIDIA RTX 4060 – a graphics processing unit designed for high-performance parallel computing, essential for deep learning and machine learning applications.

- **RAM:** 16GB Physical + 4GB Swap – ensuring adequate memory for handling large datasets and computational workloads.

Chapter 8

Discussion

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Chapter 9

Results

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Chapter 10

Conclusion

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Appendix A

Appendix A

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Bibliography

[1] Caiming Zhang, Yong Chen, Hong Chen, and Dazhi Chong.
Industry 4.0 and its Implementation: a Review.
Information Systems Frontiers, 26(5):1773–1783, 6 2021.

[2] Yuehua Liu, Wenjin Yu, Wenny Rahayu, and Tharam Dillon.
An evaluative study on IoT Ecosystem for Smart Predictive Maintenance (IOT-SPM) in Manufacturing: multiview requirements and data quality.
IEEE Internet of Things Journal, 10(13):11160–11184, 2 2023.

[3] Luca Lattanzi, Roberto Raffaeli, Margherita Peruzzini, and Marcello Pellicciari.
Digital twin for smart manufacturing: a review of concepts towards a practical industrial implementation.
International Journal of Computer Integrated Manufacturing, 34(6):567–597, 4 2021.

[4] Ankita Awasthi, Kuldeep K. Saxena, and Vanya Arun.
Sustainable and smart metal forming manufacturing process.
Materials Today Proceedings, 44:2069–2079, 1 2021.

[5] Yuchen Jiang, Shen Yin, Jingwei Dong, and Okyay Kaynak.
A review on soft sensors for monitoring, control, and optimization of industrial processes.
IEEE Sensors Journal, 21(11):12868–12881, 10 2020.

[6] Andrea Toscani, Fabio Immovilli, Daniel Pinardi, and Luca Cattani.
A novel scalable digital data acquisition system for industrial condition monitoring.
IEEE Transactions on Industrial Electronics, 71(7):7975–7985, 8 2023.

[7] Hussain Nizam, Samra Zafar, Zefeng Lv, Fan Wang, and Xiaopeng Hu.
Real-Time Deep Anomaly Detection Framework for multivariate Time-Series data in industrial IoT.

IEEE Sensors Journal, 22(23):22836–22849, 10 2022.

[8] Martin Pech, Jaroslav Vrchota, and Jiří Bednář.
Predictive maintenance and Intelligent Sensors in Smart Factory: review.
Sensors, 21(4):1470, 2 2021.

[9] Sara Amer, Hoda K. Mohamed, and Marvy Badr Monir Mansour.
Predictive Maintenance by Machine Learning Methods.
IEEE, pages 58–66, 11 2023.

[10] Yixin Liu, Zhao Li, Shirui Pan, Chen Gong, Chuan Zhou, and George Karypis.
Anomaly detection on attributed networks via contrastive Self-Supervised Learning.
IEEE Transactions on Neural Networks and Learning Systems, 33(6):2378–2392, 4 2021.

[11] Chen Ou, Hongqiu Zhu, Yuri A. W. Shardt, Lingjian Ye, Xiaofeng Yuan, Yalin Wang, and Chunhua Yang.
Quality-Driven regularization for deep learning networks and its application to industrial soft sensors.
IEEE Transactions on Neural Networks and Learning Systems, 36(3):3943–3953, 2 2022.

[12] Xiaofeng Zhou, Naiju Zhai, Shuai Li, and Haibo Shi.
Time series prediction method of industrial process with limited data based on transfer learning.
IEEE Transactions on Industrial Informatics, 19(5):6872–6882, 7 2022.

[13] Mohammad Shariful Islam, Mohammad Abu Tareq Rony, Mejdl Safran, Sultan Alfarhood, and Dunren Che.
Elevating Driver Behavior Understanding with RKND: A Novel Probabilistic Feature Engineering approach.
IEEE Access, 12:65780–65798, 1 2024.

[14] Spyros Makridakis, Evangelos Spiliotis, Vassilios Assimakopoulos, Artemios-Anargyros Semenoglou, Gary Mulder, and Konstantinos Nikolopoulos.
Statistical, machine learning and deep learning forecasting methods: Comparisons and ways forward.
Journal of the Operational Research Society, 74(3):840–859, 9 2022.

[15] Ahmed Alami and Fouad Belmajdoub.
Noise Reduction Techniques in ADAS Sensor Data Management: Methods and Comparative analysis.
International Journal of Advanced Computer Science and Applications, 15(8), 1 2024.

[16] P Taskinen and D Lindberg.
Challenges facing non-ferrous metal production.
Fluxes and Salts, pages 1455–1464, 6 2024.

[17] Jonas Fausing Olesen and Hamid Reza Shaker.
Predictive Maintenance for pump systems and thermal power Plants: State-of-the-Art Review, Trends and Challenges.
Sensors, 20(8):2425, 4 2020.

[18] Joerg Leukel, Julian González, and Martin Riekert.
Adoption of machine learning technology for failure prediction in industrial maintenance: A systematic review.
Journal of Manufacturing Systems, 61:87–96, 9 2021.

[19] Cheng Chen, Yuhan Hu, Marimuthu Karuppiah, and Priyan Malarvizhi Kumar.
Artificial intelligence on economic evaluation of energy efficiency and renewable energy technologies.
Sustainable Energy Technologies and Assessments, 47:101358, 6 2021.

[20] Sunder Ali Khowaja, Kapal Dev, Nawab Muhammad Faseeh Qureshi, Parus Khuwaja, and Luca Foschini.
Toward Industrial Private AI: A Two-Tier Framework for Data and Model Security.
IEEE Wireless Communications, 29(2):76–83, 4 2022.

[21] Andrei Paleyes, Raoul-Gabriel Urma, and Neil D. Lawrence.
Challenges in Deploying Machine Learning: A survey of case studies.
ACM Computing Surveys, 55(6):1–29, 4 2022.

[22] Richard N Landers and Tara S Behrend.
Auditing the AI auditors: A framework for evaluating fairness and bias in high stakes AI predictive models.
American Psychologist, 78(1):36–49, 2 2022.