AI in Manufacturing

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SURF Literature Annotation

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The NSF *AI in Manufacturing* project seeks to innovate standard industrial processes by incorporating emerging Machine Learning (ML) and Artificial Intelligence (AI) practices for smart detection. Within this multi-university project, my team is focusing on the use of TinyML in the Industrial Internet of Things (IIoT) and using multi-sensor analysis on machines for predictive maintenance and productivity monitoring.

Provided Papers

Sound Recognition based on Convolutional Neural Network for Real-Time Cutting State Monitoring of Tube Cutting Machine

Eunseob Kim, et al.

https://www.ijpem-st.org/journal/view.php?doi=10.57062/ijpem-st.2022.0038

Summary: Evaluates the validity of internal and external sound detection on machines within a modern factory. Uses real-time Machine Learning process with CNN to recognize patterns, analyze sounds, and classify the ongoing machine process. Determines relationship between optimal sample time frame (short/long) based on ML model's use case. Provides in-depth analysis of steps and resources used to execute research.

Assessment: Yields high accuracy results, but sensor placement may not be ideal for all machine types. Requires high-level knowledge of Machine Learning and data analysis to understand more in-depth processes described in paper.

Reflection: Defines a multi-sensor, single data-type framework for collecting data that can be expanded to be a muti-sensor, multi-data-type framework. Determined sample length relationship can be useful for determining optimal window size based on the end goal of ML model. Establishes ideal sound-sensor locations based on resulting accuracies of each sensor.

Operation and Productivity Monitoring from Sound Signal of Legacy Pipe Bending Machine via Convolutional Neural Network (CNN)

Eunseob Kim, et al.

https://link.springer.com/article/10.1007/s12541-024-01018-3

Summary: Explores a non-intrusive method of sound detection ML use on legacy machines void of modern technology. Uses visual sensors (cameras) to aid in labeling of data for CNN along with microphones to collect data. Enabled real-time monitoring through cameras. Overcame obstacles faced with using ML model to predict machine productivity by using buffer algorithm and inferences of CNN model.

Assessment: Useful for understanding how wide variety of machines – even those without technology middleware – can still use Machine Learning. Helpful diagrams and graphs. Requires high prior knowledge of ML to understand more in-depth information.

Reflection: Establishes multi-sensor framework for working with machines that do not have built-in technology interfacing capabilities. Use of cameras for monitoring can be effective for ensuring correct data labeling. Use of buffer algorithm can possibly be used to rectify productivity monitoring performance issues on later projects.

Online Real-time Machining Chatter Sound Detection using Convolutional Neural Network by Adopting Expert Knowledge

Eunseob Kim, et al.

(not yet published, but will be presented at the SME NAMRC 52 Conference)

Summary: Explores remote online monitoring of machining processes with a ML model to quickly detect machine "chatter" (unstable vibrations that may affect part quality or damage tools). Studies intersection of ML and AI alongside labeling by an experienced user, integrating human expertise with ML techniques.

Assessment: Relies on expert/well-experienced operators to be present for correct labeling of data. Requires high-level ML knowledge to understand more in-depth processes, but lays down an understandable framework for machine monitoring.

Reflection: A ML model can be created to analyze the most efficient parameters or tool paths to operate machines with less chatter. Establishes IIoT monitoring framework approach involving the machine, edge computer, and human.

Purdue ME597 Course: IIoT Implementation for Smart Manufacturing

Eunseob Kim, et al.

https://github.com/purduelamm/purdue_me597_iiot

Summary: Graduate level course defining the 4-step pipeline for creating a ML model – Data Collection, Middleware, Database and visualization, then Machine Learning. Explores processes that occur within "Machine Learning" step – Data Analysis, ML Training, and Real-Time Implementation.

Assessment: Provides a comprehensive course that explores creating ML models for Industrial uses.

Reflection: Will be helpful to work through to learn how to create ML programs using Python, as well as get practice with examples. Also laid framework that is necessary to create programs.

Additional Papers

Machine Learning approach for Predictive Maintenance in Industry 4.0

Marina Paolanti, et al.

https://ieeexplore.ieee.org/abstract/document/8449150

Summary: Provides background information about the importance of Predictive Maintenance (PdM) in industrial use. Analyzes the benefits of PdM over Preventative Maintenance, particularly the economic benefits. Provides an outline of a ML PdM model for a spindle cutting machine.

Assessment: Provided useful background information to supplement understanding of PdM use.

Reflection: Can be developed further to create a more complex model with multiple sensor analysis.

Machine Learning for Predictive Maintenance: A Multiple Classifier Approach

Gian Antonio Susto, et al.

https://ieeexplore.ieee.org/abstract/document/6879441

Summary: Proposes an approach to PdM ML model that uses multiple classifiers to supplement effective automated decision making. Evalutes a simulated model using multiple-classifer model.

Assessment: Requires high-level prior knowledge of ML processes to understand most of this paper. Tests only done on simulated model, so results may vary on actual industrial machine.
Reflection: The multiple classifier approach is useful to integrate for dynamic adjustments based on changing requirements of the machine, as well lead to a more robust process for classifying data.

Multi-sensor information fusion based on machine learning for real applications in human activity recognition: State-of-the-art and research challenges
Sen Qiu, et al.
https://www.sciencedirect.com/science/article/pii/S1566253521002311
Summary: Expresses common limitations of ML models and how information fusion and deep learning aids with common encountered ML issues. Provides example of model using sensor fusion on wearable technology.
Assessment: This is a very thorough and insightful paper. All diagrams and explanations are very helpful in guiding the reader towards understanding.
Reflection: Although wearable technology contrasts from industrial technology, a similar method of sensor fusion could be used to cultivate multi-sensor data analysis within PdM ML models.

Predictive Maintenance and More: How to Use Machine Learning Without Being a Data Scientist
RealPars
https://www.youtube.com/watch?v=zXcp2HvpJLE
Summary: Although I am aware this is not a paper, this YouTube video was incredibly helpful for bridging existing gaps in my knowledge about Predictive Maintenance.
Assessment: All content of this video was explained in an understandable manner without needing extensive prior ML knowledge.
Reflection: Understanding concepts from this video will help to contribute towards the PdM efforts within my lab.

Industry Reference Design - BrickML

Edge Impulse

https://docs.edgeimpulse.com/docs/edge-ai-hardware/production-ready/the-brickml

Summary: The BrickML is an IoT device that, in conjunction with the Edge Impulse web software, aims to make predictive maintenance more accessible. The inclusion of environmental, motion, and current monitoring sensors allows direct integration of the BrickML on industrial machines.

Assessment: This website describes the BrickML sensor as well as how to get started using the device and also links to other useful documentation to understand the sensor further.

Reflection: This webpage will be very useful as the BrickML is the primary sensor of my research.