Initial Project Proposal

Introduction:

Machinery is critical in all forms of industry, whether it be agriculture, construction, manufacturing, or other market segments. Machines harvest the crops we eat, manufacture and package the products we buy, assemble the cars we drive, and much more. Like any mechanical system, industrial machinery undergoes wear and tear, and requires maintenance. Machine maintenance is typically performed reactively or preventatively. In reactive repair, machinery is fixed once it has broken. This process is expensive, as it results in unexpected downtime, and demand for speedy repairs on short notice. Additionally, reactive repair can be more serious, as minor issues can grow to become major ones over time prior to failure. Preventative maintenance refers to the act of repairing machines before failure, by replacing bearings, seals, lubricants, etc. on a regular basis. Preventative maintenance relies on engineers specifying general maintenance intervals, which often comes down to guesswork. Since operating conditions of each machine is different, maintenance intervals are typically conservative. This leads to unnecessary repairs taking place, and therefore higher costs.

A new method of performing machine maintenance has been growing in popularity: predictive maintenance. Predictive maintenance is the practice of using a large dataset on machinery operating conditions and failures to predict when machinery currently in use will fail, and therefore when it needs maintenance work to be done. Since the specific operating history of each machine can be recorded automatically, maintenance requirements can be tailored based on the history of each machine. This reduces unnecessary repairs on machines, decreasing downtime.

Prior Work:

A large body of research exists on the use of machine learning for predictive maintenance. The literature used in this project will roughly fall into two categories: general background information, and overviews of techniques. Four journal articles are listed below. A more comprehensive body of literature will be used for the project, but a sample of some articles is provided below:

Carvalho, T. P., Soares, F. A., Vita, R., Francisco, R. d., Basto, J. P., & Alcala, S. G. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering, 137*. doi:https://doi.org/10.1016/j.cie.2019.106024

Dalzochio, J., Kunst, R., Pignaton, E., Binotto, A., Sanyal, S., Favilla, J., & Barbosa, J. (2020). Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges. *Computers in Industry, 123*, 103298. doi:https://doi.org/10.1016/j.compind.2020.103298

Paolanti, M., Romeo, L., Felicetti, A., Mancini, A., Frontoni, E., & Loncarski, J. (2018). Machine Learning approach for Predictive Maintenance in Industry 4.0. *2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA)*, (pp. 1-6). Oulu, Finland. doi:10.1109/MESA.2018.8449150

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Yoo, J.-H., Park, Y.-K., & Han, S.-S. (2022). Predictive Maintenance System for Wafer Transport Robot Using K-Means Algorithm and Neural Network Model. *Electronics, 11*(9), 1324. doi:https://doi.org/10.3390/electronics11091324

Role of Machine Learning:

Predictive maintenance is an ideal use case for machine learning. With the proliferation of Supervisory Control and Data Acquisition (SCADA) systems, Internet of Things (IoT) devices, and programmable logic controllers (PLC), a vast quantity of data is now being gathered on every aspect of a given manufacturing system. With this inexpensively gathered, labeled, multivariate data, a large value proposition exists to interpret it and use it to predict machine failure. Manual interpretation of the data is complex and difficult. The relationship between the operating conditions and failure rates of machinery is often non-trivial, and expensive and labor intensive to determine. Machine learning is an excellent candidate to quickly and cheaply process the data and predict future failures.

Data:

Publicly available datasets of machinery operating parameters and failures are difficult to come by, as many implicitly contain confidential trade secrets, and other information that business would rather not have in the public domain. A suitable dataset has been selected however; the AI4I 2020 Predictive Maintenance Dataset, which is a synthetic dataset that represents real-world machinery used in industry. This dataset is comprised of six features, which include product ID, air temperature, process temperature, rotational speed, torque, and tool wear. The dataset includes five independent failure modes as targets: tool wear failure, heat dissipation failure, power failure, overstrain failure, and random failure. The AI4I 2020 Predictive Maintenance Dataset has 10,000 instances.

Approach:

Several machine learning techniques have been successfully used for predictive maintenance applications. These include support vector machines, random forest, artificial neural networks, and k-means, among others. This project will emphasize techniques described in literature, and compare their performance for a single dataset. The hope of this approach is to best develop a sense of the strengths and weakness of different machine learning techniques, and how to best apply them for a predictive maintenance use case. Existing algorithms will be modified to perform as well as possible, following prior research. Full implementation from scratch will not be performed, as the goal of this project is to demonstrate how a manufacturing engineer in the field can best use existing machine learning tools for predictive maintenance, rather than a software engineering project which develops a highly specialized and optimized tool.

Results:

The goal of this project is to predict whether failure will occur given the machine parameters, and correctly identify which failure mode is expected. False positive and false negative rates are also important, as false positives increase expense by causing unnecessary maintenance, while false negatives increase expense by causing unexpected and inconvenient machinery failures. Confusion matrices, heat maps, and scatter plots will be used to demonstrate the results of various machine learning approaches used during the project.