AI BASED SYSTEMS FOR PREDICTIVE MAINTENANCE IN THE MANUFACTURING INDUSTRY

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Abstract

As AI/ML has incorporated almost all modern sectors in business and industries, it is not without saying that AI has managed to yield outstanding results in the Manufacturing Industry too, as it continues to do so. Advancements in the automation industry lead to data explosion and the machines' downtime incur heavy costs. With heavy expenditure comes a fraction of loss, which is estimated to be about half a million dollars per hour of downtime. Predictive maintenance is an emerging technology where AI-based systems detect possible anomalies and predict maintenance scheduling to prevent equipment failures. This report focuses on the various aspects of these systems, their benefits and importance in the manufacturing sector. Examples of AI-based data collection systems include temperature, wind, oil, pressure sensors, cameras, ML engines, power consumption meters, on-premise databases, etc. These systems' collected data is then used by the ML models to predict various kinds of problems in the machinery.

1.0 Introduction

Following routine checkups and maintenance of machinery has been a decades old practice, which usually requires human intervention in the form of machine operators and technicians to fix errors or other failures. There are usually four types of maintenance: Reactive maintenance, planned maintenance, proactive maintenance, and predictive maintenance, all in the increasing order of reliability and effectiveness.

Reactive maintenance means fixing when broken, which is probably the least effective method, as it incurs the least profits and much losses. Planned maintenance, though used to prevent unplanned downtime, is not without its shortcomings as it can lead to over-maintenance or under-maintenance when proper analysis isn't carried out. Also, according to the International Society of Automation, downtimes cost $647 billion annually and estimated losses are $540,000 every hour of downtime. Proactive maintenance is fixing the reasons for equipment failure before it happens, though it calls for better technologies to help save costs and provide optimized methods, which is predictive maintenance, provided by AI or IoT in recent times.

The proposed idea is to develop and use predictive maintenance, a technique wherein AI-based systems help determine the condition of working equipment and prevent downtime costs. Every set of equipment has its own unique specification and needs different types of data in combination that can be used to predict failure. ML systems can use many types of data for learning patterns, working and specifications of the equipment. These data types include computer vision data, Programmable Logic Controller data, sensor data and historical data. Predictive Maintenance allows for safety compliance, improves product quality, and increases asset life. It also reduces human intervention to a great extent as it does the job of inspection more accurately by being trained using just a few images. It reduces the chances of unexpected failures with dire consequences by having the management always updated about the machinery.

Fig. 1.0. Benefits of Predictive Maintenance (PdM)

Specifically, the proposed idea is to design a system that uses classification task to predict presence of equipment failure and more so, types of it. This is a simple and efficient way to detect anomalies in machinery. After the implementation of this strategy, other approaches of ML can be used in addition to improve performance. For example, a prediction of RUL (Remaining Useful Lifetime) of equipment can be carried out using regression task in ML. In this way other methods can be experimented with, delving into even deep learning.

Conventional approach to implement PdM, is by using classification only, but advanced research and implementation has been carried out in unsupervised learning methods, including clustering. Deep learning has also made way in PdM, like every other sector, with solutions using RNN (Recurrent Neural Networks), and ANN (Artificial Neural Networks).

1.1 Initial Needs Statement

Many organizations get the short end of the stick annually when maintenance detection using conventional methodologies causes huge losses, due to too much planned maintenance. Planned maintenance is used to prevent unplanned catastrophes but leads to over-maintenance or under-maintenance. Secondly, a lot of man-power is required in traditional methods. Also, machines might get even more damaged if the error is not detected and fixed in time. The best solution to all these needs of the industry is predictive maintenance as it saves time, capital and manpower.

2.0 Customer Needs Assessment

The customers of the manufacturing industry include other manufacturing companies, wholesalers, retailers, and business end-users that are directly affected by the manufactured products. Without proper assessment, detection and maintenance of the machines, products these produces are affected, which in turn dissatisfies the customers and stakeholders as it incurs losses for them.

The customers directly impacted include the companies that buy the equipment itself from the manufacturing industry and come under the B2B (Business to Business) market. The needs of all these customers are clear, which are to receive good quality services that produce an optimal profit for them. In the B2B market, the customers are other businesses, hence they look for profit throughout. The customer requirements also include making up for the losses that occur due to products manufactured using faulty or average grade machinery. AI-based services/systems help the customers largely due to the efficiency and optimal results that they produce.

3.0 Revised Needs Assessment and Target Specification

The needs and objectives do not change much as the producers and customers both want desirable, profitable results. It is a continuous cycle of losses that both the manufacturers and customers have to go through once the products that have been developed are developed by machines that are not up to par. This leads to a waste of a lot of time. The main requirements include improved performance by incorporating predictive aspects into the manufacturing process and schedule maintenance according to the appropriate outcomes.

The target specifications include developing and using systems that are capable of achieving the ideal or at least realistic goals of the companies at heart. The results should be at least better than the conventional methods and previous methods used by the company. The outcomes of the predictive systems are required to be realistically accurate with various types of evaluation done.

AI-based devices or systems are supposed to observe the functioning of the machines and take inputs to be able to produce outcomes. The devices like sensors can take inputs of various parameters like temperature, oil, pressure, and vibration.

4.0 External Search

Search for this subject has been conducted online, using various articles and websites regarding Predictive Maintenance using AI. They are listed below:

1. AI Predictive Maintenance, Industlabs
2. Predictive Maintenance using ML, Javatpoint
3. Importance and benefits of predictive and preventive maintenance, TMASystems
4. How to implement ML for Predictive Maintenace, TowardsDataScience
5. Maintenance strategies, Fiixsoftware
6. PdM Sensors and implementation, The Manufacturer
7. Choosing the most suitable sensor, Analog

4.1 Benchmarking

There are many companies globally that use AI-based systems for the purpose of Predictive Maintenance. Some of these companies are Infrabel (Belgian government-owned public company), Komatsu Ltd. (A Japanese manufacturing company), Mondi (global company), and Chevron (American multinational energy corporation).

The devices used by these companies to detect machine conditions are temperature sensors (Resistive Temperature Detectors), pressure sensors (microphones), vibration sensors (accelerometers), databases, and cameras and ML engines. These sensors keep track of the machine's potential failure modes and the warning signs associated with these modes.

- Temperature sensors (RTD): Used to monitor critical machine components to detect changes in machine condition by sensing increased temperatures in them.
- Piezo Accelerometer: Used to monitor the acceleration present during machine operation and focus on the increased vibration levels in the components.
- Microphones: These are the sound pressure monitoring sensors that focus on the bearing conditions, misalignment of the components and look for possible pressure leaks.
- Particle monitors: Used to measure the oil quality in the components and detects debris from wear.
- Cameras: Used to watch the equipment function and conduct a qualitative assessment of products.

Measurement	Sensor	Key Information	Target Faults
Temperature	RTD, Thermocouple	Low cost, accurate	Change in temperature due to friction, excessive start/stop, insufficient power supply
Vibration	Piezo Accelerometer	Low noise, frequencies up to 30kHz	Bearing condition, imbalance, misalignment, load condition
Sound pressure	microphone	Low cost, low power, frequencies up to 20kHz	Bearing condition, gear meshing, pump cavitation
Oil quality	Particle monitors	Viscosity, particles and contamination	Detects debris from wear.
Magnetic field	Magnetometer	Low cost, frequencies up to 250Hz	Rotor bar, end ring issues

Fig. 4.0. Sensor types and their uses in table format

4.2 Applicable Patents

Some important patents include the following:

- US5963884A: A predictive maintenance system for plurality of machines
- US7457763B1: A system for maintaining an item of equipment supports the provision of predictive maintenance in a manner that eliminates the downtime of the equipment.
- US11307570B2: A predictive maintenance server based on machine learning used for prediction of the equipment condition.
- US10890904B2: A model predictive maintenance system for building equipment.

5.0 Business Model

As mentioned previously, Predictive Maintenance costs less than reactive maintenance and saves costs that result from repeated repair and downtime. But a business model is crucial for any industry to survive and to be able to use predictive maintenance devices, it is necessary to understand where the capital is going to be flown in from.

Predictive Maintenance is a smart investment in the years to come with hardly any business implications as the IoT Analytics report from April 2021 estimates that the predictive maintenance market, which is currently worth about $6.9 billion, will reach $28.2 billion by 2026. The potential business models for predictive maintenance are:

- Cloud subscriptions: By providing plants owners with online tools to monitor their equipment status, it brings some financial benefits. These tools are offered as cloud services and hence the model involves sales of cloud subscription with every tool purchased. This model is perceived as an up-selling opportunity for Original Equipment Manufacturers (OEMs).

- Funds: PdM requires high capital investment in technology and labor to implement. Funds reserved for unplanned downtime and reactive maintenance can be used to cater to predictive maintenance (PdM) for obvious reasons of cost-saving. PdM majorly reduces the risks of catastrophic failures of component parts thus saving huge capital.
- Stakeholder sponsors: Stakeholders of this business that include OEMs (Original Equipment Manufacturers), Plant Owners, Solution integrators and supply chain partners can sponsor necessary PdM tools which in turn benefit them by bringing in effective and efficient results.
- Uptime as a service: OEMs could choose to sell the uptimes of the tools when they are in use, and not the tools themselves. Like cloud services, this could profit the OEMs hugely, also while providing the same services.
- Warranty as a service: Warranty claims create friction between the OEMs and the equipment vendors. Hence proving the correct use of equipment is important. For this purpose, warranty based on time, or warranty based on usage schemes can be applied.

6.0 Concept Generation

As machine learning is used to implement PdM in the industry, machine learning methods are mainly categorized into 2 classes: supervised ML and unsupervised ML.

Supervised learning:

We have classification and regression tasks, both of which can be used to implement PdM. Both share the same goal, which is to map a relationship between the input and output variables.

- Classification in PdM: This type of ML class uses labeled data to predict test data and classify it into two or more groups. Through the various types of data collected, classification task in PdM is used to predict failure within a given time window. Classification can predict multiple types of failures or a simpler scenario includes using classification to predict if there is a failure occurrence or not. Classification is also used to classify various causes of failure in the components.
- Regression in PdM: Regression task also uses labeled data to predict a continuous range of outcomes rather than dividing the test data into categories. Regression needs more amount of data compared to classification. This task is used to predict Remaining Useful Lifetime (RUL). Usually, regression is helpful when the degradation process is linear. Regression tasks are also used to predict the temperatures of the components.

Unsupervised learning:

Unsupervised data is used when the labeled data is not available. If the company doesn't have critical maintenance information in its historical data, a solution for PdM is to build an unsupervised ML model and use it to detect anomalies. The major difference is that unsupervised learning methods can work on unlabeled raw data while supervised learning models are dependent on the labeled data.

Though both these learning methods (supervised and unsupervised) have their own benefits, it is a more common practice to use either classification or regression models for PdM.

6.1 Initial Screening for Feasibility and Effectiveness

A feasible approach to PdM is based on the problem that is being solved. There are many sub-tasks in PdM that can be solved using Machine Learning approaches. ML can solve problems like:

- Detect anomalies in data readouts.
- Identify exact faults in equipment.
- Predict optimal life and subsequent failure period of an asset.
- Predict Remaining Useful Lifetime (RUL).
- Classify different types of failures.
- Predict various causes of failures.
- Analyze or predict some parameters of components, like temperature, etc.

The feasibility of a specific ML approach depends on the tasks or subtasks it is trying to solve.

7.0 Concept Selection

For this report, the idea is to select a common approach in the subject of PdM and to conduct further research and analysis to try for improvisation in the selected concept.

The concept to be selected is Supervised Learning, specifically taking a classification task for a given problem. Classification approach for predictive maintenance is a popular method used for several tasks. This concept includes the task of predicting the presence or absence of failure in a particular equipment.

In different companies, there are different and unique kinds of equipment, so the prediction for presence of failure should be tailored to a specific equipment of a piece of machinery that is targeted. Hence, the proposed idea is to use improvements in classification tasks to find better accuracies in a given model to better suit the dataset curated and to work on solutions that solve modern problems.

Advancements in this problem statement can be introduced. There are various types of machinery and detecting errors traditionally takes many years as its lifespan is so long. Hence, gathering data using sensors takes years. Historical data is useful in this regard but modern machinery may sometimes have no substantial history. Therefore, a solution to this major issue is to build anomaly detection and classification in PdM with zero initial training.

8.0 Final Design

This section details the flow of the classification task in Predictive Maintenance (PdM). The problem statement is to classify presence or absence of errors in components and if error is present, classifying the kind of error present.

Before incorporating ML into PdM, it is important to conduct a thorough analysis of the equipment from the OEMs. The machinery on which ML is going to be applied should be studied and each component analysis should be recorded.

The first subtask includes data collection. This is one of the most important part of PdM as the data is collected from various sources and choosing specific combinations of data sources depends on some factors. Data is collected from sensors, cameras and/or seismometers. Data types include:

- Computer vision data: Information collected from a camera as it monitors the functioning equipment and assesses the quality of products produced.
- Programmable Logic Controller (PLC) data: The human-machine interaction is captured in this type of data. Human inputs and machine outputs are analyzed.
- Sensor data on equipment: It includes an important set of data collected from sensors. These sensors measure the temperature, humidity, oil quality, pressure, vibrations, and other parameters. This is the important data that is to be included in the dataset.
- Historical data: Data collected over the years is the historical data, which includes the previous malfunctions, wear cycles, and basically the bell-curve of the lifespan of equipment.
- External data: The more the data, the more the chances of analysis being accurate. Data from other similar equipment and the general environment can be used to measure the impact on the equipment's functioning.

These data types in combination are used to build a dataset required for the classification task. The historical data helps in labelling the data for the supervised learning task. Also, huge amounts of data are required. This is the data acquisition phase.

Next subtask is data cleaning which deals with missing data, outliers, fixing the data types and other steps.

Data cleaning is followed by feature engineering where the features of the dataset are handled which includes deleting trivial features not important for the given task. Techniques like frequency spectrum, statistics analysis and time frequency are used in this phase.

Following feature engineering phase is the fault detection and diagnostic prognosis which includes selecting and implementing the appropriate classification model. The right model is selected completely based on the dataset. It can be SVM (Support Vector Machines), KNN (K-Nearest Neighbors), Logistic Regression and many others.

Implementing the classification is carried out by dividing the dataset into training and testing sets. Then the model learns from the training set and verifies its accuracy on the testing set.

This is the last step of the implementation in PdM classification task. Based on the results and accuracy of the results, replacement or repairment of the detected components is performed.

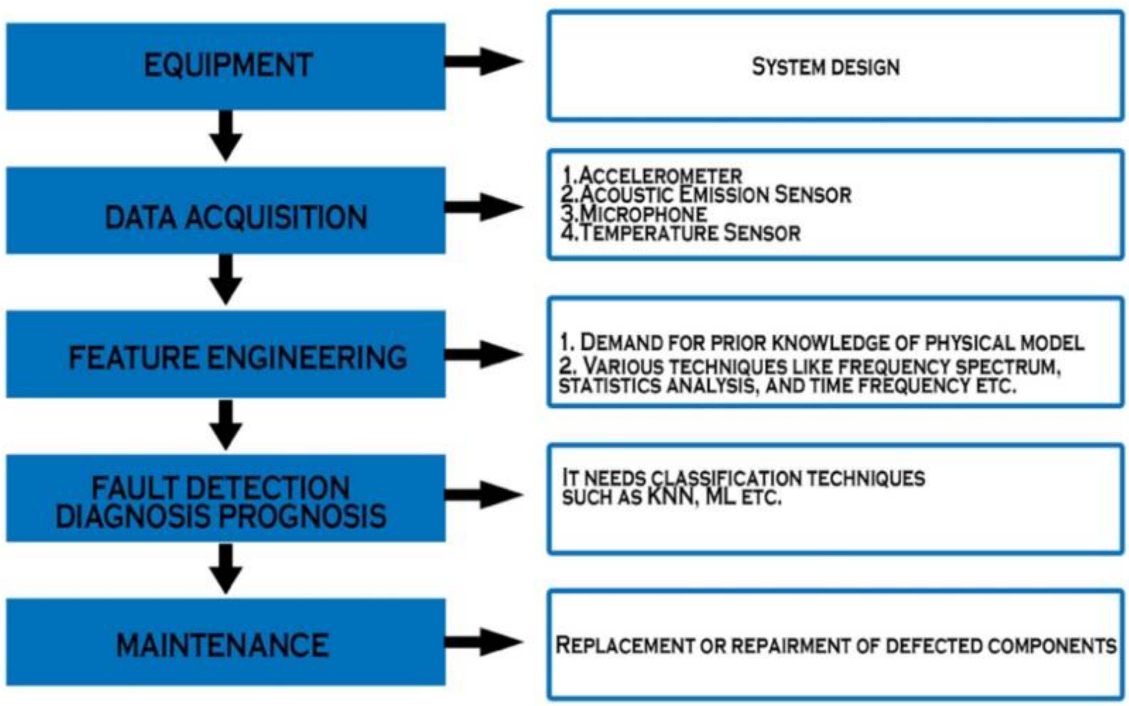

Fig. 8.0 Predictive Maintenance Classification Task Process

9.0 Product Details

This section curtly mentions the contents within the following sub-topics:

9.1 How does it work?

The product works like conventional ML systems which includes first data collection, data cleaning, data visualization, data modelling, and evaluating the results. The data is collected using data collection systems mentioned below and then processed and cleaned. Then after dividing the data into training and testing a suitable model is selected and worked upon, to achieve accurate results.

9.2 Data sources

Data sources are mainly ML devices that are deployed to observe and assess the functioning of the machine components. These devices mainly include sensors, cameras, seismometers, etc. The sensors are used to measure temperature, pressure, oil quality, etc. of the components.

CODE IMPLEMENTATION

GitHub Link:
https://github.com/Shrutij516/ML_mini_projects/tree/main/Predictive%20Maintenance

10.0 Conclusion

The objective of the report was to explore Predictive Maintenance in depth and to propose methods important for solving a myriad of problems using ML. The objective is now complete as the report discusses various aspects of PdM in detail and proposes a classification task problem to detect anomalies in the machinery manufactured by the OEMs.

The report discusses the importance of PdM and its benefits, along with the understanding of many stakeholders and their needs. The report also proposes a few effective business models which can be deployed to make this proposal work in the industrial market and take care of the capital that comes in.

Throughout this project report, a dive is taken into the manufacturing industry and its various stages of maintenance including reactive maintenance, planned maintenance, proactive maintenance and predictive maintenance, in increasing levels of effectiveness and outcomes.

Finally, the report encompasses a simple but efficient task of classification used in PdM to detect failures in the equipment. Understanding of the steps for this task have been discussed in detail.

This report concludes by suggesting further advancements in predictive maintenance by using more complex ML approaches, for example RNN in deep learning.

11.0 References

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

2. S. Vollert, M. Atzmueller and A. Theissler, "Interpretable Machine Learning: A brief survey from the predictive maintenance perspective," 2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), Vasteras, Sweden, 2021, pp. 01-08, doi: 10.1109/ETFA45728.2021.9613467.

3. O. Motaghare, A. S. Pillai and K. I. Ramachandran, "Predictive Maintenance Architecture," 2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), Madurai, India, 2018, pp. 1-4, doi: 10.1109/ICCIC.2018.8782406.

4. https://blog.vsoftconsulting.com/blog/using-ai-for-predictive-maintenance-in-manufacturing

5. https://industlabs.com/news/ai-predictive-maintenance

6. https://www.javatpoint.com/predictive-maintenance-using-machine-learning#:~:text=Predictive%20maintenance%20with%20Machine%20learning%20helps%20machines%20or%20systems%20predict,with%20sensors%20to%20monitor%20failures

7. https://www.tmasystems.com/resources/the-importance-and-benefits-of-predictive-and-preventive-maintenance#:~:text=Predictive%20maintenance%20allows%20for%20safety,maintenance%20schedule%20adjustments%2C%20and%20repairs

8. https://towardsdatascience.com/how-to-implement-machine-learning-for-predictive-maintenance-4633cdbe4860

9. https://www.fiixsoftware.com/maintenance-strategies/predictive-maintenance/

10. https://www.themanufacturer.com/articles/predictive-maintenance-sensors-and-implementation-a-solution-overview-from-dell/#:~:text=Temperature%20sensors%20monitor%20critical%20machine,contact%20infrared%20sensors%20are%20used

11. https://www.analog.com/en/technical-articles/choosing-the-most-suitable-predictive-maintenance-sensor.html

12. https://www.businessnewsdaily.com/10920-predictive-maintenance-business.html

13. https://www.researchgate.net/figure/Predictive-maintenance-process_fig1_352155128