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RESEARCH ARTICLE

# MACHINE PREDICTIVE MAINTENANCE SYSTEM FOR INDUSTRIAL APPLICATIONS

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**ABSTRACT**

Predictive Maintenance is attracting a great deal of interest, as it is beneficial to detect anomalies and possible defects in the equipment before they fail. To do so, we can use Machine learning models to analyze the data patterns and predict the equipment maintenance status. In this study, we aim to predict an industrial machine's maintenance status with the help of air temperature, process temperature, relational speed, torque, and tool wear. The main parameters to foresee the failure are Tool Wear Failure (TWF), Heat Dissipation Failure (HDF), Power Failure (PWF), Overstrain Failure (OSF), and Random Failures (RNF). We aim to explore different machine learning algorithms to predict the machine maintenance status and pave the way for a new methodology to anticipate the maintenance schedule in order to reduce factory downtime.



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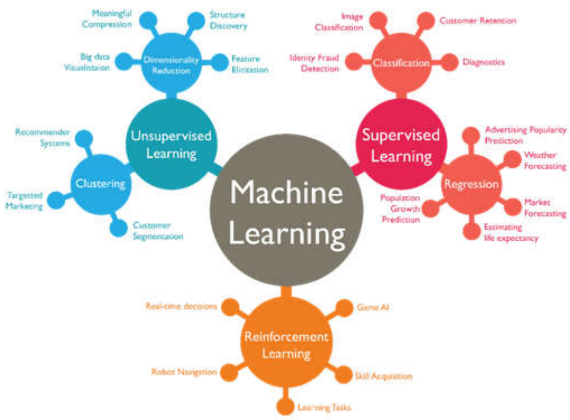
# INTRODUCTION

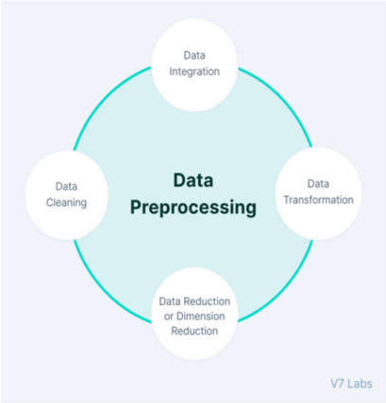
Machine learning (ML) is the study of computer algorithms that can improve automatically through experience and by the use of data. Machine learning algorithms build a model based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so. Predictive maintenance is a technique that uses data analysis tools and techniques to detect anomalies in the operation and possible defects in equipment and processes so that we can fix them before they result in failure. Predictive maintenance uses historical and real-time data from various parts of the operation to anticipate problems before they happen.

**EXISTING SYSTEM:** Machines are managed by factory managers and machine operators are required to carry out scheduled maintenance and need continuous maintenance to prevent downtime. Computerized maintenance management system (CMMS) maintains a computer database of information about an organization's maintenance operations. This information is intended to help maintenance workers do their jobs more effectively.




IOT predictive maintenance systems analyze machine operating conditions in real time to forecast when and how a machine might malfunction. It involves the use of sensors to collect equipment data and software to analyze the collected data and generate reports.

**PROPOSED SYSTEM:** Here we are using predictive maintenance to detect anomalies and predict the maintenance status.



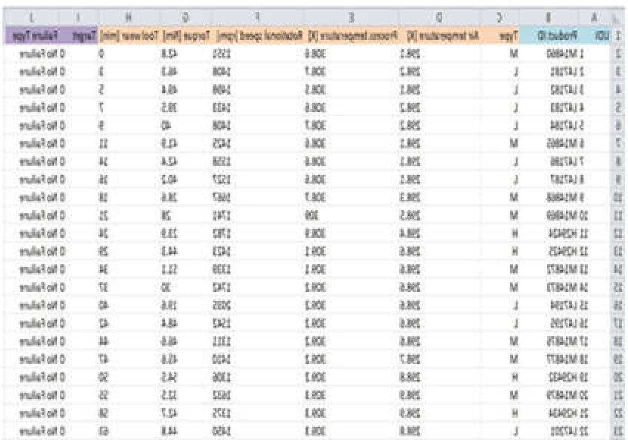


We use air temperature, process temperature, relational speed, torque and tool wear for predicting the maintenance of machine. We deal with five failures such as Tool Wear Failure(TWF), Heat Dissipation Failure (HDF), Power Failure (PWF), Overstrain Failure (OSF) and Random Failure (RNF). We use python pandas to analyze the data sets.

## MODULE DESCRIPTION

**The proposed work can be divided into a number of modules as shown below.**

- Data Preprocessing
- Types of inputs
- Types of Process
- Algorithm Used



### Data Preprocessing

- Importing libraries:

Importing libraries like numpy, matplotlib, Pandas and sklearn for processing array, plot diagram and importing processing dataset and caring dataset.

- Importing dataets:

Using pandas you can import dataset as csv.

- Finding Missing Data:

Using sklearn (scikit learn) and importing imputer for find and replacing the missing data based on the strategy.

- Encoding Categorical Data:

As we process dataset we can't able to process string as fast as a numerical value so need to convert the string into a value using sklearn library.

- Splitting dataset into training and test set:

Here you need to split the dataset into training and testing set using sklearn train_test_split. The most efficient way is to train 80% of dataset and test 20% of dataset.

### Types of inputs

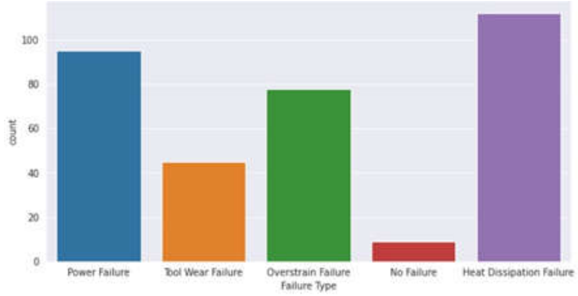
- Product ID consisting of a letter L, M, or H for low (50% of all products), medium (30%) and high (20%) as product quality variants and a variant-specific serial number.
- Air temperature [K] generated using a random walk process later normalized to a standard deviation of 2 K around 300 K.
- Process temperature [K] generated using a random walk process normalized to a standard deviation of 1 K, added to the air temperature plus 10 K.
- Rotational speed [rpm] calculated from a power of 2860 W, overlaid with a normally distributed noise.
- Torque [Nm] torque values are normally distributed around 40 Nm with σ = 10 Nm and no negative values.
- Tool wear [min] the quality variants H/M/L add 5/3/2 minutes of tool wear to the used tool in the process.

### Types of process

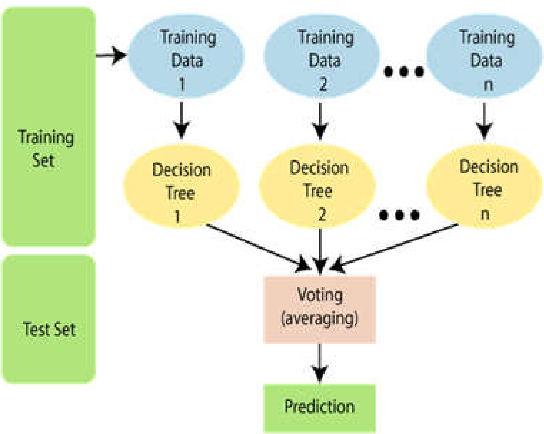
- Tool wear Process the tool will be replaced or fail at a randomly selected tool wear time between 200 – 240 mins (120 times in our dataset). At this point in time, the tool is replaced 74 times, and fails 46 times (randomly assigned).
- Heat dissipation Process heat dissipation causes a process failure, if the difference between air- and process temperature is below 8.6 K and the tool's rotational speed is below 1380 rpm. This is the case for 115 data points
- Power Calculation the product of torque and rotational speed (in rad/s) equals the power required for the process. If this power is below 3500 W or above 9000 W, the process fails, which is the case 95 times in our dataset.
- Overstrain Process if the product of tool wear and torque exceeds 11,000 minNm for the L product variant (12,000 for M, 13,000 for H), the process fails due to overstrain. This is true for 98 datapoints.
- Random Calculation each process has a chance of 0, 1 % to fail regardless of its process parameters. This is the case for 19 datapoints, more frequent than could be expected for 10,000 datapoints in our dataset.

## IMPLEMENTATION

The Types of failure were calculated for the dataset provided by the inputs and processed using machine learning algorithm. The results of the of failure is generated and displayed below.




**Algorithm Used**




**Random Forest:** As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of over fitting**.**

## CONCLUSION

Machine predictive maintenance is high level maintenance software as we use more number of data to train and test. The machine will be experienced with more number of data, it is highly effective in real time environment.

As we use various types of failures, it is easy to find what type of failure in real time. As our algorithm is highly effective, we can find the failure status.

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