Predicting Milling Machine Failures using Machine Learning

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Abstract* – *The problem of reducing unplanned downtime in the manufacturing sector via predictive maintenance approach is explored in this report. This research aims to create machine learning approaches for milling machine failure prediction, with the goal of minimizing operational disruptions caused by failures. The study shows that Random Forest models are good at forecasting when machines would break down by using a dataset with 10,000 observations. Overall accuracy is 98.5%, and precision and recall rates are quite high, according to quantitative study. Not only that, but the study also manages to cut unplanned downtime by 98.5%, which is far better than the initial aim of 50% reduction. Implementing an early problem detection system and improving resource allocation tactics are examples of qualitative enhancements that further enhance operational efficiency and productivity.

***Keywords* – Milling machine, unplanned downtime, random forest**

I. INTRODUCTION

Continuing from CA1, this paper focuses on implementation of the machine learning technique and critical analysis of modelling to solve real world problem of unplanned milling machine failure that can make the companies lose millions of dollars per year and in some cases millions of dollars per day. This paper focuses on developing a predictive maintenance model for milling machine failure prediction. This paper outlines the business objectives, hypothesis, and methodology to achieve the goal of reducing unplanned downtime by 50%. After exploring the dataset that consists of milling machine parameters and failures, various machine learning algorithms have been explored and finally Random Forest is chosen for it's ease of implementation and accurate interpretation of the results. The result indicates a reduction of 98.5% reduction in unplanned downtime. Furthermore, qualitative improvements such as early fault detection system and optimized resource allocation strategies enhance the reliability of the proposed model and enhance the productivity of the factories that rely on milling machine output.

II. BUSINESS VALUE AND OBJECTIVE

This section will discuss the business value and objectives of this project. But, before that, it is important to understand the importance of predictive maintenance relevant to this topic.
This section is divided into two sections. First section will throw some light on why predictive analysis is needed on this topic and some industry norms. Second section will discuss the business objectives and hypothesis that the authors are trying to solve.

A. Predictive Maintenance

There are various types of downtime in a business that rely on manufacturing products. In this paper, the authors focus on reducing the unplanned downtime of milling machine by predicting its failure beforehand by using machine learning technique. Unplanned tool failure can cost a lot to the companies as explained in section I above. According to the industry Arc report, the prescriptive and predictive analytics market is forecasted to reach 22.72 billion Dollars by 2026 [8]. According to a survey, machine downtime on an average is about $260,000/ hour [9]. On the contrary, the automobile industry can lose up to 3 million Dollars per hour [10] which is huge loss to a company.

Month	Work time available (minute)	Delay of Machine						
		Cleaning time (minute)	Planned downtime (minute)	Warm up time (minute)	General breakdowns (minute)	Machine Break (minute)	Power cut-off (minute)	Total delay (minute)
March	30240	310	8505	292	605	2890	120	12722
Apr	30240	240	8505	288	651	2142	108	11934
Mei	28800	270	8100	275	744	1680	111	11180
June	31680	240	8910	312	715	1980	114	12271
July	23040	360	6480	312	560	1440	120	9272
August	31680	270	8910	332	733	1584	120	11949
Sept	30240	330	8505	275	639	1764	108	11621
Oct	30240	330	8505	280	717	1512	108	11452
Nov	31680	360	8910	292	823	2244	120	12749
Dec	28800	270	8100	292	605	1680	114	11061
Jan	30240	300	8505	300	602	1512	108	11327
Feb	28800	330	8100	292	608	1560	120	11010
Total	355680	3610	100035	3542	8002	21988	1371	138548

Fig. Annual working time of Milling Machine. Adapted from []

The figure above shows annual work time of a milling machine of an industry. The delay of the machine section can be divided into two sections – Planned and Unplanned downtime as shown in TABLE.

TABLE I

1. Total Work Time (mins)	355680
2. Total Downtime (mins)	138548
a. Planned Downtime (mins)	107187
b. Unplanned Downtime (mins)	31361
i. Machine Breakdown	21988
ii. Power cut - off	1371
iii. General Breakdown	8002

Unplanned downtime consists of Power cut off, general breakdowns and machine breakdowns. Focus of this paper is on Machine breakdown and general breakdown which totals to 29,990 minutes. Alternatively, it can be said that 8.43% of the time in the year, the milling machine is down unplanned due to machine breakdown. As discussed, this downtime can hurt the companies up to millions of dollars per hour.

The next section will discuss the business value and hypothesis of this research and will eventually discuss the machine learning method to predict this downtime and then end with the conclusion and results.

B. Business objective and hypothesis

The main goal of this project is to facilitate machine operations failure prediction which allows the organizations and industries to take preventive measures for machine breakdown. We will be analysing the past data and develop a predictive machine learning model that can be applied to the future dataset. By achieving this goal, the project will aim to:

- Improve operational efficiency by decreasing the unplanned downtime of the machine by 50 percent.
- Provide early measures in machine maintenance by giving warning signals.
- Reduce wear and tear of the machine and to extend the life of it by performing routine maintenance.

Hypothesis:

"By analysing feature importance rankings from predictive models, it is possible to identify the most critical factors contributing to the failure of the milling machine."

We anticipated that the features such as process temperature, torque and rotational speed will emerge out to be a significant predictor (see the next section for detailed overview on this), but we will be quantifying these factors using appropriate machine learning methods so that businesses can take informed decisions about the maintenance strategies.

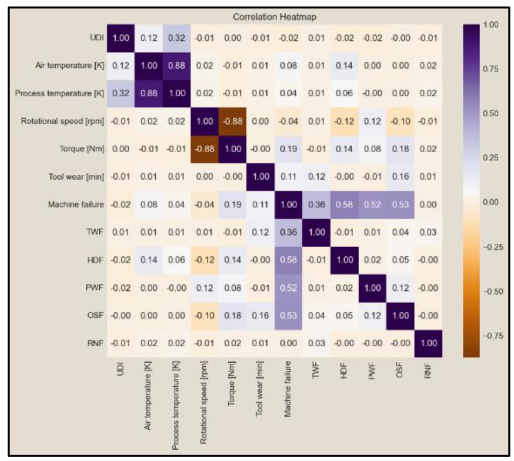
III. EXPLORATORY DATA ANALYSIS

Milling machine dataset [6] that has total of 10,000 rows and 14 columns was used for this analysis. The 14 columns / variables that are present, are related to the working milling machine specification like – process temperature, air temperature, rotation speed etc. When a milling machine works, these are the parameters that are taken into consideration. When something rotates at a very high speed, air surrounding that is hot as compared to the room temperature and that can cause internal machine parts failure and ultimate milling machine failure.

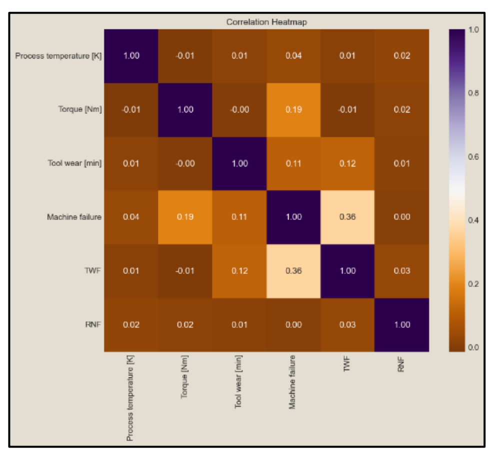
The product key is the unique key of a product that can be traced back to the product itself. Due to ethical concerns, we have masked this product ID and have removed from the analysis.

The data is clean and has no missing values. Fig. ___ below shows the summary of the same.

In this, the output variable is machine failure and hence correlation matrix was derived form this as shown in fig. .

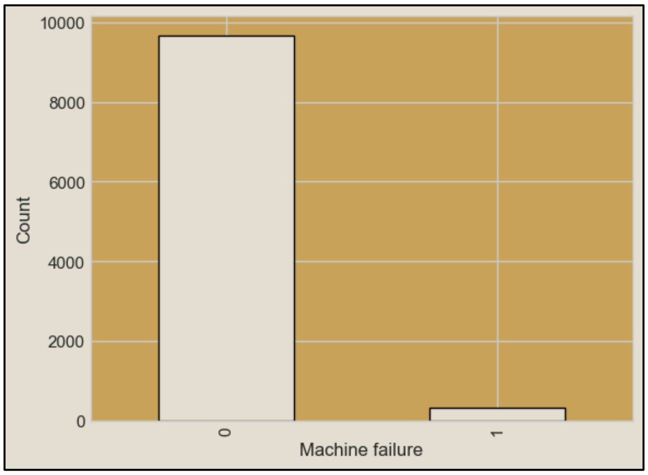


Highly correlated variables were removed and below is the final correlation matrix that was achieved.



A. *Output Variable*

The output variable distribution is shown below:



The data is highly skewed with 9661 “Not Failed” and “339” failed because it is a real-world scenario. In real world, **companies cannot even afford 3.5 percent of unplanned downtime due to monetary loss that they face.**

Next sections discuss the different techniques that can be applied to this dataset. However, one technique is chosen out of that for better interpretation of the results and analysis.

IV. CRITICAL ASSESMENT OF APPLICABLE TECHNIQUES

In this section techniques that can be applied to this problem at hand is discussed. As the output variable is binary, various classification machine learning algorithms were kept in mind, but Random Forest was chosen amongst them. This section talks about the rationale behind the selection of RF over others.

A. *The choice*

Random Forest was chosen as the primary predictive model for this problem. The dataset consists of a complex relationship between target variable and other variables. Random forest is known for its ability to capture nonlinear relationships between variables.

Our data is highly skewed with 9661 un-failed cases and 339 failed cases. This might have resulted in overfitting if other methods would have been used. As random forest consists of decision trees, each tree is selected from samples which make predictions [12].

Random forest provides feature importance measure which is crucial for our prediction. These features are important as it gives a better understanding as in which factors contribute to machine failure.

Real world data also has outliers in them. It is a blessing that this dataset doesn’t have any. However, it is important to take this into consideration and implement a model that also is less sensitive to it like Random Forest.

Due to all these reasons above, Random Forest was chosen as the appropriate model for implementation.

B. *Other Techniques*

As Random Forest was chosen as the applicable technique, this section will contrast other techniques and give better understanding of the choice.

Initially, Logistic regression (LR) was taken into consideration for the technique but after intensive research, it was found out that LR assumes a linear relationship between the predictors and the target variable, which is not true for the current dataset as the relationship is non-linear [13].

Support Vector Machine (SVM) is another technique that was brainstormed a lot but after careful consideration, it was dropped because it takes a lot of time to train the dataset. Even for 10,000 rows long dataset, SVM’s interpretability and complexity was a question.

Neural Networks was the last choice at hand for implementation but due to the requirement of large computational resources.

In conclusion, all these techniques were found to be accurate model for training the current dataset, but Random Forest emerged out to be the best fit for this scenario.

V. IMPLEMENTATION OF MODEL

This section discusses the random forest methodology and lays the ground for the results and interpretation.

A. *Splitting of the Data*

The represented x and y variables in the dataset are split accordingly into training and test data. In this model, 80% of the data is training set and 20% of the data is test set. The train_test_split function from sklearn.model_selection is used with test_size set to 0.2 and random_state set to 42 for reproducibility.

B. *Model Training:*

Random Forest classifier is built using RandomForestClassifier. The number of estimators is set to 100 and the random state is set to 42 for consistency. The model is trained on training and test data using fit method. The predictions of the model are made on testing data using the predict method and the results are stored in y_pred. The model accuracy is calculated using the accuracy score function.

C. *Evaluation Metrics*

The performance of the Random Forest model is assessed using various evaluation metrics:

- **Precision:** The percentage of correctly predicted positive cases.

- **Recall:** The proportion of actual positive cases that were correctly identified by the model.
- **F1-score:** The harmonic mean of precision and recall, providing a balance between the two metrics.

D. Hyperparameter Tuning & Cross Validation

This part is where the tuning of hyperparameters of the built Random Forest model is done to potentially improve performance. GridSearchCV is used to define a grid of hyperparameters to search through. The grid search is performed with 3-fold cross-validation to find the best hyperparameter combination. The best parameters are selected and printed, max_depth, min_samples_split, n_estimators. The scores were Cross-validation scores: [0.9675 0.9715 0.7855 0.9675 0.9805] and Mean cross-validation score: 0.934.

E. Feature Importance

The code extracts the important features from the trained model. These values indicate how each feature is important and what are the contributions to the model's predictions. A Pandas Data Frame is created to store feature names and their importances accordingly. The Data Frame is then sorted by importance in descending order. TABLE shows the feature importance score of top 3 important variables.

TABLE

Torque (Nm)	0.557
Tool Wear (min)	0.287
Process Temperature (K)	0.154

VI. RESULTS AND INTERPRETATION

This section focuses on the results and interpretation of the model and will apply it back to the business objective to correctly predict the machine failure.
This section is divided into two parts – quantitive findings of the project and qualitative findings that tie to the business objective.

A. Quantitative Findings

After running the random forest fig. correctly depicts the model performance metrics.

	Precision	Recall	F1 Score
0	0.988	0.996	0.992
1	0.847	0.639	0.728
Accuracy	0.985	0.985	0.985

For class 0, the Random Forest (RF) model achieved a high precision of 98.8% that means that the non-failure is correctly predicted by the model.
The recall on the other hand for class 0 is high at 99.6 percent suggesting that the model identifies the actual non failure cases. F1 score od 99.2% reflects the balanced measure of precision and recall.
However, when talking about the failed cases (1), the precision and recall are lower than that of the class 0. The model is correctly predicting the failed machine with a precision of 84.7%.
Overall, 98.5% of accuracy suggests that model performs well overall in predicting the failure and non-failure instances.

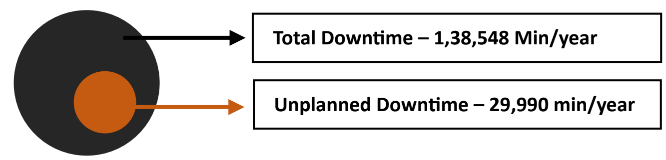


Fig.

Focusing on the unplanned downtime, which is equivalent to 29990 min/year (as discussed in section II – A), this model will reduce this unplanned downtime.

Unplanned downtime -> 29,990 min/year

Unplanned downtime -> $\frac{29990}{60*10}$ ***days/year = 49.9 working days/year***

Machine Learning Model -> 98.5% accuracy

Predicts efficiently -> $49.9 * 0.985$ ***= 49.2 working days/year***

New unplanned downtime -> 49.9 days/year – 49.2 days/year = 0.7 working days/year

With our random forest model, the new unplanned downtime is now only 0.7 working days/year from 49.9 days per year. In hours, it is just 7 hours per year.
Our business objective of decreasing the operational unplanned downtime of milling machine by 50 percent is achieved through random forest and is reducing it by 98.5 percent instead.
Next section discusses the qualitative improvements of the business.

B. Business value qualitative improvements

As discussed in the business objective above, this project decreased the unplanned downtime by 98.5 percent. With this, let us look at the business value of the qualitative improvements.

1) Early fault detection system: By detecting early warning signals in machine performance such as temperature and torque, maintenance teams can intervene proactively to address the issue and decrease the time related to downtime. RF model correctly predicts the most important feature related to the milling machine. With approximately 50 percent weightage, Torque emerges out to be the most important feature that takes the milling machine to failure. When an early warning signal is given, the torque of the system can be reduced to maintain the working standards of the machine.

2) Improved Resource Allocation: One advantage of warning signals is that the resource allocation becomes easier. If a machine is about to breakdown, certain steps can be controlled to ensure its longevity. If a machine is producing 100 parts per minute and is about to fail, this will give a signal to the respected works to lower the output of current machine and increase the output of another machine which is working fine. With this model being implemented, resource allocation can greatly be improved.

REFERENCES

[1] B. Christiansen, “Equipment Failure Causes, Risks, and How to Avoid Them,” Limble CMMS, [Online]. Available: https://limblecmms.com/blog/equipment-failure/ (accessed Feb. 17, 2024).

[2] CNC Masters. “CNC Milling Machines.” [Online]. Available: https://www.cncmasters.com/milling-machine (accessed Feb. 22, 2024).

[3] CNC Masters, “Types of Milling Machine,” 2022. [Online]. Available: https://www.cncmasters.com/types-of-milling-machine [Accessed: 22-Feb-2024].

[4] Future Market Insights, “Milling Machine Market Sizde, Share, Growth, Forecast | FMI”, Futuremarketinsights.com, 2024.[Online]. Available: https://www.futuremarketinsights.com/reports/milling-machine-market [Accessed: 17- Feb- 2024].

[5] P. Jacobs, “Beginner’s Guide to Milling Machines: Types, Prices, Uses,” CNC Masters, Nov. 22, 2023. [Online]. Available: https://www.cncmasters.com/milling-machine [Accessed: Feb. 22, 2024].

[6] S. Matzka, AI4I 2020 Predictive Maintenance Dataset. (August 29, 2020). Distributed by UCI Machine Learning Repository. Accessed: February 17, 2024. [Online]. Available: https://archive.ics.uci.edu/dataset/601/ai4i+2020+predictive+maintenance+dataset

[7] ‘Data-Driven Remaining Useful Life Estimation for Milling Process: Sensors, Algorithms, Datasets, and Future Directions,’ IEEE Access, vol. PP, no. 99, pp. 1-1, July 2021. [Online]. Available: https://doi.org/10.1109/ACCESS.2021.3101284. [Accessed: 16-April-2024].”

[8] Prescriptive and Predictive Analytics Markett—Forecast(2021– 2026). IndustryARC. [Online]. Available: https://www.industryarc.com/Report/111/predictive-prescriptive-business-analytics-market.html

[9] J. Rapoza. (2016). Maintaining Virtual System Uptime in Today’s Transforming IT Infrastructure. Aberdeen Group. [Online]. Available: https://www.stratus.com/assets/aberdeen-maintaining-virtual-systemsuptime.pdf

[10] . Downtime Costs Auto Industry 22k/Minute—Survey. [Online]. Available: https://news.thomasnet.com/companystory/downtime-costsauto-industry-22k-minute-survey-481017

[11] Overall Equipment Effectiveness Analyse for Performance of CNC Milling Machine Operation,’ IOP Conference Series Materials Science and Engineering, vol. 505, no. 1, Art. no. 012139, July 2019. [Online]. Available: https://doi.org/10.1088/1757-899X/505/1/012139. [Accessed: 16-April-2024]

[12] K. Huh, ‘Surviving in a Random Forest with Imbalanced Datasets,’ SFU Professional Computer Science, Medium, Feb. 13, 2021. [Online]. Available at: https://medium.com/sfu-cspmp/surviving-in-a-random-forest-with-imbalanced-datasets-b98b963d52eb (Accessed: 27-April-2024).

[13] A. Lekhtman, ‘When logistic regression simply doesn’t work,’ Towards Data Science, Feb. 19, 2021. [Online]. Available at: https://towardsdatascience.com/when-logistic-regression-simply-doesnt-work-8cd8f2f9d997 (Accessed: 28-April-2024).”