Best Machine Ever

Yara Yaghi, Muhammad Arfin, Shakir Azami, Paula Schultz, Austin Yoo, Sheena Gandham

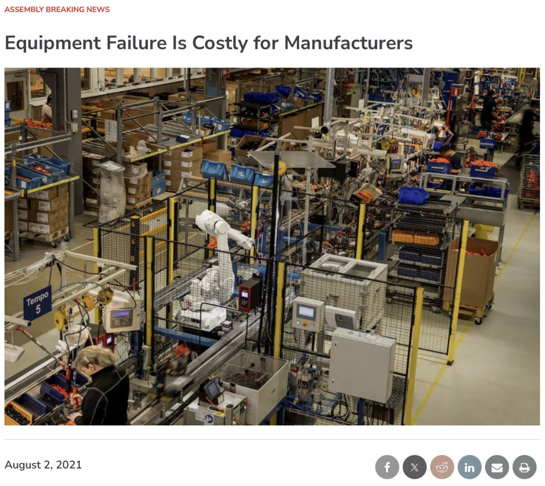
Business Problem

How can we reduce the frequency of factory machine failures by identifying and addressing the most impactful failure causes?

- Reducing the frequency of factory machine failures is crucial for the efficiency and reliability of machines (Marcellus, 2024)
- Identifying the most impactful failures is important for productivity, optimizing maintenance costs, and improving safety (Sensemore, 2024)

[11] [12] [13] [24]

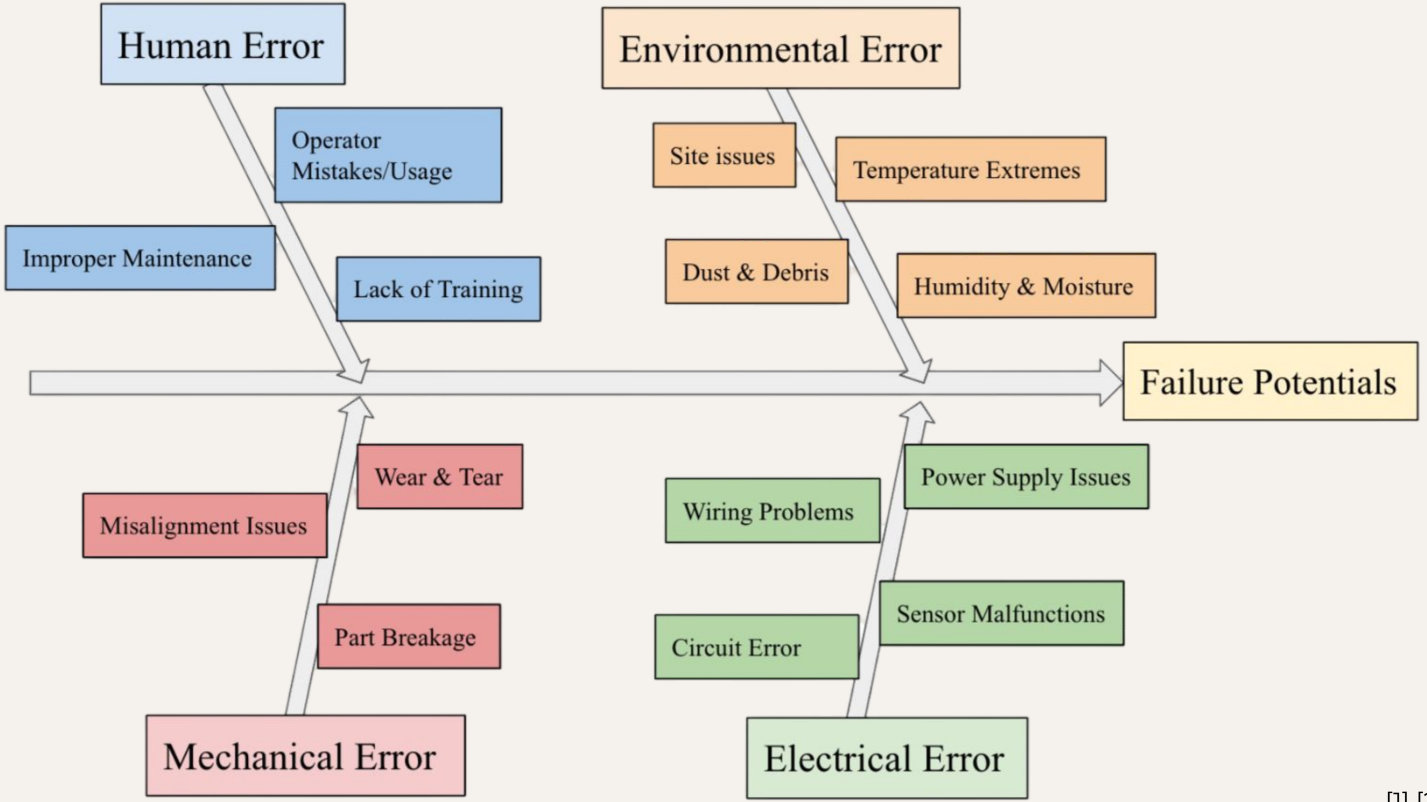
Background



- Machine failures can result in a loss of production hours, unintended downtimes, and cause issues concerning safety (Marcellus, 2024)
- Studies estimate the average downtime cost from machine failure is up to about $532,000 per hour (Weber et al., 2021)

[11] [12] [13] [24]

Analytic



[1] [2] [3] [4] [5] [6] [24]

Data Summary

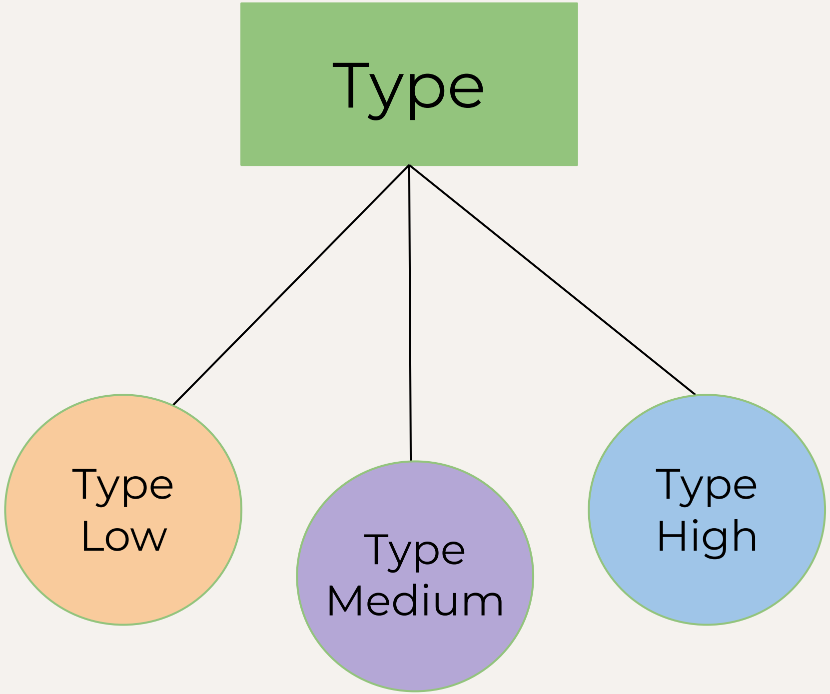
- **Name:** AI4I 2020 Predictive Maintenance Dataset
- **Original Data Set:** Matzka, Stephan. “Explainable Artificial Intelligence for Predictive Maintenance Applications.” *2020 Third International Conference on Artificial Intelligence for Industries (AI4I)* (2020): 69-74. (MLA)
- **Data File:** Excel Spreadsheet (2D Array)
- **Structure:** Tabular
- **Rows:** 10,000 rows
- **Features:** 15
- **Target:** derived binary failure variable

Data Features

	Feature Name	Data Type	Missing Values	Sample/Unique Values	Description
0	UDI	int64	0	5190	Unique identifier for each data point
1	Product ID	object	0	[H35323, L47249, M16184, L48676, L50791, L5103...	ID representing the product being manufactured
2	Type	object	0	[H, L, M]	Category of the product (H, L, M)
3	Air temperature [K]	float64	0	298.5	Temperature of the air in Kelvin
4	Process temperature [K]	float64	0	311.1	Temperature of the process in Kelvin
5	Rotational speed [rpm]	int64	0	1596	Speed of the machine in rotations per minute
6	Torque [Nm]	float64	0	72.0	Torque applied during operation in Newton-meters
7	Tool wear [min]	int64	0	210	Time of tool usage before wear in minutes
8	Machine failure	int64	0	0	Binary indicator of machine failure
9	TWF	int64	0	0	Tool wear failure indicator
10	HDF	int64	0	0	Heat dissipation failure indicator
11	PWF	int64	0	0	Power failure indicator
12	OSF	int64	0	0	Overstrain failure indicator
13	RNF	int64	0	0	Random failure indicator

[24]

One Hot Encoding

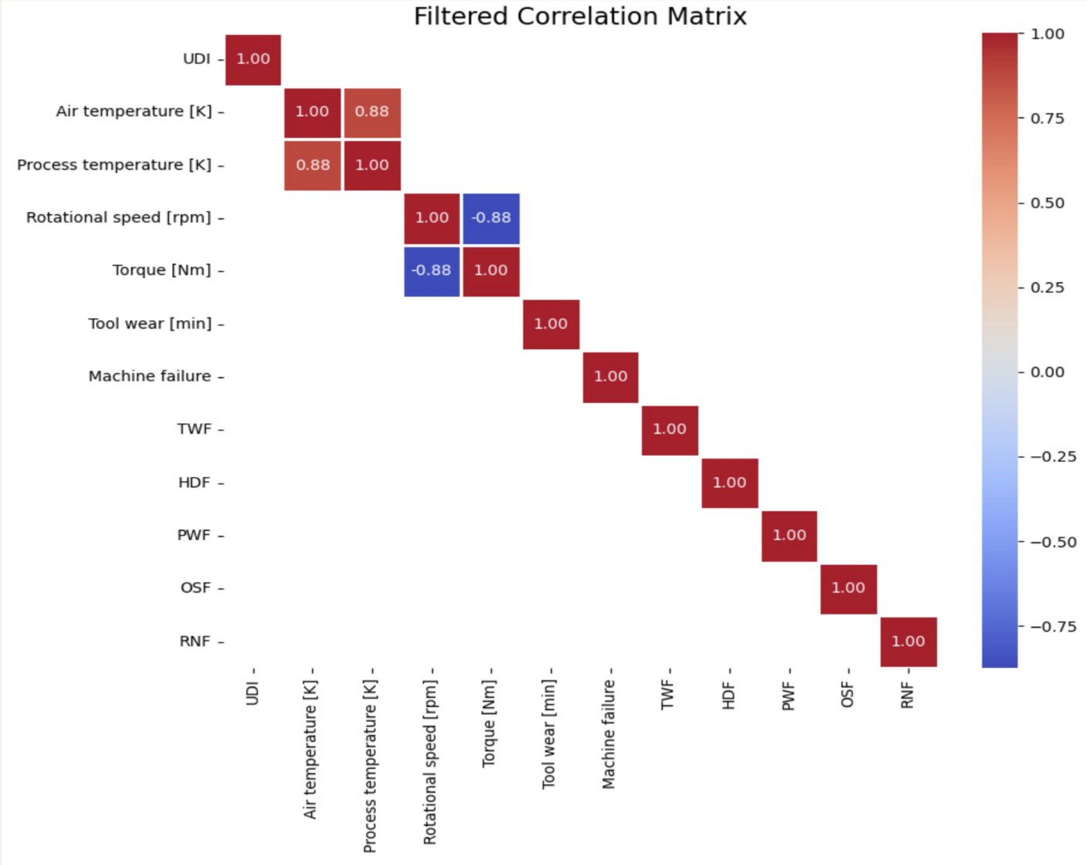


- Processed machine type column (H/M/L) using one-hot encoding
- Updated failures to boolean

Type means Quality (Low, Medium, High) (2/3/5 mins to cause failure)

[24]

Feature Selection

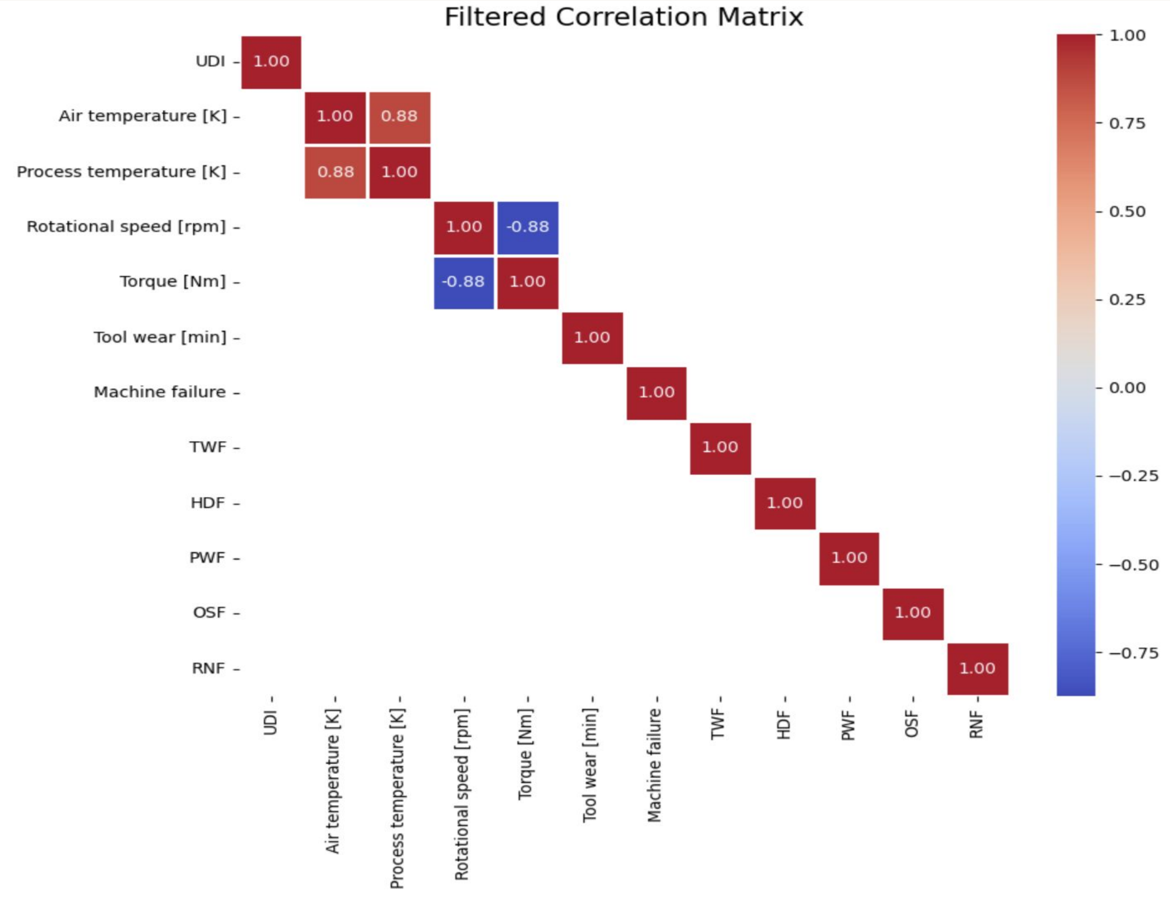


High relationships between
"Air temperature"
"Process temperature"
And
"Rotational speed"
"Torque".
Merged into
"Temperature difference"
"Power"

"Tool wear [min]"adjusted
to account for quality

Temperature Difference =
'Process Temperature' - 'Air Temperature'
Power = 'Rotational speed' * 'Torque'
Tool Wear Adjust =
H/M/L - 5/3/2 min from Tool Wear
[24]

Feature Selection



Dropped Features:
UDI
ProductID

[24]

Scaling

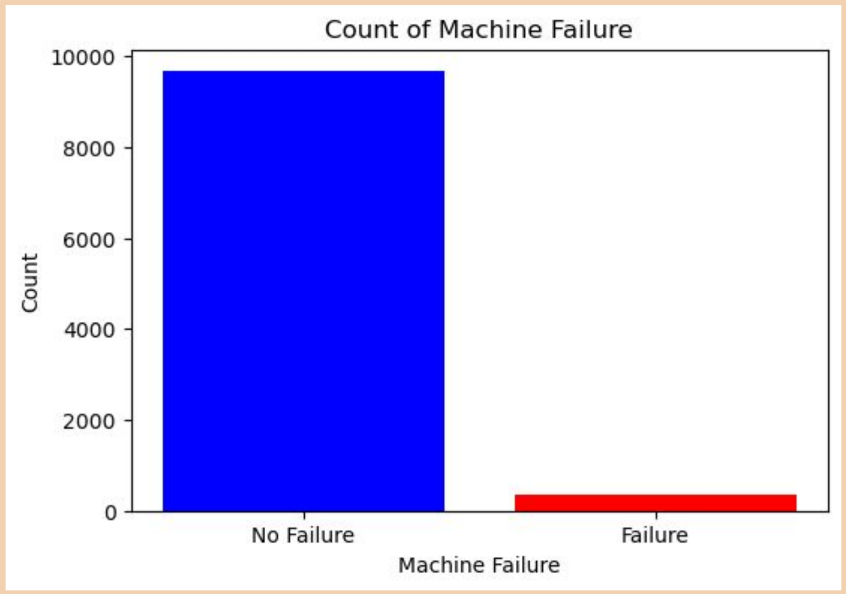
	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	300.004930	310.005560	1538.776100	39.986910	107.951000
std	2.000259	1.483734	179.284096	9.968934	63.654147
min	295.300000	305.700000	1168.000000	3.800000	0.000000
25%	298.300000	308.800000	1423.000000	33.200000	53.000000
50%	300.100000	310.100000	1503.000000	40.100000	108.000000
75%	301.500000	311.100000	1612.000000	46.800000	162.000000
max	304.500000	313.800000	2886.000000	76.600000	253.000000

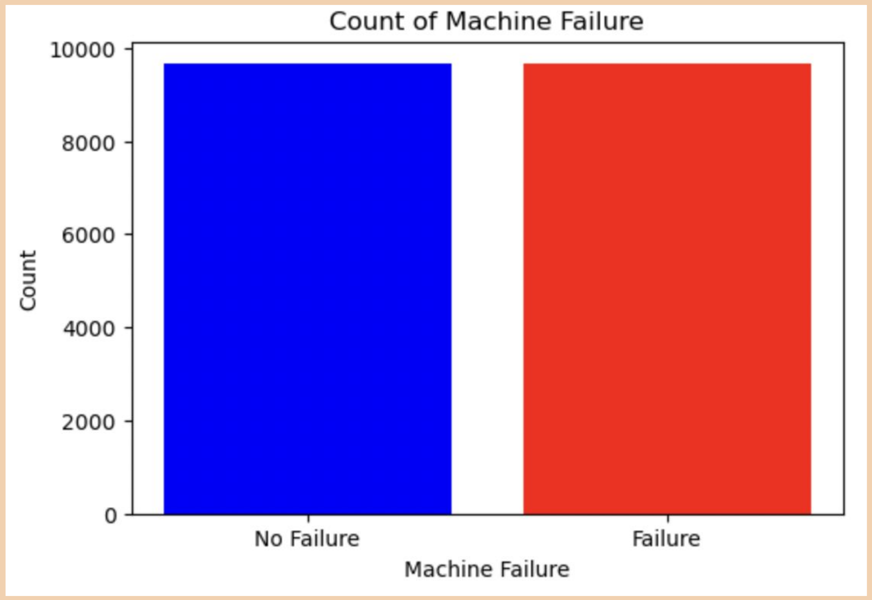
	norm_power	norm_temp_diff	norm_tool_wear_adjusted
count	19304.000000	19304.000000	19304.000000
mean	0.600788	0.470674	0.494346
std	0.168741	0.229215	0.255698
min	0.000000	0.000000	0.000000
25%	0.501356	0.299809	0.278431
50%	0.606479	0.444444	0.505882
75%	0.715278	0.672361	0.729412
max	1.000000	1.000000	1.000000

[16] [24]

Balanced

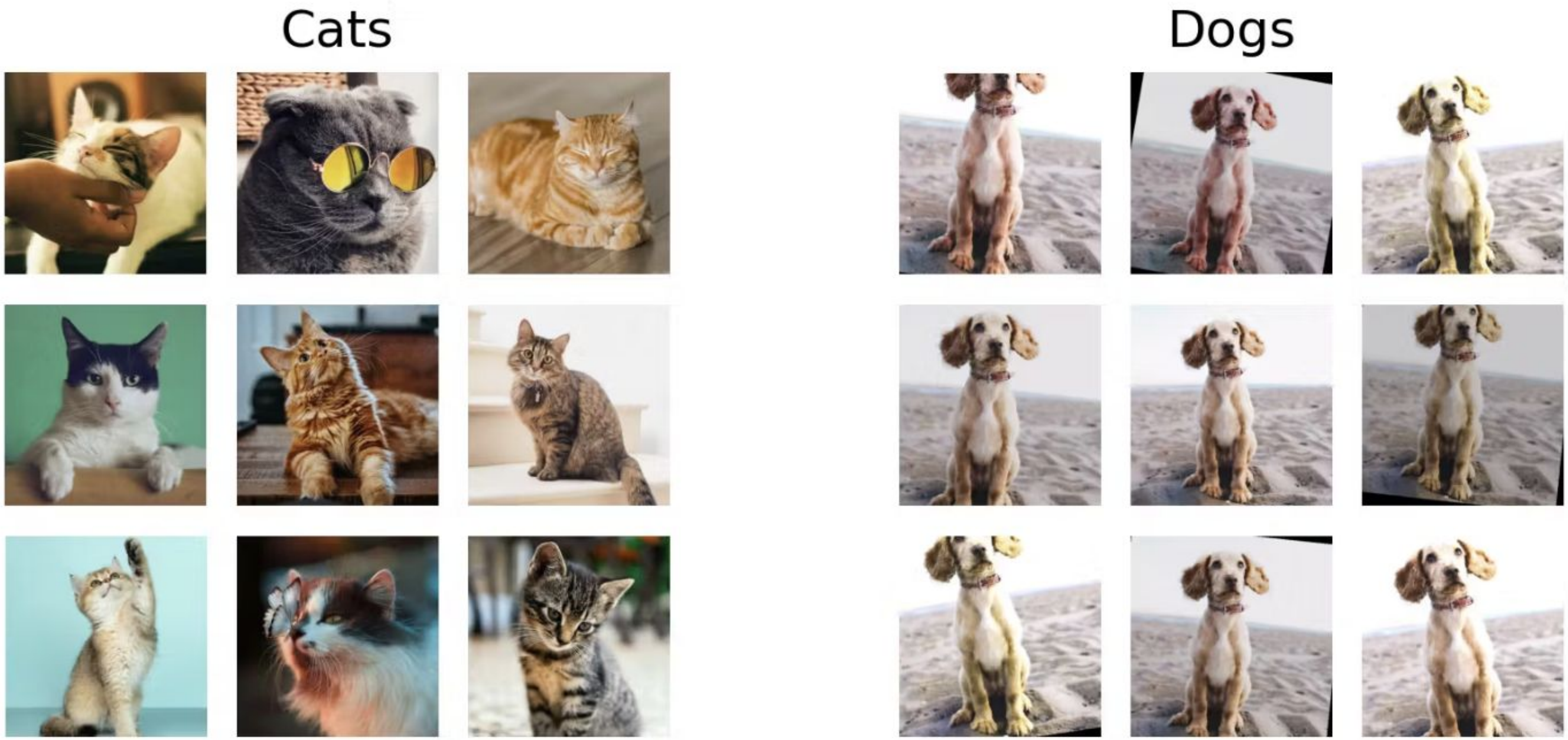
Synthetic Minority Over-sampling Technique (SMOTE) to balance dataset.





[14] [15] [24]

Oversampled



[14]

Assumptions

Assumptions Before Cleaning Dataset:

- The ‘Machine Failure’ labels (0 and 1) are accurate.
- Sensor data reflects actual machine health.
- Each row is treated as an independent observation.

Assumptions After Cleaning Dataset:

- If any subsystem fails, we count it as a full machine failure.
- New Features created improve the model’s predictive power.
- SMOTE-generated samples are representative enough to balance the dataset.
- Normalizing the data maintains important relationships.

[24]

#	Article/Date	Author	Method Used	Improvements to our work
1	"Explainable Artificial Intelligence for Predictive Maintenance Applications." (2020)	Stephan Matzka	Supervised Classification (Decision Tree, Random Forest)	Focusing on the root cause analysis of failure rather than just predicting failure events.
2	"Predicting Machine Failures from Multivariate Time-Series: An Industrial Case Study" (2024)	Nicoló Vago et al.	Time-Series Analysis	Integrates machine learning algorithms for predicting and explaining failure causes, and real-time monitoring is considered for dynamic insights.
3	"Causes and Impact of Human Error in Maintenance of Mechanical Systems" (2020)	Mfundo Nkosi et al.	Human Factors Analysis	Focusing on predictive maintenance using data analytics and machine learning algorithms to predict potential failures before they occur.

#	Article/Date	Author	Method Used	Improvements to our work
4	"Towards prediction of machine failures: overview and first attempt on specific automotive industry application" (2020)	Vincent Ciancio et al.	Predictive Health Monitoring (PHM), FMEA, Bayesian Networks, statistical models, and AI-driven techniques.	They use traditional predictive maintenance with regression model and failure mode analysis based on expert input which doesn't account for complex interactions between failure causes. Our approach will improve predictive accuracy, identify key failure causes and provide more interpretable results for cost effective maintenance.
5	"Predicting machine failures using machine learning and deep learning algorithms" (2024)	Devendra Yadav et al.	Machine Learning and Deep Learning	Focuses on comparing ML models (Random Forest, XGBoost, etc.) with deep learning (LSTM) to predict machine failures. It highlights hyperparameter optimization for better performance.

Power

Temp diff

Quality adjusted tool wear

Supervised Classification Model

- Decision Tree
- Random Forest
- XGBoost

Machine Failures 0 or 1

***Normalized Values**

[24]

Algorithm Selection for Failure Prediction

- Problem: Classification to Predict Failure from Features
- Selected Algorithms:
  - Decision Tree (DT): Capture non-linearities, may overfit
  - Random Forest: Ensemble of DT, may reduce overfit
  - XG Boost: Gradient Boosted Trees, high performance and accuracy, can utilize GPU support
  - Stacking Ensemble: Combine predictions from other models to potentially improve performance
  - MLP and KNN are rejected not handle collinearity

[24]

Hyperparameter Optimization

Configuration settings to improve performance and reduce overfitting

Not part of original data, tuned iteratively in model development

Ranges Tuned to control complexity and reduce overfitting and keeping accuracy

Decision Tree:	Random Forest:	XGBoost:
GridSearchCV Exhaustive Search over Values	RandomizedSearchCV Efficient Random Search	RandomizedSearchCV and RepeatedKFold for Robustness
criterion: ['gini', 'entropy'] max_depth: [6, 8, 10] min_samples_split: [5, 10, 15] min_samples_leaf: [2, 4, 5, 7] ccp_alpha: [0.0, 0.001, 0.01]	n_estimators: 50-200 max_depth: 3-20 min_samples_split: 2-10 min_samples_leaf: 1-4	n_estimators: 100-300 max_depth: 4-10 learning_rate: 0.01-0.15 subsample/colsample_bytree: 0.7-1.0 gamma/reg_alpha/reg_lambda: 0-1 / 0-1 / 1-3 (Regularization) [17] [18] [19] [20] [24]

Final Hyperparameter Selection

Model	Final Hyperparameters after Tuning
DT (Base)	Basic decision tree with default parameters.
DT (Best)	Tuned with GridSearchCV: 'ccp_alpha': 0.0, 'criterion': 'gini', 'max_depth': 10, 'min_samples_leaf': 2, 'min_samples_split': 5
RF (Base)	Basic random forest with default parameters.
RF (Best)	Tuned with RandomizedSearchCV: 'max_depth': 18, 'min_samples_leaf': 1, 'min_samples_split': 3, 'n_estimators': 160
XGBoost (Base)	Baseline classifier on GPU with DMatrix & early stopping.
XGBoost (Best)	Tuned using RandomizedSearchCV, refitted with DMatrix. 'subsample': 0.9, 'reg_lambda': 1.5, 'reg_alpha': 0.1, 'n_estimators': 200, 'max_depth': 10, 'learning_rate': 0.1, 'gamma': 0.5, 'colsample_bytree': 0.9}

Metrics

1. Accuracy, most popular evaluation metrics for classification model.

    * balanced data   50% failure and 50% non-failure   acc = tp +tn/tp+tn+fp+fn

    * using decision tree, random forest and XG boost   acc = 1759+1644/3861 = 0.88 %

    * large data/ classification   Rec = tp/tp+fn

2. Recall, most failures can be detected   Rec = 1759/1759+217 = 0.89 %

    1. Using classification   pre = tp/tp+fp, pre =1759/2000=0.87

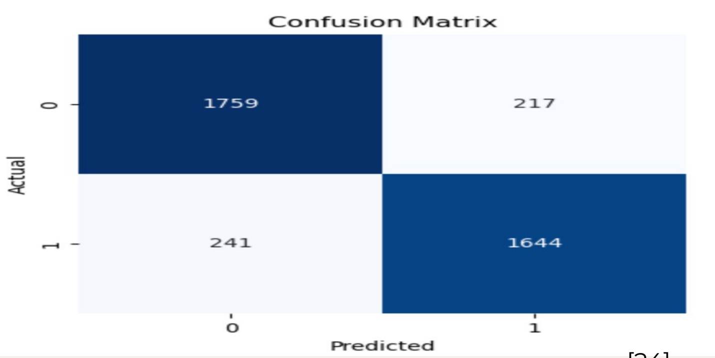
    2. number failure, missing failures

3. Precision, predicts actual number of failures

    * predicted failure vs actual failures

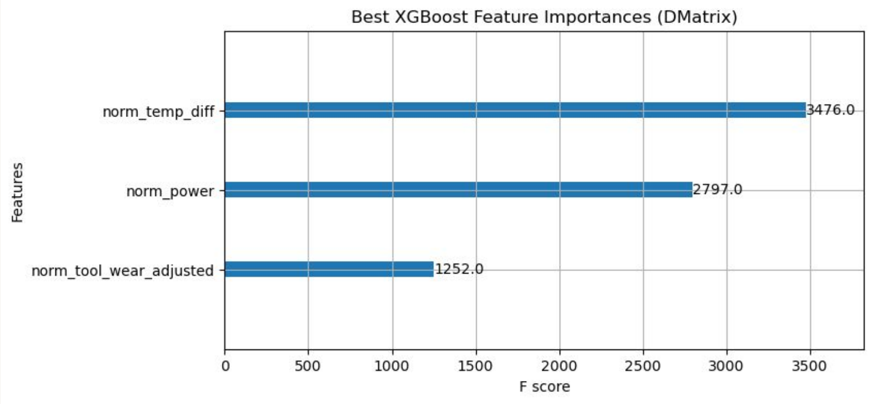
    * high precision means lower false positive

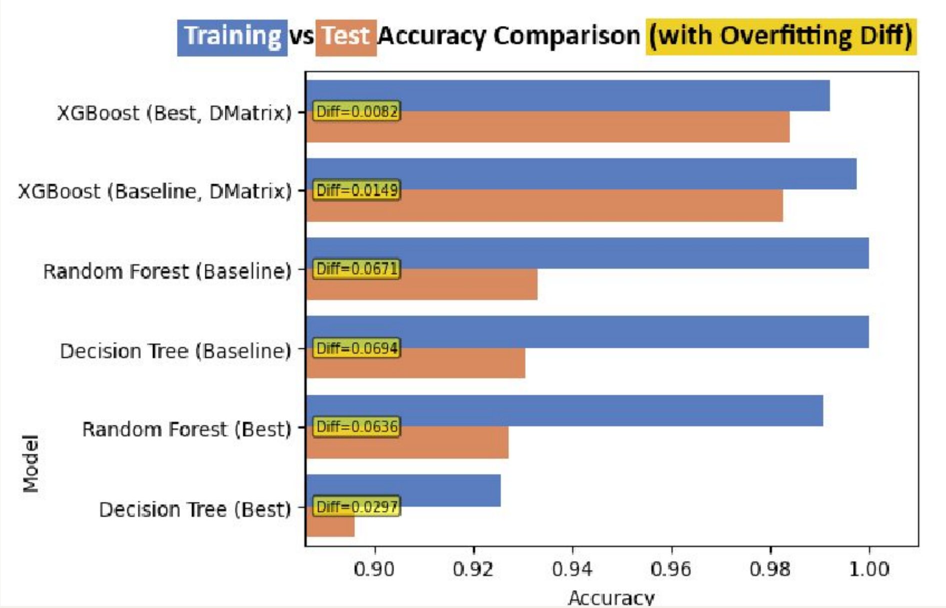
    * machine failure prevents unnecessary cost



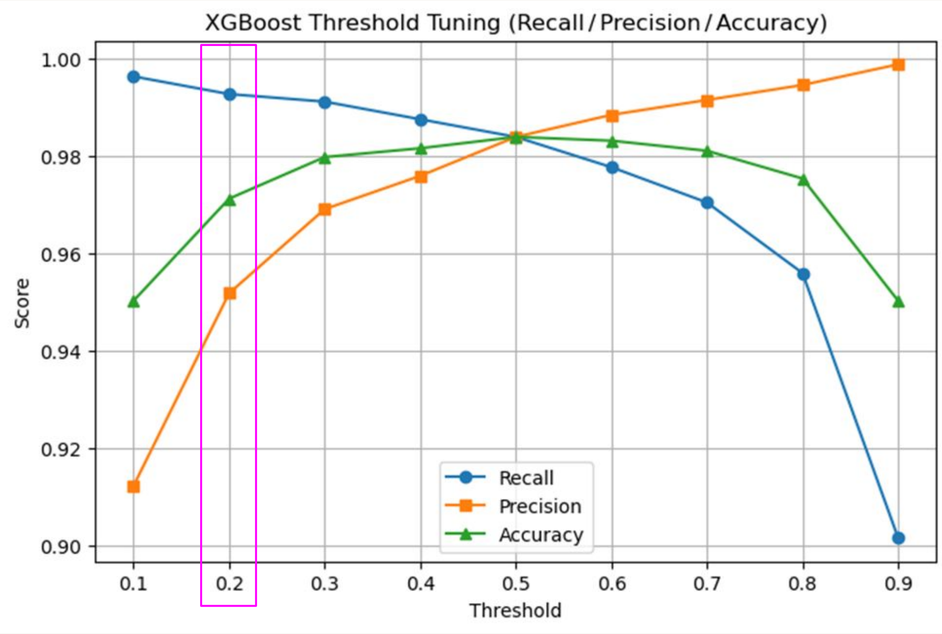
[24]

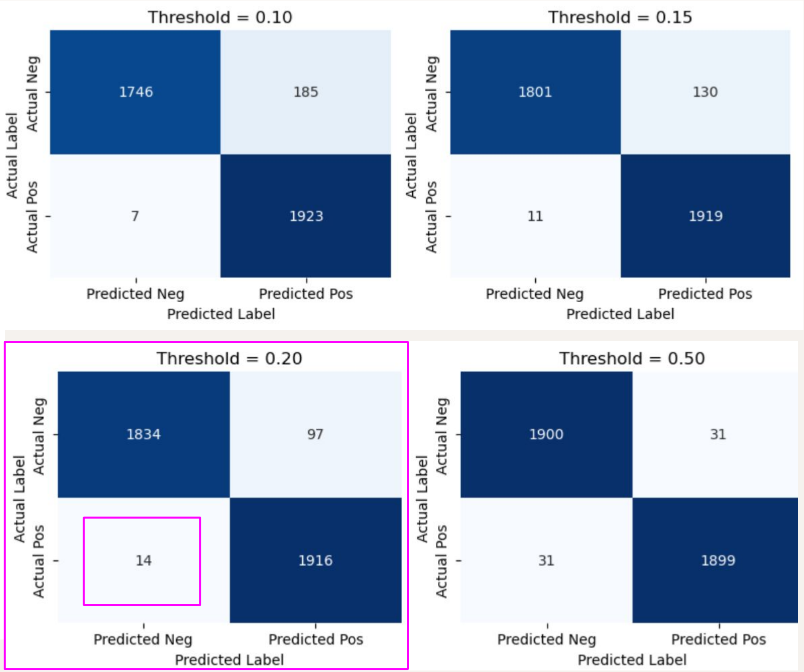
Initial Results





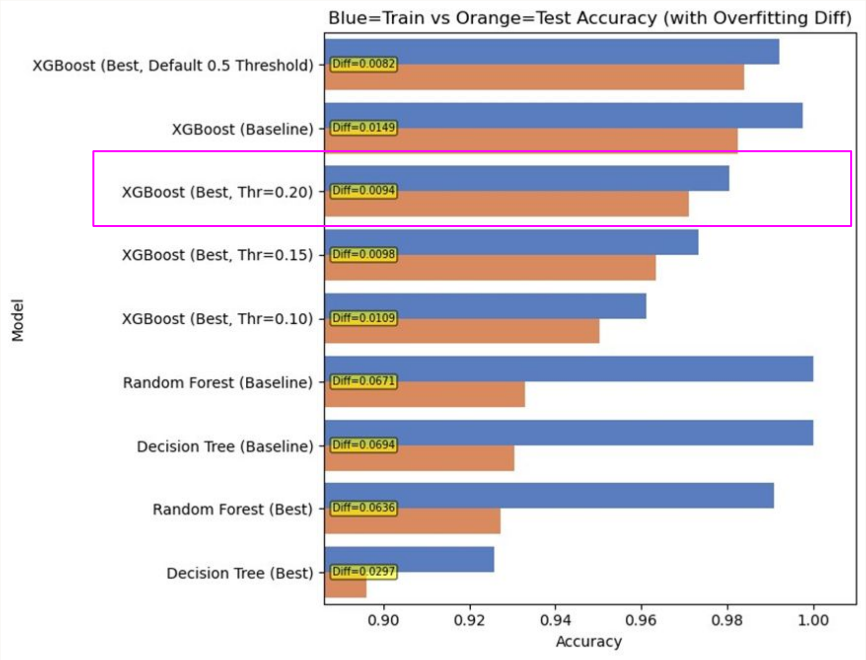
Final Results - Threshold Adjustment





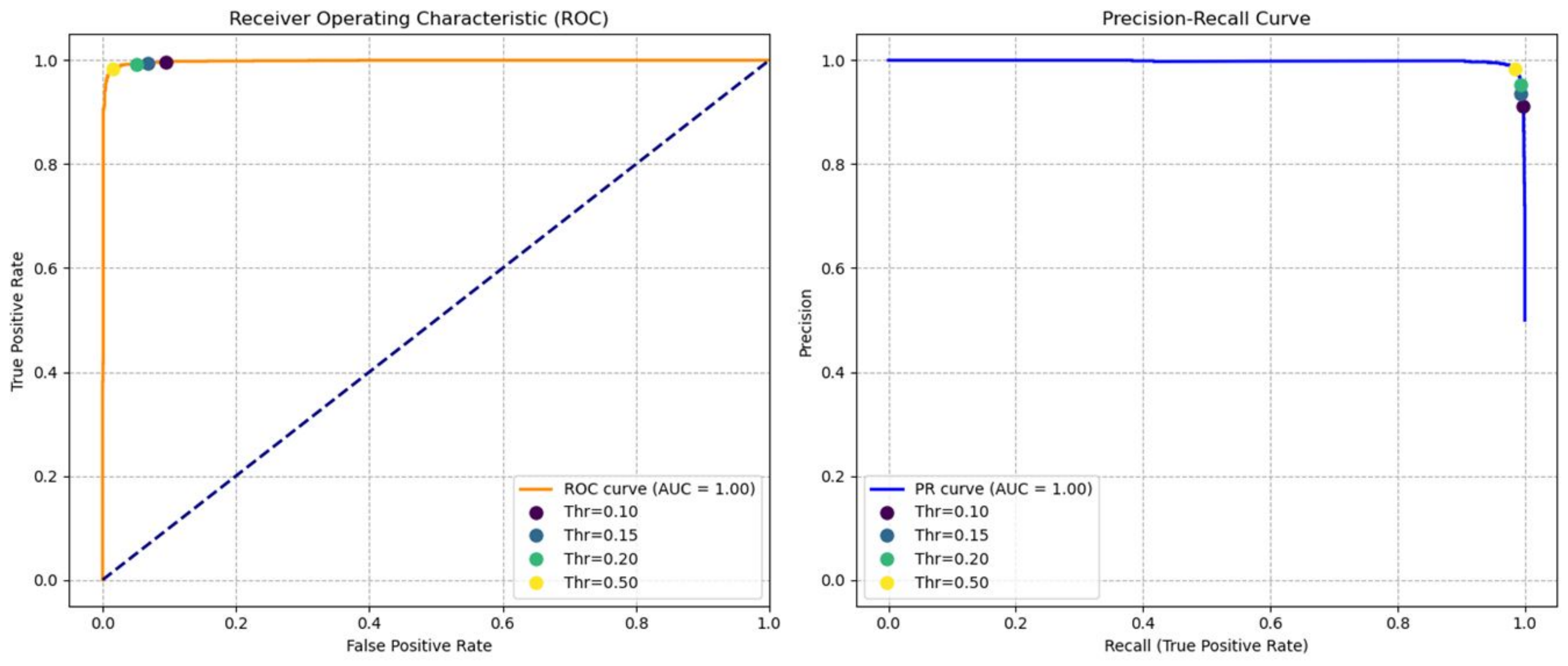
Lower threshold, fewer expensive false negatives

Final Results - Threshold Adjustment



Threshold	0.20
Accuracy (Training)	.9806
Accuracy (Test)	.9733
Accuracy Difference	.009388
Precision	.9518
Recall	.9927
F1-Score	.9718

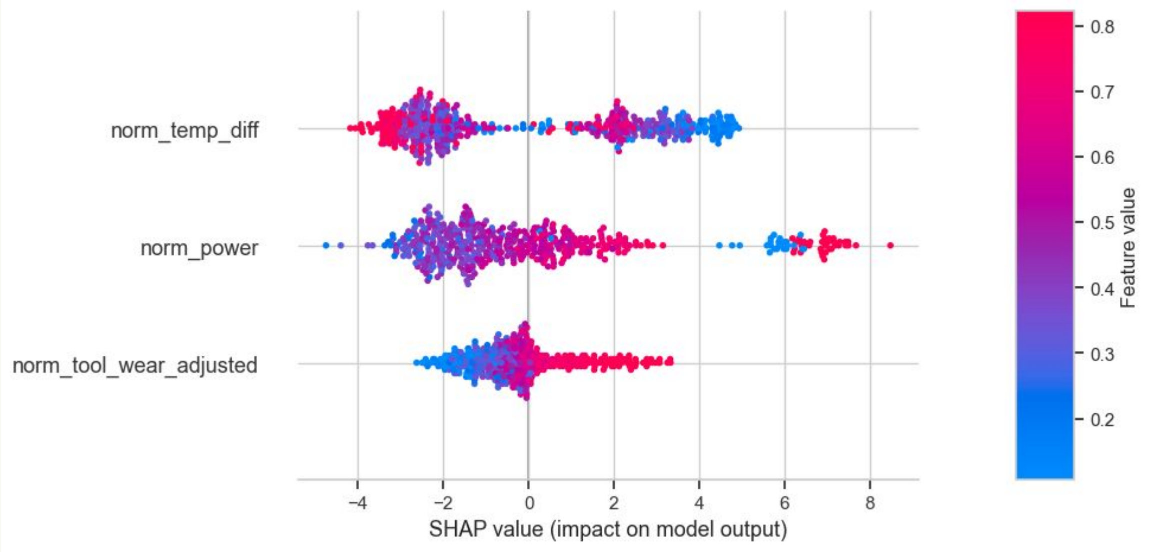
Final Results - ROC/PRC Curves



Concerning, but may be an artifact of data being synthetic?

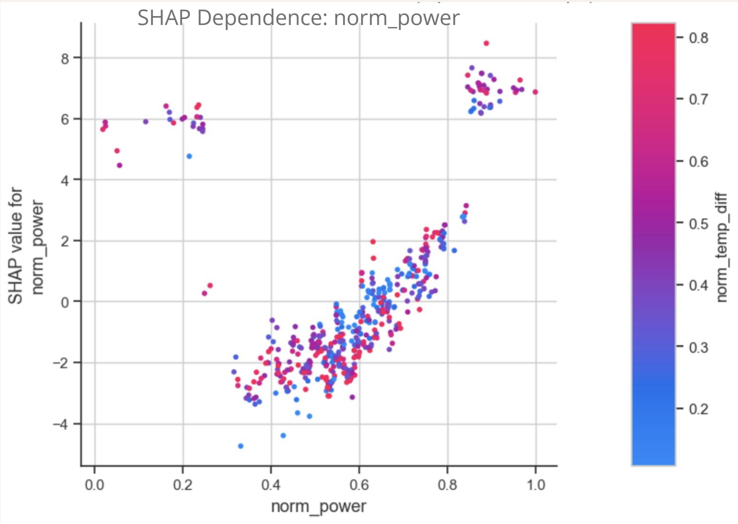
[24]

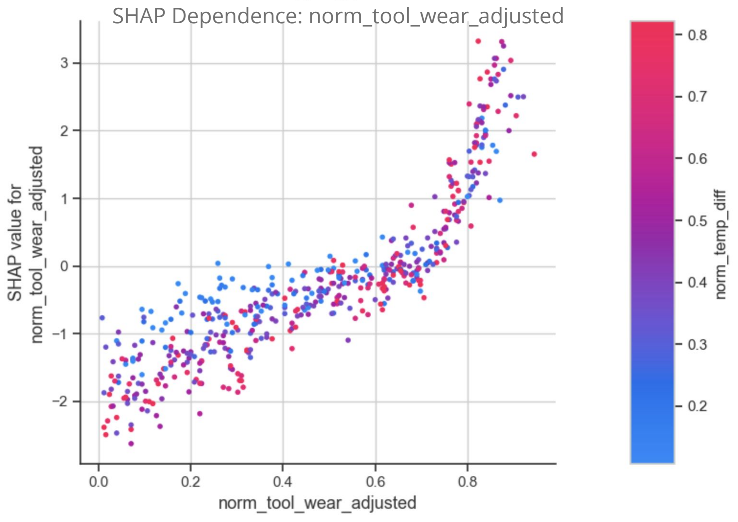
Final Results - SHAP Data



Shows that insufficient cooling (blue on norm_temp_diff), and high power (red on norm_power) contribute to failure

Final Results - SHAP Data





Shows that aside from cooling, power can have a significant influence on failures once out of ideal ranges, and while extreme tool wear can have an effect, current maintenance does a fairly good job of mitigating that risk.

Improvements over first Model Tuning

- Reduced false negatives, still excellent accuracy and small differences between training and test accuracy, indicates not overfitting
- Model exported as JSON to reduce need to rerun expensive training, still need to streamline preprocessing and scaling to use on future data
- Further identified values that contribute the most, may need to explore and understand the SHAP plots more

Evaluation

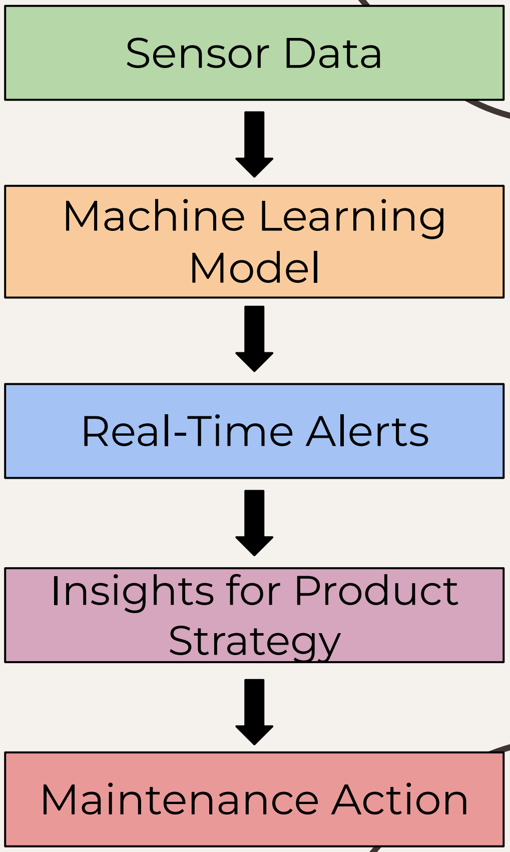
How can we reduce the frequency of factory machine failures by identifying and addressing the most impactful failure causes?

- Target top failure causes (cooling, power issues, tool wear)
- Move from routine to targeted maintenance
- Use real-time monitoring to act before failures
- Invest in continuous machine data tracking
- Use predictions to rank and address failure risks efficiently

[24]

Next Steps

- Deploy model in real-time factory systems for proactive failure detection
- Expand model to different machine types and industries
- Use failure insights to guide upgrades for high-risk systems
- Develop product offerings targeting top failure causes:
  - Temperature management solutions
  - Power stabilization tools
  - Tool wear monitoring systems
- Bridge the gap between raw data and actionable maintenance decisions



[24]

Citation

[1] Stephan Matzka, 2020. Explainable Artificial Intelligence for Predictive Maintenance Applications. 2020 Third International Conference on Artificial Intelligence for Industries (AI4I), 69–74. https://ieeexplore.ieee.org/document/9253083

[2] Shubhangi Gurav, 2022. Review of Study of Effect of Misalignment on Rotating Shaft. ResearchGate. https://www.researchgate.net/publication/362517988_REVIEW_OF_STUDY_OF_EFFECT_OF_MISALIGNMENET_ON_ROTATING_SHAFT

[3] Mfundo Nkosi, P. M. Mashinini, 2020. Causes and Impact of Human Error in Maintenance of Mechanical Systems. ResearchGate. https://www.researchgate.net/publication/340402281_Causes_and_Impact_of_Human_Error_in_Maintenance_of_Mechanical_Systems

[4]Dave Westrom, 2020. Top Causes of Machine Failure and How to Prevent Them. MachineMetrics Blog. https://www.machinemetrics.com/blog/machine-failure

[5] Vortec, 2020. Electronic Equipment Failures: Cause, Effect and Resolution. Vortec. https://www.vortec.com/en-us/electronic-equipment-failures-cause-effect-and-resolution?srsltid=AfmBOooYEDxsqKB8BBjsP3hw1zcUcf-nTPLloBGZXnO6gnXZZnmGOIFk

[6] Graceport, 2020. Top 10 Electrical Failures by Cause. Graceport Blog. https://www.graceport.com/blog/top-10-electrical-failures-by-cause

[7] Steven Aliano, n.d. World's Largest Manufacturers Lose $1 Trillion/Year to Machine Failure. ISA Blog. https://blog.isa.org/worlds-largest-manufacturers-lose-1-trillion/year-to-machine-failure

[8] VIAR, n.d. The True Cost of Downtime from Human Error in Manufacturing. Rewo Blog. https://www.rewo.io/the-true-cost-of-downtime-from-human-error-in-manufacturing/

[9] Vecto, n.d. How Much Do Power Quality Disruptions Cost US Industry? Vecto. https://vectosystem.com/how-much-do-power-quality-disruptions-cost-us-industry/

[10] eWorkOrders, n.d. Dust Threat to Equipment. eWorkOrders. https://eworkorders.com/cmms-industry-articles-eworkorders/dust-threat/

[11] Marcellus, n.d. Equipment Malfunction | A Costly Business Challenge and How to Overcome It. Nonstop Group. https://reliability.thenonstopgroup.com/equipment-malfunction/

[12] Assembly Magazine, 2021. Equipment Failure is Costly for Manufacturers. Assembly Magazine. https://www.assemblymag.com/articles/96518-equipment-failure-is-costly-for-manufacturers#:~:text=%E2%80%9CWhen%20expensive%20production%20lines%20and,in%20almost%20all%20industrial%20sectors.%E2%80%9D

[13] Sensemore, 2024. Ensuring Machine Reliability: The Role of Predictive Maintenance. Sensemore. https://sensemore.io/ensuring-machine-reliability-the-role-of-predictive-maintenance/?srsltid=AfmBOorWTGILUkNlEbtbBzGPqp68jQav8N4DYDSTr109xwpIh4yAmO-Q

[14] Encord Blog, 2022. Introduction to Balanced and Imbalanced Datasets in Machine Learning. Imbalanced-learn. https://encord.com/blog/an-introduction-to-balanced-and-imbalanced-datasets-in-machine-learning/

Citation

[15] Analytics Vidhya, 2020. Overcoming Class Imbalance Using SMOTE Techniques. Analytics Vidhya Blog. https://www.analyticsvidhya.com/blog/2020/10/overcoming-class-imbalance-using-smote-techniques/

[16] Megha Natarajan, 2023. Mastering Data Scaling Techniques: Visualizations and Insights. Medium. https://medium.com/@megha.natarajan/mastering-data-scaling-techniques-visualizations-and-insights-a00b2cb422c2

[17] Ken Hoffman, 2020. Decision Tree Hyperparameters Explained. Medium. https://ken-hoffman.medium.com/decision-tree-hyperparameters-explained-49158ee1268e

[18] GeeksforGeeks, 2025. Random Forest Hyperparameter Tuning in Python. GeeksforGeeks. https://www.geeksforgeeks.org/random-forest-hyperparameter-tuning-in-python/

[19] GeeksforGeeks, 2021. Hyperparameters of Random Forest Classifier. GeeksforGeeks. https://www.geeksforgeeks.org/hyperparameters-of-random-forest-classifier/

[20] Analytics Vidhya, 2025. XGBoost Parameters Tuning: A Complete Guide with Python Codes. Analytics Vidhya. https://www.analyticsvidhya.com/blog/2016/03/complete-guide-parameter-tuning-xgboost-with-codes-python/

[21] Vincent Ciancio, Lazhar Homri, Jean-Yves Dantan, Ali Siadat, 2020. Towards prediction of machine failures: overview and first attempt on specific automotive industry application. IFAC-PapersOnLine, 53(3), 289–294. https://www.sciencedirect.com/science/article/pii/S2405896320301932

[22] Devendra K. Yadav, Aditya Kaushik, Nidhi Yadav, 2024. Predicting machine failures using machine learning and deep learning algorithms. Engineering Reports, 3, 100029. https://www.sciencedirect.com/science/article/pii/S2667344424000124

[23] Nicolò Oreste Pinciroli, Francesca Forbicini, Piero Fraternali, 2024. Predicting Maintenance Using Vibration Analysis: Machine Learning Approaches. Machines, 12(6), 357. https://www.mdpi.com/2075-1702/12/6/357

[24] Professor Holly Russo Slide Deck