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Predictive Maintenance Using Internet of Things Sensors and Machine Learning: An Applied Study of Small Manufacturing Enterprises

G. Magesh

School of Computer Science Engineering and Information Systems, Vellore Institute of Technology, Vellore, India

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Abstract

Predictive maintenance offers small manufacturing enterprises a data-driven alternative to corrective and time-based maintenance, but adoption is constrained by limited technical, financial, and data resources. In this study, the authors assessed if machine-condition variables that could be accessed using IoT could be used to support practical equipment-failure prediction. The AI4I 2020 Predictive Maintenance Dataset with 10,000 observations was analysed for the product type, air temperature, process temperature, rotational speed, torque, and tool wear as predictors. The 80:20 split of the data was made and class-weight was adjusted for each logistic regression, decision tree and random forest classifiers, and three-fold stratified cross validation was also performed to examine the stability of the random forest model. The precision, recall, F1-scores, ROC-AUC, PR-AUC, balanced accuracy, Matthews correlation coefficient and confusion matrix were used to evaluate performance. Random forest had the highest values for precision (0.780), F1-score (0.661), ROC-AUC (0.962), and PR-AUC (0.753). The rotational speed, torque, and tool wear were most influential predictors, while failure recall was moderate and decreased when validated under order. The results show that with human supervision, threshold tuning and periodic retraining, the machine-condition variables and machine learning enabled by IoT could be used to assist the maintenance prioritization in SMEs. Before it is used in operations, more validation using real-time SME data is needed.

Keywords: Predictive maintenance; Internet of Things; Machine learning; Random forest; Small manufacturing enterprises

1. Introduction

Manufacturing companies are faced with fierce competition, faster production cycles, higher customer expectations, and the need to cut costs without compromising quality. This equipment reliability is a primary factor to maintain productivity, delivery and continuity of business operations. When a failure occurs, corrective maintenance is frequently performed, resulting in unnecessary expenses, and when a device is likely to fail a preventive maintenance is scheduled to take place before the failure. If unplanned downtime occurs due to corrective maintenance, it can lead to production losses, emergency repairs, delayed orders and time-based maintenance can lead to unnecessary inspections, or the premature replacement of still functioning components. Industry 4.0 is essentially a more data-driven approach, connecting machines, automating processes, creating digital platforms and having real-time information available in manufacturing processes. Frank et al. (2019) suggest that there are varying patterns of how Industry 4.0 is being implemented with connectivity and data collection serving as a basis for implementing more advanced intelligent applications.

One of the most practical uses of this transformation will be predictive maintenance. It primarily includes watching machines and analysing operating data to determine the likelihood of failure, identify irregular operation or machine maintenance needs. The Internet of Things (IoT) sensors can measure variables like vibration, temperature, pressure, acoustic signals, electrical current, speed and energy consumption. When used in conjunction with machine-learning tools, these data can be used to make decisions for maintenance instead of following a schedule. Carvalho et al. (2019) demonstrate that machine learning is widely used for fault detection, diagnosis, classification and remaining useful life prediction. Çınar et al. (2020) also note the relationship between machine-learning based predictive maintenance and sustainable smart manufacturing as better maintenance decisions can lead to decreased waste, increased equipment utilization and efficient resource consumption.

Even with these advantages, it's challenging for small manufacturing businesses to implement them in practice. Small companies may not have as much capital, information-technology (IT) staff, outmoded equipment, integrated data systems, or large, high-quality data sets as do large manufacturers. According to Hassankhani Dolatabadi and Budinska (2021), predictive-maintenance solutions for small and medium-sized enterprises (SMEs) should be cost-effective, technically feasible, scalable and suitable for the current production environment. This puts a huge distance between what is state-of-the-art in predictive modeling and what is feasible, and actually used in the small manufacturing world. Several solutions that are reported require a complicated infrastructure, a large number of failure records, cloud platforms or expertise of a specialist which may not be available to smaller companies.

This study aims to tackle the issue of limited applied evidence of a viable combination of IoT sensors and machine-learning methods to implement a usable, economical and effective predictive-maintenance solution for small manufacturing businesses. Dalzochio et al. (2020) highlight some ongoing challenges including data quality, model selection, interoperability, explainability, security and the translation of the analysis into appropriate maintenance actions. It is also not just a predictive maintenance forecasting problem, but also predicting when to conduct maintenance, what resources to allocate, what production priorities to consider, and the repercussions of false alarms and missed failures. The authors Bousdekis et al. (2019) state that the effective use of predictive information for decisions to take the necessary measures for maintenance. This is especially true of small businesses as they may have a restricted budget for maintenance, spare parts, skilled staff and production.

The study is limited to machine-condition variables and machine-learning techniques that can be used in a predictive maintenance system for IoT-based machines in the simulated manufacturing environment that is relevant to small manufacturing enterprises. It emphasizes the data pre-processing, model building, model performance analysis, and application of the model predictive output to provide useful insights. It is not a physical deployment of the sensors, or involvement of participating enterprises, continuous machine monitoring, or a direct measurement of maintenance costs and downtime. The results can be affected by the artificial construction of the dataset, the small amount of failure data available, lack of time series data and by the choice of modelling methods. These data could be used to develop a model that needs to be recalibrated and external validated for application in actual manufacturing environment. Using a predictive-maintenance approach in the decision-making process of a CNC-based SME should be evaluated based on the expenses of maintenance, failure cost and the economic value of downtime reduction, as shown by Adu-Amankwa et al. (2019).

The study is important as it can offer a realistic route for small manufacturers to increase the reliability of equipment, without implementing overly complex and expensive systems. It contributes by connecting the variables of the machines with the IoT, the machine learning analysis, the maintenance decisions, and the constraints of the SMEs in a simulation investigation environment. It can also aid in the selection of the appropriate data source, the selection of appropriate analytical techniques, and if it can provide measurable operational value, whether or not predictive maintenance is feasible. According to Bokrantz et al. (2020), smart maintenance is a combination of data-driven analysis and human competence, internal process and strategic objectives in an organizational and technological capacity. In this study, predictive maintenance is thus considered as a technology system and a management approach.

The study pursues the following research objectives:

To evaluate whether IoT-compatible machine-condition variables can effectively predict equipment failure in a

simulated manufacturing environment.
To develop and compare logistic regression, decision tree, and random forest models for binary machine-failure classification.
To assess the practical relevance, limitations, and potential applicability of the proposed predictive-maintenance approach for small manufacturing enterprises.

2. Literature Review

Predictive maintenance is emerging as a key aspect of Industry 4.0, as it integrates connected devices, ongoing condition monitoring, data analytics, and intelligent decision-making. As demonstrated in a systematic review by Zonta et al. (2020), the literature on predictive-maintenance research is scattered across a variety of industrial applications, methods, standards and technological architectures, with a lack of coherent pattern when it comes to data integration and implementation practices. In this context, intelligent sensors offer the data needed for operation to detect equipment degradation prior to failure. According to the authors of Pech, et al. (2021), the machine condition information produced by smart sensors is huge in volume, so effective analysis of this information is needed for the maintenance and production decision-making process.

The predictive-maintenance process is often divided into four steps: data acquisition, feature construction, health assessment and fault prediction, remaining useful life estimation. The work of Lei et al. (2018) categorizes the machinery prognostics into data collection, development of health indicators, identification of health stages and prediction of remaining useful life, showing that the quality of predictions is dependent on the quality of each stage. Machine learning can help this process as it can find patterns that traditional threshold-based monitoring might not be able to. Deep-learning techniques are especially useful in fault diagnosis, degradation classification, pattern recognition, and remaining useful life estimation, but numerous architectures are still specific to the equipment and challenging to choose for or adapt to various manufacturing settings (Khan & Yairi, 2018).

Applied studies show how these techniques can be applied to monitor manufacturing equipment. Paolanti et al. (2018) proposed an architecture of random-forest based predictive maintenance, which, they showed, classifies the operating conditions of industrial equipment from sensor measurements and can be used for predictive maintenance. Traini et al. (2019) suggested a framework for cutting-tool wear prediction in milling process using data from Industrial Internet of Things (IIoT) and machine learning analyzers. Their work shows that their predictive output can be used for timely tool replacement, minimising production downtime, and reduce the risk of unexpected downtime. In a similar fashion, Lee et al. (2019) used the artificial-intelligence in cutting-tool wear and spindle-motor bearing faults, proving the importance of data-driven models for monitoring critical machine-tool components. All of these studies demonstrate the technical potential of machine learning-driven maintenance, but the success of the models will only be known when applied to representative data, suitable features, and under realistic operating conditions.

Industrial IoT platforms offer the backbone needed to connect the sensors, machine data, and share information about the health of the machines. Resende, M., et al. (2021) introduced the concept of TIP4.0 as a modular Industrial IoT platform, with the support of sensor networks and predictive-maintenance applications in the edge-computing gateways and commercially available hardware. The moduler is significant for small manufacturing enterprises, since it allows to introduce it gradually without changing the existing machinery and information systems. In a similar study, Sezer et al. (2018) suggested an architecture for low cost small manufacturing enterprise with vibration and temperature measurements for cyber-physical architecture. Their approach shows that predictive-maintenance capabilities can be added by using low-cost sensing, communication, and data-processing devices.

But, if the technology is available, it doesn't necessarily mean that it is implemented successfully in SMEs. SMEs often do not have the technical, financial and managerial resources to effectively use all of the Industry 4.0 technologies, especially in the production planning and control (PPC) processes (Moeuf et al., 2018). The existing maturity models for Industry 4.0 may also not be suitable for SMEs as they tend to focus on resources, competencies and digital infrastructure that are more applicable to the context of large manufacturing organisations (Mittal et al., 2018). While the benefits of the adoption of Industry 4.0 are acknowledged, such as flexibility, efficiency, product quality, cost reduction, and competitive advantage; nevertheless, there are significant barriers to the implementation of Industry 4.0, including financial constraints and lack of technical knowledge (Masood & Sonntag, 2020). In a wider adoption perspective, Ghobakhloo et al. (2022) define the factors of Industry 4.0 implementation in three main categories: technological, organizational and environmental. Digital readiness goes beyond just purchasing sensors, software, and connected machines.

The literature reviewed thus shows that there is a gap between the technical feasibility of IoT and machine learning (ML) based predictive maintenance (PM) and its implementation into small manufacturing enterprises (SMEs). The benefits of intelligent sensors and prognostic models, machine learning algorithms, edge platforms and low-cost architectures have been well established in existing work. However, most studies are limited to single technologies, specific data sets and unique machines. Less focus is on integrated implementations that can effectively tackle affordable sensor installation, existing machine, limited historical failure data, employee competencies, usable machine-learning outputs, and measurable operational benefits. This gap is to be bridged by a simulation study to assess the predictive performance and the possible affordability, usability, scalability, and organization relevance of predictive maintenance for small manufacturing enterprises.

3. Methodology

3.1 Research Design

The design in this study was quantitative, applied, and machine learning based to assess the machine failure prediction using machine-condition variables that are compatible with IoT. The analytical problem was defined as supervised binary classification – where each observation is assigned to either one of two classes: "machine failure" or "normal operation." The same training and testing partitions were used to evaluate 3 classification algorithms: logistic regression, decision tree and random forest. The analysis was not on the actual placement of the IoT sensors in a manufacturing plant, but on the data-processing and predictive-modelling aspects of a maintenance system.

3.2 Data Source

The analysis was performed on the AI4I 2020 Predictive Maintenance Dataset from UCI Machine Learning Repository (2020). It is an observed dataset with 10,000 observations and 14 original variables of the machine operating conditions in a synthetic industrial production environment. The observations are synthetic but the variables are based on those variables that can be measured in industrial monitoring devices such as air temperature, process temperature, rotational speed, torque, and tool-wear measurement. It was therefore considered that the data set could be used as a simulation based representation of the operating conditions of a small manufacturing enterprise.

3.3 Variable Selection

Machine failure was the dependent variable (0 = normal functioning, 1 = machine failure). The predictor set included product type, air temperature in Kelvin, process temperature in Kelvin, rotational speed in revolutions per minute, torque in Newton-metre and tool wear in minutes.

The UDI and Product ID were eliminated since they were unique record identifiers and not machine-operating conditions. The tool-wear failure, heat-dissipation failure, power failure, overstrain failure, and random-failure indicators were also not included in the predictor set. As the failure outcomes describe specific failure cases, their contribution would have resulted in target leakage, as these would be directly connected to the dependent variable.

3.4 Data Screening and Preprocessing

The data set was reviewed for missing records, duplicate observations, incorrect data types, inconsistent category codes, unrealistic numerical data, and differences between the overall failure and the failure mode indicators. No missing values or duplicate records with the same values were found. Twenty-seven inconsistencies were found between the overall failure label and the combined failure-mode indicators. The original Machine failure variable was kept as the study focused on overall binary failure prediction, not failure-mode classification.

One-hot encoding was applied to product type, creating binary indicators for low, medium, and high quality product types. Logistic regression was performed on standardized continuous variables (z score) to analyze associations.For continuous variables logistic regression was performed using Z score. Only the training data was used to get the mean and standard deviation for standardization. The decision-tree and random-forest models did not need to be scaled numerically. To avoid data leakage, all the preprocessing transformations were fitted to the training subset and then applied to the test subset.

There were 339 failure and 9,661 non-failure observations in the target variable with a failure rate of 3.39%. Stratified sampling and balanced class weights were applied in the process of estimation of models, in order to alleviate class imbalance. No oversampling and no synthetic data was used.

3.5 Exploratory Data Analysis

The air temperature, process temperature, rotational speed, torque, and tool wear were calculated by descriptive statistics. These comprised the mean, standard deviation, minimum, median, maximum and interquartile range. Summary of predictor values were also obtained separately for failures and non-failure observations.

The target-class distribution was analysed by frequencies and percentages. The distributions of continuous predictors were compared by box plots according to the failure status. Pearson correlation coefficient was used to explore the linear relationships between continuous predictors. Correlations between the air and process temperatures, between the rotational speed and torque were given special attention as strong correlations among the predictors could affect correlations interpretation.

3.6 Machine-Learning Models

An interpretable linear model, logistic regression, was employed as a baseline model to estimate the probability of machine failure. The decision-tree classifier was used to recognize the nonlinear decision boundaries and interaction between machine operating variables. Random forest was assessed as an ensemble approach that builds a forest of decision trees to decrease the variance and increase the stability of the classification.

A class weighting was used to increase the penalization of failure observations misclassified. The logistic regression model was set up with balanced class weights, a maximum of 2000 iterations and a random seed of 42. The weights of classes were balanced, the maximum depth of the tree was 6, the minimum number of observations per terminal leaf was 10 and the random seed was 42. The random-forest classifier was based on 400 trees, minimum two observations per terminal leaf, class weighting based upon balanced subsample, parallel processing with a random seed set to 42. The set-up of these configurations was determined prior to test-set evaluation. A threshold value, 0.50, was employed to transform the predicted probabilities to binary classes.

3.7 Training and Validation Procedure

The data were randomly split into 80% training and 20% testing sets and stratified random sampling was used to generate the data set. The resulting test subset comprised of 2,000 observations, 68 of which were failures and 1,932 were non-failures. The training data were employed in the pre-processing and model fitting process, and the test data were held to evaluate the model performance.

Random-forest model was also tested using three-fold stratified cross-validation. Failure proportion was kept in each fold and the mean and standard deviation of the evaluation metrics were determined across the three different folds used for validation.

In addition an order-based sensitivity analysis was carried out. The first 8000 observations were used for training and the last 2000 observations with no random shuffling were used for testing. This was not considered a temporal validation, but rather an order-based robustness assessment, due to a lack of time stamps in the dataset.

3.8 Model Evaluation and Interpretation

The accuracy, precision, recall, specificity, F1-score, balanced accuracy, receiver operating characteristic area under the curve, precision–recall area under the curve and Matthews correlation coefficient were used to measure the model performance. True-positives, true-negatives, false-positives and false-negatives were reported using confusion matrices.

The accuracy measure was considered as an ancillary output because the high proportion of non-failure cases could give an erroneous result. In model comparison, precision, recall, F1-score, precision–recall area under the curve, balanced accuracy and Matthews correlation coefficient were emphasized. The receiver operating characteristic and precision–recall measures were calculated using predicted probabilities.

To assess the importance of predictors for the random-forest model, the feature-important scores based on impurity were calculated. The scores were the average of the contribution of each predictor to the reductions in classification impurity over the ensemble of trees.

3.9 Software, Reproducibility, and Ethical Considerations

Data management and analysis were performed in Python using pandas, NumPy, scikit-learn, and Matplotlib. All random numbers were generated with a fixed random seed of 42 to enable reproduction. The data has been made public and includes no private information, confidential information or information about human participants. There was not therefore a need for formal ethical approval. Findings were interpreted taking the synthetic nature of the data and absence of direct deployment of sensors in real small manufacturing enterprises.

4. Results

4.1 Data Quality and Sample Characteristics

The analytical dataset contained 10,000 machine-operation observations and 14 original variables. Screening identified no missing values, exact duplicate records, or invalid product-type codes. Machine failure occurred in 339 cases, while 9,661 represented normal operation, giving a failure prevalence of 3.39% and an imbalance ratio of approximately 1:28.5. Table 1 summarizes the final data-quality and target-class profile.

Table 1. Dataset quality and target-class profile

Characteristic	Result
Total observations	10,000
Original variables	14
Missing values	0
Exact duplicate rows	0
Low-quality product observations	6,000
Medium-quality product observations	2,997
High-quality product observations	1,003
Non-failure observations	9,661
Failure observations	339
Failure prevalence	3.39%
Imbalance ratio	1:28.5
General/failure-mode label inconsistencies	27

There were 27 discrepancies identified when consistency was done between all the general failure label and the five specific failure indicators. These included 18 random failures (no general positive label) and nine positive general failures (no named mode). Machine failure variable was included in the supplied data as this occurred as a binary overall failure. As shown in figure 1, the problem is extremely imbalanced, and a simple classifier that classifies all of the samples as normal operation will be accurate in 96.61% of the cases.

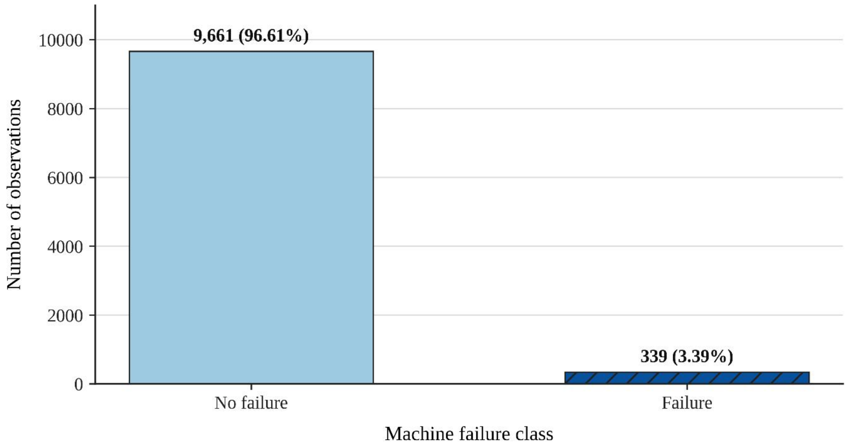

Figure 1. Distribution of machine-failure and non-failure observations in the AI4I 2020 dataset

4.2 Descriptive and Correlation Results

Failure cases had higher mean air temperature, process temperature, torque, and tool wear but lower rotational speed. Table 2 shows that the largest group differences occurred for torque, which was 10.538 Nm higher in failure cases, and tool wear, which was 37.088 minutes higher. Mean rotational speed was 43.773 rpm lower among failures.

Table 2. Descriptive statistics and mean values by machine-failure status

Variable	Overall mean ± SD	Range	No failure mean	Failure mean	Difference
Air temperature (K)	300.005 ± 2.000	295.3–304.5	299.974	300.886	+0.912
Process temperature (K)	310.006 ± 1.484	305.7–313.8	309.996	310.290	+0.295
Rotational speed (rpm)	1538.776 ± 179.284	1168–2886	1540.260	1496.487	−43.773
Torque (Nm)	39.987 ± 9.969	3.8–76.6	39.630	50.168	+10.538
Tool wear (min)	107.951 ± 63.654	0–253	106.694	143.782	+37.088

Two dominant predictor relationships were identified by the Pearson analysis, as shown in Figure 2. There was a strong positive correlation between air temperature and the process temperature (r = 0.876) and a strong negative correlation between the rotational speed and torque (r = −0.875). Other pairwise correlations between the five continuous predictors were all less than 0.03.

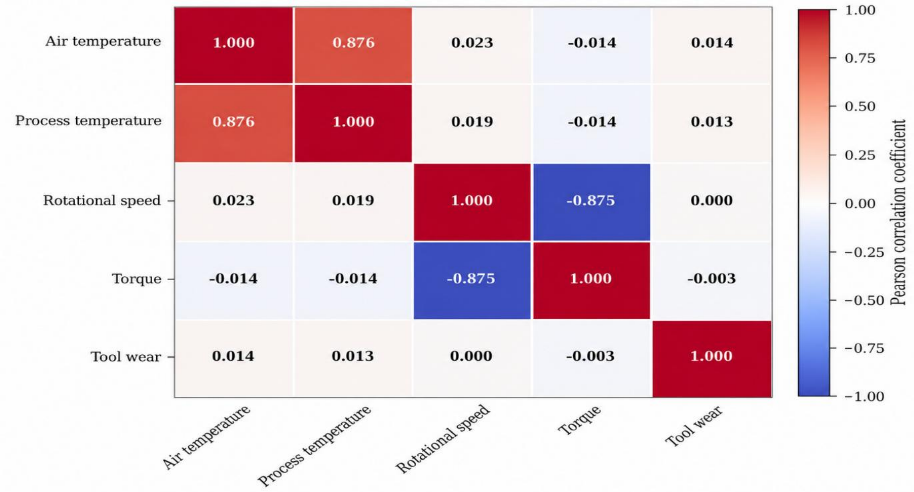

Figure 2. Pearson correlation matrix for the continuous IoT-compatible machine condition variables

4.3 Test-Set Model Performance

The stratified 80:20 split produced a test set of 2,000 observations containing 68 failures and 1,932 non-failures. Table 3 reports performance at the 0.50 classification threshold. Balanced logistic regression achieved high recall of 0.824 but low precision of 0.142. The balanced decision tree produced the highest recall of 0.853 and precision of 0.317. Random forest provided the strongest overall balance, with precision of 0.780, F1-score of 0.661, ROC-AUC of 0.962, PR-AUC of 0.753, and MCC of 0.659.

Table 3. Performance of machine-learning models on the stratified test set

Model	**Accuracy**	**Balanced accuracy**	**Precision**	**Recall**	**F1-score**	**ROC-AUC**	**PR-AUC**	**MCC**
Logistic regression	0.825	0.824	0.142	0.824	0.242	0.907	0.382	0.295
Decision tree	0.933	0.894	0.317	0.853	0.462	0.879	0.655	0.495
Random forest	0.980	0.784	0.780	0.574	0.661	0.962	0.753	0.659

The random forest correctly classified 1,960 of 2,000 test observations. Figure 3 shows 1,921 true negatives, 11 false positives, 29 false negatives, and 39 true positives. Specificity was 0.994, while sensitivity was 0.574.

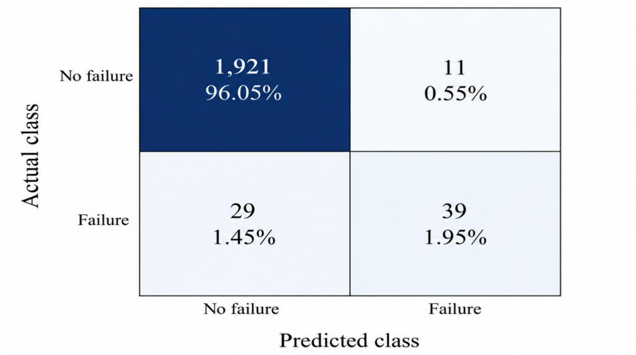

Figure 3. Confusion matrix of the random-forest model on the stratified 20% test set

4.4 Cross-Validation and Robustness Analysis

Three-fold stratified cross-validation was used to assess variability across partitions. Table 4 indicates that random forest maintained a mean ROC-AUC of 0.965 ± 0.006 and PR-AUC of 0.717 ± 0.022. Mean precision was 0.801 ± 0.036, recall was 0.531 ± 0.027, and F1-score was 0.638 ± 0.022.

Table 4. Random-forest cross-validation and order-based sensitivity results

Evaluation design	Precision	Recall	F1-score	Balanced accuracy	ROC-AUC	PR-AUC
Three-fold CV, mean ± SD	0.801 ± 0.036	0.531 ± 0.027	0.638 ± 0.022	0.763 ± 0.013	0.965 ± 0.006	0.717 ± 0.022
Stratified 80:20 test	0.780	0.574	0.661	0.784	0.962	0.753
Order-based 80:20 test	0.850	0.436	0.576	0.717	0.952	0.686

For the order-based sensitivity analysis, the first 8,000 observations were used for training and the final 2,000 for testing. The final subset had 1.95% failures. Precision increased to 0.850, but recall declined to 0.436 and F1-score to 0.576. ROC-AUC remained high at 0.952.

4.5 Predictor Importance

Random-forest importance ranked rotational speed first at 0.316, followed by torque at 0.289, tool wear at 0.200, air temperature at 0.105, and process temperature at 0.071. The three one-hot encoded product-type indicators contributed 0.019 in total. Figure 4 displays the concentration of predictive importance in the mechanical-operation variables.

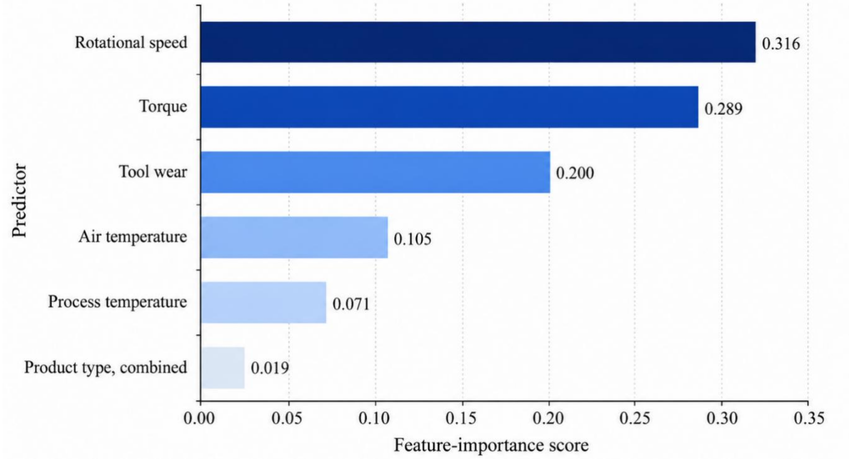

Figure 4. Impurity-based feature-importance scores obtained from the random-forest classifier

All of the six IoT-compatible predictors were useful in distinguishing failure from normal operation with useful discriminatory performance. Logistic regression and the decision tree were more likely to identify failures, but yielded significantly more false alarms. Random forest had the highest combined F1, ROC-AUC, PR-AUC, precision and MCC scores. However, moderate recall and lower order based recall revealed that some errors went undetected and that there was partial dependence on data partitioning.

5. Discussion

The results show that a small number of operational variables, that are compatible with the Internet of Things, can be used to predict machine failure with a useful discriminatory performance. Overall, the random forest algorithm outperformed the other two algorithms evaluated with precision of 0.780, F1 score of 0.661, ROC-AUC of 0.962, PR-AUC of 0.753 and Matthews correlation coefficient of 0.659. Logistic regression and decision tree had more recall values but with significantly lower values of precision, meaning that they issued more false maintenance alerts. In this way, random forest proved to be a more feasible compromise between detection of failures and unnecessary interventions. However, it has a recall of 0.574 which indicates that 29 of the 68 failures in the test set were not caught. The model is therefore not to be used as a complete maintenance system, but rather as a decision support system. Although the ROC-AUC was still high at 0.952, further reduction of the recall to 0.436 under the order based validation further indicates that performance of the model was sensitive to the composition and ordering of the data.

The overall better performance of random forest is in line with the results presented by Paolanti et al. (2018), who showed that architectures based on random forest could be suitable for the classification of the condition of industrial equipment using sensor measurements. This is further confirmed in the present results, which demonstrate that random forest can be effective even with only six operational predictors, and when only 3.39% of the observations are failures. This also aligns with the overall review by Carvalho et al. (2019) that classified classification, fault detection, diagnosis and remaining useful life estimation as important applications of machine learning in predictive maintenance. The present study does also show that a high ROC-AUC does not necessarily mean that a high failure-detection sensitivity is achieved. Precision, recall, PR-AUC and the confusion-matrix outcomes give a more operationally meaningful evaluation of the manufacturing dataset than does accuracy alone, especially if the dataset is imbalanced.

The predictor importance results give a technically sound understandability of failure risk. The rotational speed, torque and wear of the cutting tools were the most important factors for the random-forest predictions, whereas the temperature factors were moderately important and the type of product was of low importance. Higher average torque and tool wear and lower rotational speed were also the parameters that were correlated with failure. These patterns indicate that it may be possible to get more direct information about abnormal operating conditions from mechanical loads, operating speed and from information from the amount of product that has been produced than from information provided by the product category. The good negative correlation between the rotational speed and torque, and the positive correlation between air temperature and process temperature also shows that the machine parameters cannot simply be interpreted independently. Practical realisation can then be realised by small manufacturers with a configuration of sensors that provides them with useful predictive information, as opposed to a large and expensive monitoring infrastructure.

The results have several implications for small manufacturing enterprises. Such a model could be integrated into a relatively inexpensive monitoring system, to prioritize the inspections, schedule maintenance and determine which machines need to be attended to. It aligns with the views of Hassankhani Dolatabadi and Budinska (2021) that predictive-maintenance solutions for SMEs needs to be affordable, scalable, manageable and equipment compatible. The relevance of the random forest is its ability to work with structured sensor data without the need for computational resources that can be typically required by more complex deep-learning systems. But the implementation should have variable thresholds of probability, operator review and considerations of the costs of maintenance. Raising the classification threshold could reduce false alarms and lower the threshold could reduce failure recall but increase the number of false alarms. Also, Dalzochio et al. (2020) pinpoint data quality, explainability, model selection, interoperability and output of model to maintenance action as ongoing challenges in Industry 4.0 predictive maintenance.

Several limitations must be acknowledged. The data set was not real and there were no time-stamps, data from repeatable measurements on known machines, maintenance history, downtime history, repairing costs, or data directly from small companies. The analysis was thus based on classification of failure from operational snapshots instead of continuous condition monitoring or remaining useful-life (RUL) prediction. The class imbalance problem and the distinction between the level of the general failure and the level of each individual failure mode can also have influenced the model learning, as there are 27 inconsistencies. Besides, the random-forest importance by impurity will be favor towards continuous variable and should not be considered as cause and effect evidence. Future work should test the models with real multi-machine time-series data from SMEs, add vibration sensor, electrical current sensor etc., and compare random forest with boosting, cost-sensitive learning, and temporal models. There should be a correlation between threshold optimization and the cost associated with false alarms and missed failures. Validation across various machine types, factories, and/or operating conditions would further enhance generalizability, transparency, and managerial usefulness, as would permutation importance or SHAP analysis.

6. Conclusion

This study examined the feasibility of using IoT-compatible machine-condition data and machine-learning techniques to support predictive maintenance in small manufacturing enterprises. The results showed that rotational speed, torque, tool wear and temperature measurements are useful to determine whether a machine is in normal operation or failure. Overall the best-performing model was random forest with a precision of 0.780, an F1-score of 0.661, and a ROC-AUC of 0.962, although with moderate recall, some failures were not detected. This means that using machine learning for predictive maintenance could be used to help small manufacturers prioritise inspections, curtail unnecessary maintenance activities, minimise unexpected equipment breakdowns and increase equipment reliability, without being constrained by high levels of complex analytical infrastructure. The research suggests that more sensible sensor systems, with interpretable machine learning models and human maintenance monitoring, be progressively implemented. For small enterprises, the thresholds for classification should be modified based upon the relative costs of a false alarm and a missed failure, and re-trained models should be done periodically as the machine conditions and production requirements change. However, the results are difficult to directly translate into the general case due to the following: the synthetic data set; class imbalance; lack of timestamps; and lack of actual maintenance-cost and downtime records. Future research work needs to validate the approach with real-time multi-machine sensor data from small manufacturing companies, extend the sensor data to include vibration measurements and electrical-current data, compare ensemble and temporal models, apply SHAP or permutation-based interpretation, and assess the economic and operational impact of predictive maintenance in various industrial settings.

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