e-ISSN 3108-026X
International Multidisciplinary Research Journal Reviews (IMRJR)
A Peer-reviewed journal
Volume 3, Issue 3, March 2026 | DOI 10.17148/IMRJR.2026.030305

A Multi-Class Predictive Model for Manufacturing Equipment Maintenance Systems

Nikitha Gandra[1], Chukwuasia Madike[2], Naaram Srichandana[3], Eve Thullen[4]

Thullen Research Lab, USA[1-4]

University of the Cumberlands, USA[4]

Abstract: Unplanned equipment failures in manufacturing systems lead to production downtime, increased operational costs, and safety risks. While predictive maintenance techniques have advanced significantly, much of the existing work focuses on binary failure detection and provides limited insight into specific failure mechanisms. This paper presents a multi-class predictive modeling approach for manufacturing equipment maintenance systems that aims to identify distinct failure types using operational sensor data. The study formulates failure type prediction as an imbalanced multi-class classification problem representative of real-world industrial environments, where failure events are rare compared to normal operation. Model performance is evaluated using imbalance-aware metrics to ensure reliable assessment across both dominant and minority failure classes. The results demonstrate that the proposed approach can effectively distinguish major mechanical and thermal failure types despite severe class imbalance. These findings highlight the importance of multi-class failure prediction for enabling more targeted maintenance decisions and improving the reliability of manufacturing equipment.

Keywords: Predictive Maintenance, Multi-Class Classification, Machine Learning, Manufacturing Systems, Failure Type Prediction, Equipment Reliability

I. INTRODUCTION

Manufacturing systems depend on sophisticated equipment which needs to achieve maximum productivity while delivering high quality products and keeping operations safe. Unplanned equipment breakdowns in such environments create production halts which result in rising operational expenses while equipment experiences faster deterioration and workers face increased safety hazards. Manufacturing facilities that operate at full capacity experience their worst challenges because even brief work stoppages will cause major disruptions to their production processes which will result in severe productivity losses throughout their entire operation. The development of efficient maintenance methods creates a critical requirement which manufacturers need to achieve their operational goals through dependable maintenance practices.

The needs of contemporary industrial systems require organizations to use advanced maintenance methods instead of traditional maintenance systems which include reactive maintenance and fixed-interval preventive maintenance. The process of reactive maintenance fixes equipment after it breaks down which causes unplanned work interruptions and expensive repair expenses. The procedure of time-based preventive maintenance requires organizations to conduct equipment checks at specific times which results in unneeded inspections and causes them to overlook initial indicators of equipment breakage. Predictive maintenance has emerged as a data-driven alternative that uses operational and sensor data to predict equipment failures through its monitoring system which allows for timely maintenance actions that enhance system dependability.

The existing research on predictive maintenance shows considerable advancement yet most studies concentrate on detecting equipment failures through binary testing which determines whether equipment operates normally or shows faults. The models can detect abnormal behavior but their maintenance decision-making value decreases because they fail to show which failure mechanisms are present. The different ways equipment fails in manufacturing plants require distinct diagnostic methods and repair processes for each failure type. The existing predictive maintenance methods cannot effectively predict equipment failures because they lack the ability to identify precise breakdowns.

This study aims to explore multiple failure types for equipment maintenance systems because of the existing research gaps. The proposed approach establishes failure prediction as an imbalanced multi-class classification problem which models actual industrial conditions by showing normal operation as more common than actual breakdowns. The model evaluation process uses metrics which measure performance across both the majority and minority categories. The study establishes identification of different failure types through practical testing which leads to development of predictive maintenance strategies that enable focused maintenance activities and enhance operational efficiency.

II. LITERATURE REVIEW

The research field of predictive maintenance has become essential to contemporary manufacturing practices and Industry 4.0 because it enables condition-based decision-making through analysis of operational and sensor data. The research findings demonstrate that organizations now use data-driven maintenance approaches which combine machine learning with analytics instead of their previous reactive and time-based maintenance methods. The studies demonstrate that sensor monitoring and data modeling and performance evaluation together help decrease equipment downtime and enhance equipment reliability, yet they face ongoing problems with implementation and data quality and industrial setting performance testing.

The existing literature on predictive maintenance uses two main approaches to describe equipment failure prediction which includes either anomaly detection or binary classification that divides equipment states into normal and faulty categories. The warning systems work well with these formulations yet they do not help maintenance planning because they do not reveal the particular failure mechanisms that are involved. Manufacturing environments experience different failure modes which create unique root causes and risks and necessary corrective actions. The use of binary failure detection does not provide enough information for maintenance teams to create effective maintenance plans.

Researchers have developed multi-class fault and failure-type classification systems which use both classical machine learning and deep learning techniques to solve existing challenges. The combination of tree-based ensemble models with gradient-boosting methods delivers strong results on structured industrial datasets while neural network architectures handle temporal and high-frequency signal data. The research demonstrates that achieving high overall accuracy does not guarantee success in detecting rare failure modes which makes class-level performance assessment necessary because it provides better detection capabilities than using aggregate metrics.

The industrial datasets which researchers use to predict failure types experience a major problem because of their extreme class imbalance. Historical records show that normal operating conditions meet most of their data requirements while specific failure events show up only on rare occasions. The majority class in predictive models represents an imbalance which causes the model to lose ability to detect critical failures that occur only on rare occasions. Researchers have developed data-level methods which include oversampling and undersampling techniques and they have created algorithm-level methods which utilize cost-sensitive learning and class weighting. The approaches help detect minority-class data of the studied group, but they create a need to assess how their implementation affects model performance and how the results are presented.

Current research efforts focus on developing models for predictive maintenance that offer better interpretability and trustworthiness. Engineers use explainable machine learning techniques to understand model predictions and find out whether the system behavior matches learned patterns. Organizations now consider interpretability as an essential requirement because maintenance operations need both predictive capacity and transparent domain validation to make their decisions. Manufacturing facilities need predictive maintenance frameworks that can identify multiple failure types while using evaluation methods designed for imbalanced data to function properly in actual production settings. The existing research concentrates on detection performance while providing minimal information about its usefulness for making operational choices. This research gap drives the current study which aims to create and assess a multi-class failure prediction system that delivers practical maintenance guidance for manufacturing equipment.

III. METHODOLOGY

This study adopts a quantitative research design to investigate multi-class failure type prediction in manufacturing equipment maintenance systems. The methodology aims to evaluate whether operational sensor data can effectively distinguish between different equipment failure types under realistic industrial operating conditions. The research design emphasizes practical applicability by ensuring that the analytical framework reflects constraints commonly observed in real-world manufacturing environments.

The study utilizes historical operational and sensor data collected from manufacturing equipment during both normal operation and failure events. Each observation represents a snapshot of machine operating conditions and is associated with a labeled failure type. The dataset includes key mechanical and thermal measurements that characterize equipment health, such as indicators related to load conditions, temperature behavior, and component degradation. As is typical in industrial datasets, observations corresponding to normal operation constitute the majority of the data, while specific failure types occur infrequently. This class imbalance is treated as a fundamental characteristic of the problem rather than a limitation of the data.

The analysis approach focuses on transforming raw operational data into a structured representation suitable for predictive modeling. Feature design is guided by physical relevance and interpretability, ensuring that selected variables reflect meaningful failure mechanisms rather than purely statistical correlations. The methodology emphasizes alignment between data characteristics and modeling objectives, allowing the model to capture operational patterns relevant to maintenance decision-making.

Failure prediction is formulated as an imbalanced multi-class classification problem, enabling systematic evaluation of the model's ability to distinguish among multiple failure types. This formulation provides a conceptual foundation for model selection and training strategies that prioritize balanced predictive performance across both majority and minority classes, supporting maintenance applications where accurate identification of rare failures is critical.

IV. MODEL IMPLEMENTATION AND EVALUATION

This study adopts a quantitative, data-driven research design to investigate multi-class failure type prediction in manufacturing equipment maintenance systems. The overall methodology is structured to evaluate whether operational sensor data can effectively differentiate between multiple equipment failure types under realistic industrial conditions. The design emphasizes practical applicability by ensuring that modeling decisions reflect constraints commonly observed in real-world manufacturing environments, such as class imbalance and limited failure samples.

The study utilizes historical operational and sensor data collected from manufacturing equipment during both normal operation and failure events. Each observation represents a snapshot of machine operating conditions and is associated with a labeled failure type. The dataset contains mechanical and thermal measurements that characterize equipment health, including indicators related to load conditions, rotational behavior, temperature levels, and component degradation. As is typical in industrial datasets, normal operating conditions constitute the majority of observations, while specific failure types occur infrequently. This inherent class imbalance is treated as a fundamental characteristic of the problem rather than a data limitation.

Feature design is guided by physical relevance and interpretability to ensure that selected variables reflect meaningful failure mechanisms. Core sensor measurements are used to represent mechanical load, thermal stress, and tool degradation, while engineered interaction features are incorporated to capture combined operational effects. The focus of feature design is to enhance class separability while maintaining alignment with domain knowledge, rather than maximizing model complexity.

For model building, the failure prediction task is formulated as an **imbalanced multi-class classification problem**. An **XGBoost-based gradient boosting classifier** is selected as the primary predictive model due to its suitability for structured sensor data, ability to capture non-linear feature interactions, and robustness in imbalanced classification settings. XGBoost is well suited for industrial datasets where failure mechanisms arise from complex interactions among multiple operational variables.

The model training strategy incorporates imbalance-aware learning to ensure that minority failure types receive sufficient emphasis during optimization. Training and evaluation are conducted using a stratified data split to preserve the original class distribution across datasets. This modeling framework establishes a robust foundation for evaluating predictive performance across both dominant normal-operation classes and rare but operationally critical failure types

V. RESULTS ANALYSIS AND CONCLUSION

This section presents the experimental findings of the multi-class failure type prediction study. The results are organized to reflect the sequential analysis performed on the dataset, beginning with failure type distribution, followed by feature-level summaries and visual analysis, and concluding with classification performance metrics.

1. Failure Type Distribution

The initial analysis examined the distribution of failure types in the dataset. Table 1 reports the number of observations associated with each failure category in the test dataset. The results show a highly imbalanced class distribution, with normal operating conditions comprising the majority of samples (1,931 observations). Failure events occur infrequently, with heat dissipation failure (22 samples), power failure (19 samples), overstrain failure (16 samples), and tool wear failure (9 samples).

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Table 1. Distribution of failure types in the test dataset

Failure Type	**Support**
No Failure	1,931
Heat Dissipation Failure	22
Power Failure	19
Overstrain Failure	16
Tool Wear Failure	9
Total	**1,997**

2. Average Feature Values by Failure Type

To summarize operational characteristics associated with each failure category, average values of key sensor features were computed for each failure type. This analysis provides a descriptive overview of how mechanical and thermal variables differ across failure classes. The resulting averages are presented in Table 2.

Table 2. Average sensor feature values by failure type

Average Values per Failure Type (excluding UDI + target columns):

Failure Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]
Heat Dissipation Failure	302.568	310.799	1337.964	52.779	107.339
No Failure	299.973	309.994	1540.324	39.624	106.679
Overstrain Failure	299.868	310.051	1354.244	56.878	208.218
Power Failure	300.076	309.955	1763.968	48.515	101.884
Random Failures	300.767	310.756	1489.444	43.522	119.889
Tool Wear Failure	300.289	310.164	1570.667	37.227	216.556

3. Feature–Failure Type Heatmap

Figure 1 presents a heatmap illustrating the relationship between average sensor feature values and failure types. The heatmap provides a visual comparison of operational characteristics across failure categories, highlighting relative differences in mechanical and thermal features without attributing causal relationships.

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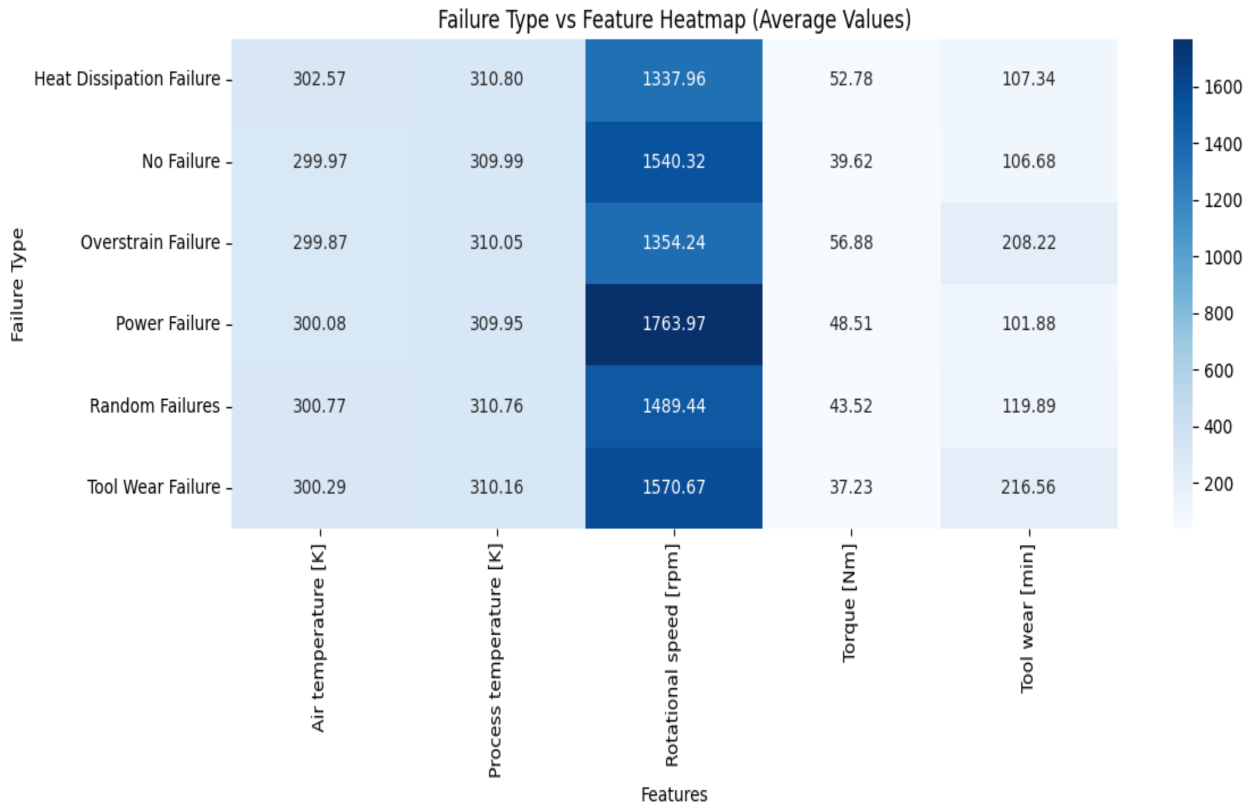
Figure 1. Heatmap of average feature values across failure types



4. Classification Performance

The predictive performance of the proposed model is evaluated using precision, recall, F1-score, and overall accuracy. Table 3 summarizes the class-level classification results on the test dataset.

Table 3. Class-level classification performance

Failure Type	**Precision**	**Recall**	**F1-score**	**Support**
Heat Dissipation Failure	0.78	0.95	0.86	22
No Failure	0.99	0.98	0.99	1,931
Overstrain Failure	0.58	0.94	0.71	16
Power Failure	0.81	0.89	0.85	19
Tool Wear Failure	0.09	0.11	0.10	9

The model achieves an overall classification accuracy of **0.98** on the test dataset.

5. Aggregate Performance Metrics

To assess balanced performance across all classes, macro-averaged and weighted evaluation metrics are reported in Table 4. Macro-averaged metrics assign equal importance to each failure category, while weighted averages account for class frequency.

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Table 4. Aggregate classification metrics

Failure Type	Precision	Recall	F1-score	Support
Heat Dissipation Failure	0.78	0.95	0.86	22
No Failure	0.99	0.98	0.99	1931
Overstrain Failure	0.58	0.94	0.71	16
Power Failure	0.81	0.89	0.85	19
Tool Wear Failure	0.09	0.11	0.10	9

Summary of Results

The presented tables and figures provide a comprehensive and objective summary of dataset characteristics and classification outcomes. The results demonstrate high overall accuracy, measurable performance across multiple failure types, and variation in predictive performance among minority failure categories. These findings establish a quantitative foundation for subsequent discussion.

VI. DISCUSSION

The results demonstrate that the proposed XGBoost-based multi-class failure prediction model is capable of distinguishing between normal operating conditions and multiple equipment failure types using operational sensor data. The high overall classification accuracy and strong weighted performance metrics indicate reliable identification of the dominant normal-operation class, while macro-averaged metrics provide insight into model behavior across minority failure categories. Together, these results confirm the feasibility of multi-class failure type prediction in highly imbalanced industrial datasets.

Class-level performance reveals meaningful variation across failure types. Heat dissipation failure, power failure, and overstrain failure achieve high recall values, indicating that the model is effective in identifying these failure modes when they occur. These failures are associated with clearer operational patterns in mechanical and thermal features, which likely enhances separability in the feature space. In contrast, tool wear failure exhibits lower precision and recall, reflecting the limited number of samples available for this class and the gradual nature of wear-related degradation, which may be less distinguishable from normal operation at isolated time points.

The comparison between macro-averaged and weighted metrics highlights the importance of imbalance-aware evaluation. While weighted metrics remain high due to class dominance, macro-averaged scores reveal reduced performance for minority classes, underscoring the limitations of relying solely on overall accuracy in predictive maintenance applications. This finding aligns with prior predictive maintenance studies that emphasize the need for class-balanced evaluation when failure events are rare but operationally critical.

From a practical perspective, the results support the value of multi-class failure prediction for maintenance decision-making. Unlike binary failure detection, the ability to identify specific failure types enables more targeted maintenance actions, improved fault diagnosis, and better allocation of maintenance resources. The observed performance differences across failure types also highlight the importance of incorporating domain knowledge and failure-specific characteristics when developing predictive maintenance systems.

Despite its strengths, the proposed approach has limitations. The severe class imbalance inherent in industrial datasets restricts predictive performance for rare failure types, particularly those with very limited sample sizes. In addition, the analysis is based on static snapshots of operational data, which may limit the model's ability to capture temporal degradation patterns. These limitations suggest opportunities for further refinement and extension of the proposed framework.

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VII. CONCLUSION

Conclusion

This study presents a data-driven framework for multi-class failure type prediction in manufacturing equipment maintenance systems. By formulating failure prediction as an imbalanced multi-class classification problem and applying an XGBoost-based modeling approach, the study demonstrates that operational sensor data can be used to identify distinct failure types with high overall accuracy and meaningful performance across multiple failure categories. The results highlight the limitations of binary failure detection and underscore the practical benefits of failure-type-level prediction for predictive maintenance applications.

The main contribution of this work lies in demonstrating the feasibility of multi-class failure prediction under realistic industrial conditions and emphasizing the importance of imbalance-aware evaluation. By integrating feature-level analysis, visualization, and class-level performance reporting, the study provides a structured and interpretable approach to predictive maintenance modeling that supports real-world maintenance decision-making.

Future Work

Several directions for future research can further enhance the proposed framework. First, expanding the dataset to include a larger number of failure instances, particularly for rare failure types, would improve model generalization and class-level performance. Second, incorporating temporal modeling techniques, such as sequence-based or time-series models, could capture progressive degradation patterns more effectively than static feature representations. Third, hybrid approaches combining gradient boosting with deep learning or physics-informed modeling may improve detection of subtle failure mechanisms such as tool wear. Finally, applying the proposed methodology to other industrial domains and equipment types would help assess its generalizability and practical impact across different manufacturing environments.

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