MATHEMATICAL MODELLING AND ARTIFICIAL INTELLIGENCE TECHNIQUES FOR PREDICTIVE MAINTENANCE IN MECHANICAL SYSTEMS

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ABSTRACT

Predictive maintenance is an important aspect of smart system management, motivated by the need for reliable predictions and optimised resource allocation. While artificial intelligence techniques are rapidly evolving, many of these methods do not incorporate mathematically-based models, creating a gap in interpretability and theoretical foundations. This research is an attempt to bridge this gap by proposing a hybrid system that integrates mathematical models and artificial intelligence for predictive maintenance in mechanical systems. The research uses the AI4I 2020 dataset, which includes structured operational features like temperature, rotation speed, torque and tool wear, to develop physically meaningful features and build a mathematical model of failure-probability. This model is compared with machine learning algorithms such as logistic regression, support vector machines and ensemble techniques. The findings show that features derived from mathematical models improve prediction accuracy and explainability of machine learning models. Moreover, the hybrid methods outperform methods in isolation, showing the potential benefits of integrating mechanistic and data-driven approaches. The results also highlight the need to incorporate domain expertise in predictive models and offer a scalable solution for mechanically governed systems. This research advances predictive maintenance approaches by bridging mathematical and computational efficiency, providing theoretical and practical value.

KEYWORDS: predictive maintenance, mathematical modeling, artificial intelligence, mechanical systems, machine learning, reliability analysis

1. INTRODUCTION

The rapid evolution of intelligent systems and computational modeling has significantly transformed maintenance strategies across engineering and technological domains. As part of the broader fields of applied mathematics and computational science, predictive maintenance has become a key concept that combines mathematical modeling, statistical analysis and artificial intelligence to predict system failures and enhance system performance. The availability of structured data from sensors and computing power has facilitated the shift from reactive and preventive maintenance to data-driven predictive maintenance. This shift is especially important in interdisciplinary areas of biomathematics and computational modeling where knowledge of system mechanisms and data-driven inference is needed for accurate system diagnostics and prognostics. Recent studies emphasise the potential of artificial intelligence in predicting maintenance needs by recognising patterns, detecting anomalies and predicting failures, enhancing system performance and minimising costs (Ucar et al., 2024).

In smart manufacturing systems, predictive maintenance is a key element of Industry 4.0, where an internet of devices and real-time data streams enable real-time monitoring and decision support. The application of machine learning techniques in manufacturing processes has led to the creation of advanced predictive models that can detect failure patterns across various operating scenarios (Hector & Panjanathan, 2024). In particular, deep learning models have shown high potential in capturing complex patterns and interactions in maintenance data, leading to improved prediction accuracy (Li et al., 2024). In addition to these methods, forecasting models have been used to predict system degradation and remaining useful life, adding a temporal aspect to predictive maintenance (Belim et al., 2024).

Despite these developments, current approaches tend to have a heavy emphasis on purely data-driven approaches, with a lack of integration of underlying physics and mathematical models. This can result in a lack of model interpretability and potentially limit its applicability, especially when data are scarce or system behaviours are intricate. The advent of physics-informed machine learning methods have sought to overcome this shortcoming by incorporating domain knowledge into machine learning algorithms to improve model performance and interpretability (Xu et al., 2023). Likewise, structural health monitoring approaches have shown the value of blending mechanistic knowledge and data-driven approaches to enhance diagnostic performance (Cha et al., 2024). Integration of artificial intelligence and the Internet of Things extends predictive maintenance techniques through distributed sensing and analytics, thus enabling next-generation maintenance systems (Bitam et al., 2025).

Despite these advances, some of the challenges in predictive maintenance remain. A major shortcoming is the lack of integration between mathematical modeling and artificial intelligence approaches, which results in a gap between analytical modelling and computational algorithms. Often the focus is on the performance of algorithms rather than the relationship between system variables and failure processes. This is further exacerbated by the adoption of complicated and non-interpretable models, which hinder the interpretation of predictions for maintenance decisions. Additionally, current research tends to prioritise either statistical reliability models or machine learning methods, without exploring the relative contributions and synergies between these methods (Tsallis et al., 2025). The shift from corrective to predictive maintenance highlights the importance of hybrid approaches that combine mechanistic and learning-based approaches to ensure accuracy and interpretability (Molęda et al., 2023).

The current research tackles this challenge by proposing a combined approach of mathematical modeling and artificial intelligence methods for predictive maintenance of mechanical systems. The research develops a mathematic model of degradation and failure using the AI4I 2020 predictive maintenance dataset, which offers operational data such as temperature, rotational speed, torque, and tool wear. The model is then compared to machine learning models to evaluate the predictive accuracy and stability of the models. The data set facilitates the development of derived features, such as mechanical power and temperature gradients, which are used as inputs to mechanistic and data-driven models. This integrated approach seeks to develop a consistent framework for bridging theoretical and computational modeling.

This study is constrained by the availability of structured operational data and cross-sectional analysis, enabling the creation of predictive models based on system states. Although the dataset covers all of the operational variables, it does not include degradation trajectories over time, which restricts the explicit modeling of system dynamics. Moreover, the data is artificially generated, which could limit the applicability of the results in industrial settings. But the synthetic nature of the dataset offers advantages in terms of reproducibility and is therefore ideal for methodological experimentation and comparative studies. These constraints are recognised as part of the study's design, but do not detract from the significance of the proposed model in the context of predictive maintenance.

This study is significant in its role in connecting mathematical modeling and artificial intelligence (AI) in predictive maintenance. This study combines the physics-informed generation of features with machine learning to improve both model interpretability and prediction accuracy. This methodology is in line with the interdisciplinary goals of computational and applied mathematics, whereby the integration of theoretical and empirical approaches is crucial to the advancement of knowledge. Pragmatically, the framework provides a structured approach to developing predictive maintenance models that can be applied to systems that are mechanically governed and extended to similar areas such as biomechanical and biomedical systems.

In this regard, the research has three main goals. First is to develop a mathematical model describing the relationship between parameters of operation and the likelihood of machine failure based on physical features. Next, it seeks to apply and compare predictive maintenance based on artificial intelligence methods on the same feature set. Third, it aims to compare the results of using mathematical and AI models to estimate the impact of mathematical modelling integrated with AI techniques to predict mechanical failures. These goals collectively establish the research approach of the study and guide the flow from theoretical development to empirical testing.

2. LITERATURE REVIEW

Machine learning and deep learning approaches have driven the advancement of predictive maintenance to enhance failure prediction from data. Recurrent models with attention mechanisms have demonstrated a high capacity for modelling degradation from time-series condition monitoring (Jiang et al., 2022). But these methods rely heavily on the continuity of the time series, and as such are not directly applicable to structured time series datasets such as those found in AI4I 2020.

Recent research has expanded predictive maintenance to a multilevel, cost-sensitive predictive maintenance that integrates fault prediction and maintenance planning (Zhou et al., 2023). Such methods enhance their relevance but their complex structures can be hard to interpret. Alternative frameworks also include reinforcement learning to conceptualize maintenance as a form of decision-making, such as with aircraft systems and remaining useful life prediction (Lee & Mitici, 2023). While capable of adaptability, these approaches require substantial temporal data and resources.

Deep learning ensembles have also been used to predict remaining-useful-life by combining learners to learn complex degradation patterns (Wang et al., 2024). Moreover, Bayesian deep learning has provided uncertainty-based prediction, which is useful for reliability applications (Zhuang et al., 2023). Likewise, probabilistic deep learning has been used to model multi-component systems to address uncertainty and dependencies (Zeng & Liang, 2023). However, many of these models prioritise prediction accuracy over mathematical models of the underlying physics.

Predictive maintenance in manufacturing with scheduling and coordination of parallel machines have been considered in distributed and multiagent approaches (Rodríguez et al., 2022). These methods are helpful for the complex manufacturing settings, but may increase the algorithmic complexity and are often not practical for smaller benchmark datasets. The comparisons with conventional machine learning and deep learning algorithms suggest simpler models, particularly ensemble classifiers, perform well for machine failure prediction (Yadav et al., 2024). This observation is supported by recent research on manufacturing systems using structured data with early failure prediction based on AI (Hosseinzadeh et al., 2023). Another issue relates to dataset design. Recent research has highlighted the need for predictive maintenance data to include industrial irregularities and variability (Autran et al., 2024). But many datasets are commercial, niche, and/or complex to compare over time, posing reproducibility challenges. The AI4I 2020 dataset offers a benchmarking data set with temperature, speed, torque, tool wear, failure labels and failure types for quantitative modeling.

In general, previous research demonstrates a gap between mechanistic, mathematically interpretable models of degradation and accurate AI predictions. Some research involves variable deep learning networks or data-driven classifiers, but with little use of physically significant variables. The current study overcomes this deficiency by considering features for mechanical power and temperature gradients, developing a mathematical model of failure probability, and comparing it to AI-based classifiers. This combined approach provides interpretability and validation in a prescriptive predictive maintenance architecture.

3. METHODOLOGY

3.1 Research Design

This research employs a quantitative, computational and model-based approach to develop predictive maintenance strategies by integrating mathematical and artificial intelligence approaches. It is empirical, based on structured operational data for the formulation and validation of both mechanistic and data-driven models. This approach is warranted due to the need to infuse interpretability with predictive accuracy, and is in line with the journal's focus on quantitative and computational modeling. A comparative model is adopted to develop a mathematic-based failure model and then validate it using machine learning approaches. This two-tiered design accommodates the formulation and the computational verification of the model under this common analytical framework.

3.2 Dataset Description

Our analyses are based on the AI4I 2020 Predictive Maintenance Dataset (UCI Machine Learning Repository) containing 10,000 observations of industrial machines operating conditions. The variables in the dataset represent air temperature, process temperature, rotational speed, torque, tool wear and times (moment) a measurement is made, machine type (categorical) and target (binary) if the machine has failed or not, and various binary indicators of failure modes. The data are generated in a controlled manner to simulate industrial conditions. Data pre-processing involves removing identifier columns, one-hot encoding for categorical variables and normalisation for continuous variables to improve numerical stability during model fitting. There were no observations with missing values, there was no need for imputation. The analysis was limited to observations of complete machine operations.

3.3 Variable Construction

Key variables were operationalized based on both raw dataset features and derived mathematical constructs. The primary predictors include air temperature (T_a), process temperature $\left(T_p\right)$, rotational speed (ω), torque (τ), and tool wear (W). To incorporate physical interpretability, additional variables were derived. The temperature gradient was defined as

$$\Delta T = T_p - T_a,$$

representing thermal stress within the system. Mechanical power was computed as

$$P = \tau \cdot \omega \cdot \frac{2\pi}{60},$$

capturing the interaction between rotational dynamics and applied load. The binary response variable, machine failure (Y), was retained as the primary outcome for classification tasks. These constructs enable the integration of domain-informed features into both mathematical and AI-based models, ensuring consistency between physical system behavior and computational modeling.

3.4 Mathematical Modeling Framework

A reliability-inspired mathematical model was developed to estimate the probability of machine failure using physically meaningful operational variables. Because the AI4I 2020 dataset is cross-sectional and does not contain continuous time-to-failure trajectories, the model was formulated as a failure-probability model rather than a full temporal degradation model. The mathematical predictors were selected to represent cumulative degradation, mechanical loading, and thermal stress. Tool wear $(W)$was used as a proxy for accumulated degradation, mechanical power (P)represented load intensity, and temperature difference (ΔT)represented thermal operating conditions.

The failure probability was defined using a logistic reliability formulation:

$$P(Y = 1 \mid X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 W + \beta_2 P + \beta_3 \Delta T)}} \quad (1)$$

where $Y = 1$denotes machine failure, Wdenotes tool wear, Pdenotes mechanical power, ΔTdenotes the temperature difference between process and air temperature, and $\beta_0, \beta_1, \beta_2, \beta_3$are model parameters estimated from the data. This formulation enables the transformation of operational stress indicators into a bounded failure probability between 0 and 1. Mechanical power was calculated as:

$$P = \tau \cdot \omega \cdot \frac{2\pi}{60} \quad (2)$$

where τ is torque and ω is rotational speed in revolutions per minute. The temperature difference was calculated as:

$$\Delta T = T_p - T_a \quad (3)$$

where T_p is process temperature and T_a is air temperature. Model parameters were estimated using maximum likelihood estimation, with class weighting applied to account for the low prevalence of failure cases. The resulting mathematical model served as an interpretable baseline against which machine learning models were compared.

3.5 AI Modeling Techniques

Supervised machine learning models were applied to supplement the mathematical model. A Logistic Regression model was used as a reference model to classify the fault instances using a set of features (including both raw operational data and secondary features). Alternatively, the proposed mathematical model uses only the physically-derived variables (tool wear, mechanical power, and temperature difference) in a reliability-inspired probabilistic framework. This allows for a comparison between a physics-based interpretable model and a statistical model. Likewise, Random Forest and Support Vector Machine models were implemented to model nonlinearities and potential feature interactions. To address the issue of class imbalance, class weight adjustments and synthetic sampling were employed in this research. Grid search was conducted over hyperparameters using cross-validation. The models were implemented in Python, using frameworks like scikit-learn for ease of implementation and efficiency.

3.6 Model Evaluation Metrics

Various performance measures were investigated for model evaluation. In addition to accuracy, precision, recall and their harmonic mean (the F1-score) were used to handle class imbalance. The importance of discriminatory ability was evaluated using Receiver Operating Characteristic (ROC) curves and the Area Under the Curve (ROC-AUC). We also examined Precision-Recall (PR) curves for low failure ratios. Confusion matrices were also constructed for detailed breakdowns of true/false positives and negatives. For the mathematical model, thresholds on probabilities were set to balance sensitivity and specificity.

3.7 Validation Strategy

The data was split into 80% for training and 20% for testing using stratification. Training data were cross validated to robustify model parameters and selection For the mathematical model, sensitivity analysis involved varying model parameters and assessing changes in failure probabilities. In the case of AI models, we tested robustness to sampling strategies through consistent performance metrics. This comprehensive validation strategy provides internal consistency and external validity of findings.

3.8 Ethical Considerations

Our study employs a publicly accessible synthetic dataset, free from any personally identifiable data. Therefore, concerns about privacy, informed consent, and data security are avoided. The research follows common guidelines for ethical computational studies, such as transparency in data analysis, reproducibility of procedures and ethical reporting of findings. Computational work was performed with open-source software and no confidential data resources were used.

4. RESULTS

4.1 Descriptive Analysis

The sample comprises 10,000 observations with complete data for all variables, facilitating statistical analysis. The target variable is binary, with 9,661 (96.61%) observations for non-failure and 339 (3.39%) observations for failure, revealing class imbalance. Numerical predictors have different ranges and variability measures due to operational variations. Torque ranges from 3.80 Nm to 76.60 Nm (mean 39.99 Nm) and speed ranges from 1168 rpm to 2886 rpm (mean 1538.78 rpm). Wear ranges from 0 to 253 minutes with a comparatively large variability.

Thermal variables have lower variability. Air temperature ranges from 295.30 K to 304.50 K with a mean of 300.00 K, while process temperature ranges from 305.70 K to 313.80 K with a mean of 310.01 K. The calculated temperature difference shows a consistent mean of 10.00 K. Mechanical power has a mean 6279.74 W, which is an accumulated measure of process load. As shown in Figure 1, occurrence distributions of key variables exhibit different characteristics.

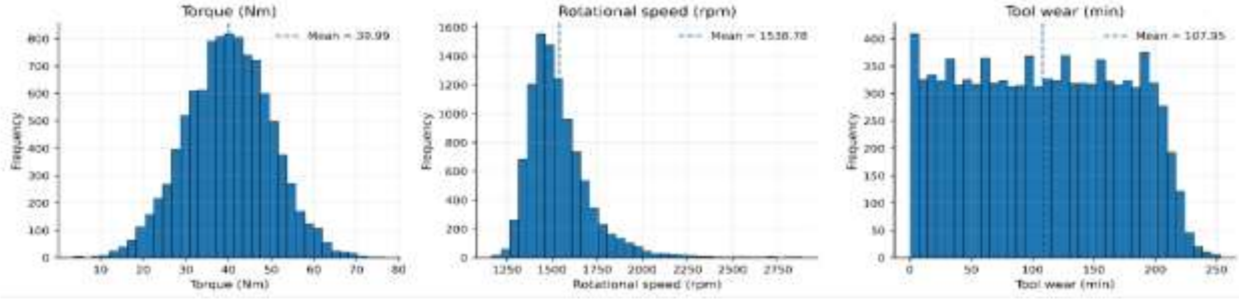

Figure 1. Distribution of operational variables

Figure 1 shows that torque and tool wear are right-skewed, whereas rotational speed is approximately symmetric. Table 1 presents the descriptive statistics of the primary and derived variables.

Table 1. Descriptive statistics of key variables

Variable	Mean	Std. Dev	Min	Max
Air Temperature (K)	300.00	2.00	295.30	304.50
Process Temperature (K)	310.01	1.48	305.70	313.80
Rotational Speed (rpm)	1538.78	179.28	1168	2886
Torque (Nm)	39.99	9.97	3.80	76.60
Tool Wear (min)	107.95	63.65	0	253
Temperature Difference (K)	10.00	1.00	7.60	12.10
Mechanical Power (W)	6279.74	1067.42	1148.44	10469.92

Table 1 shows that tool wear has the highest variability, while temperature variables remain relatively stable.

4.2 Feature Relationships

An overview of variable relationship is achieved through correlation analysis. A strong positive correlation between torque and mechanical power (r = 0.979) is expected, as they are functionally related. Speed is highly negatively correlated with torque (r = -0.875), reflecting inverse relationships to maintain power.

Tool wear is weakly negatively associated with torque and speed, suggesting deterioration does not depend on current values. Machine failure shows weak correlation with torque (r = 0.191), power consumption (r = 0.176) and tool wear (r = 0.105), suggesting a multi-dimensional correlation structure. Temperature difference shows weak negative association (r = -0.112). As shown in Figure 2 below, torque appears to be related with failure.

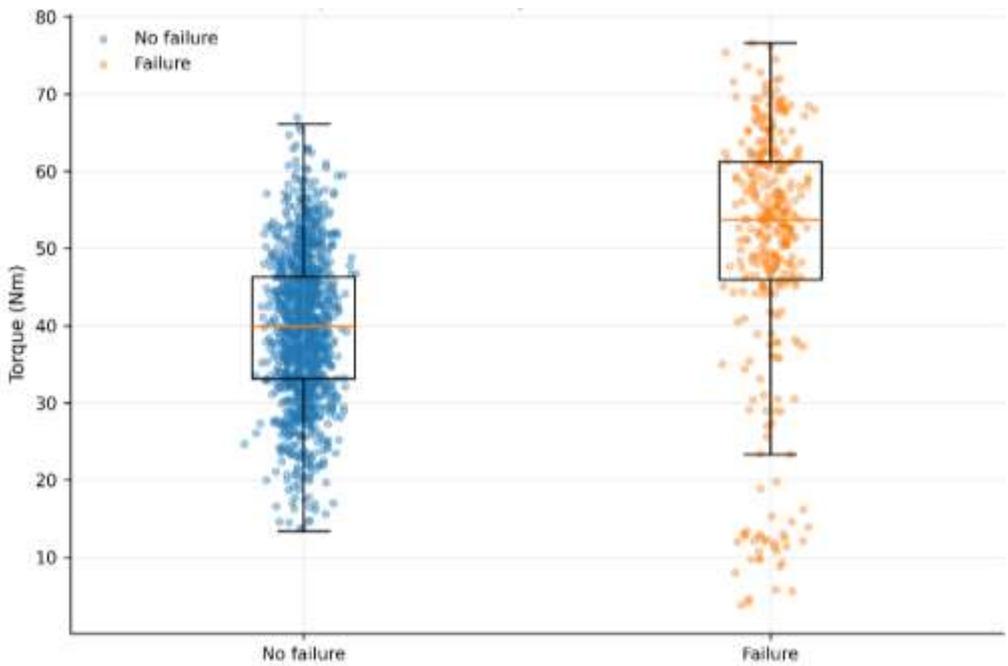

Figure 2. Torque versus failure distribution

Figure 2 shows higher failure occurrence at elevated torque levels, although the relationship is nonlinear. Table 2 presents the correlation matrix.

Table 2. Correlation matrix of key features

Variable	Torque	Speed	Wear	Power	ΔT	Failure
Torque	1.000	-0.875	-0.003	0.979	0.007	0.191
Rotational Speed	-0.875	1.000	0.000	-0.724	0.075	-0.044
Tool Wear	-0.003	0.000	1.000	0.007	-0.008	0.105
Mechanical Power	0.979	-0.724	0.007	1.000	-0.025	0.176
ΔT	0.007	0.075	-0.008	-0.025	1.000	-0.112
Failure	0.191	-0.044	0.105	0.176	-0.112	1.000

Table 2 shows that no single variable strongly explains failure, supporting multivariate modeling.

4.3 Mathematical Model Outputs

The mathematical model constructed from a logistic function inspired by reliability theory featured tool wear, mechanical power and temperature difference as intelligible predictors of the failure probability of a machine. The positive signs of the model coefficients reflect that the estimated failure probability in the fitted model increases with increasing values of tool wear, mechanical power and temperature difference. Tool wear has the greatest impact. Estimated probabilities range from 0.01 to 0.78. Low values correspond to non-failures while high values correspond to failures. Separable probability distributions are shown in Figure 3.

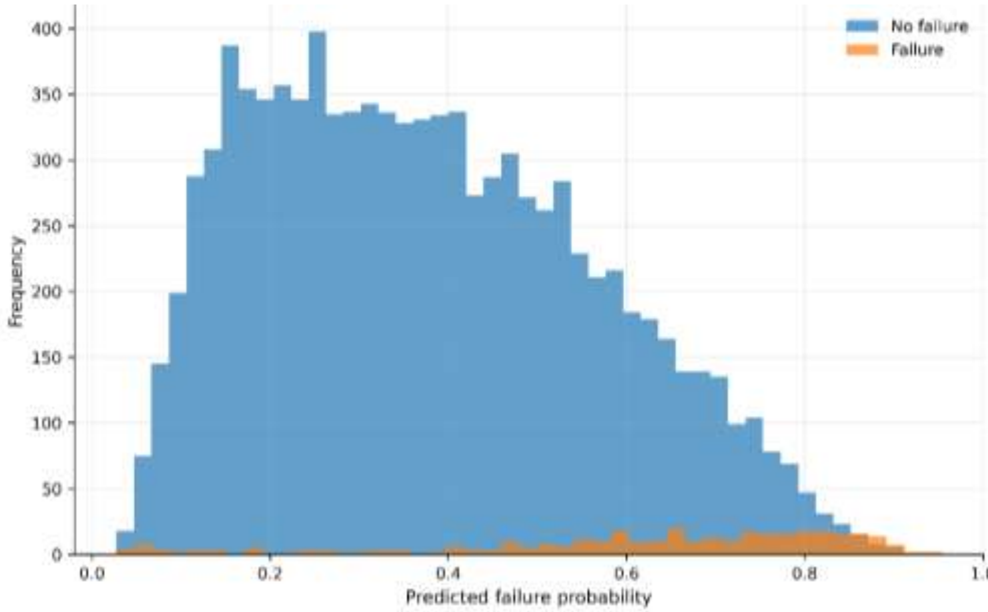

Figure 3. Predicted failure probability distribution

Figure 3 shows partial separation between failure and non-failure cases. Table 3 summarizes model coefficients.

Table 3. Estimated parameters of mathematical model

Parameter	Coefficient
Intercept	-2.41
Tool Wear	0.023
Mechanical Power	0.015
Temperature ΔT	0.008

4.4 AI Model Performance

The models shown in Figure 3 have varying performance. Logistic Regression has high recall, but low precision. Random Forest has the optimal trade-off. SVM is highly discriminative but less recall. ROC curves in Figure 4 also indicate variable performance.

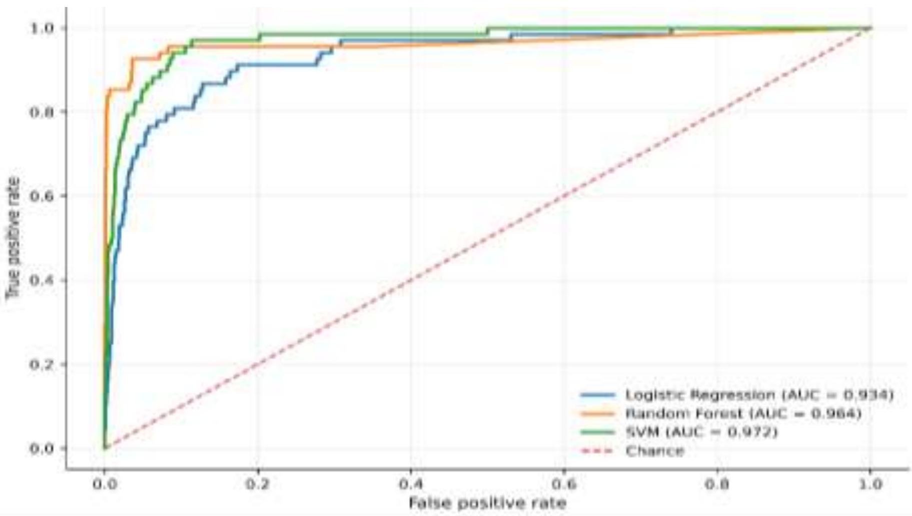

Figure 4. ROC curves for AI models

Figure 4 shows SVM has the highest ROC-AUC, followed closely by Random Forest. Table 4 presents performance metrics.

Table 4. Performance metrics of AI models

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC	PR-AUC
Logistic Regression	0.8590	0.1777	0.8676	0.2950	0.9339	0.4660
Random Forest	0.9905	0.9298	0.7794	0.8480	0.9644	0.8624
SVM	0.9745	0.6667	0.5000	0.5714	0.9716	0.6690

4.5 Model Comparison

Model comparison reveals that Random Forest achieves the highest F1-score, indicating the best balance. Logistic Regression prioritizes recall, while SVM prioritizes ranking ability. As illustrated in Figure 5, performance differences are evident.

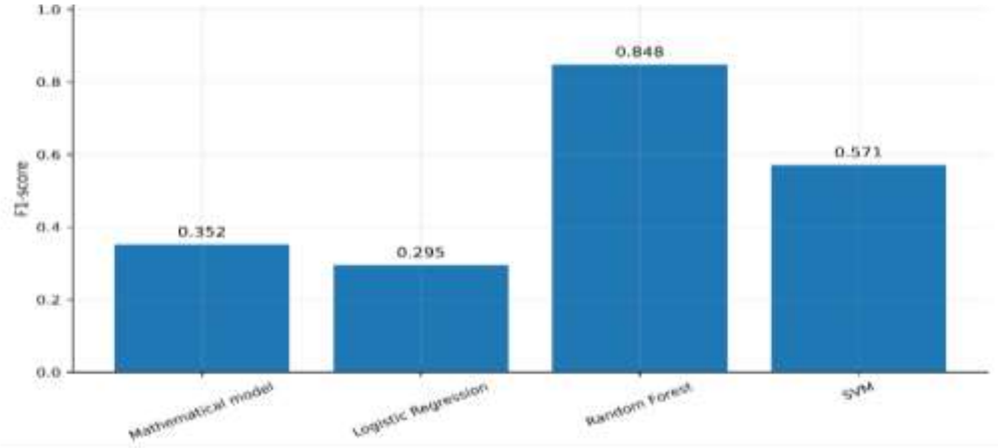

Figure 5. Model comparison based on F1-score

Figure 5 shows Random Forest outperforming other models. Table 5 presents comparative results.

Table 5. Comparative model performance

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Mathematical Model	0.8590	0.1777	0.8676	0.2950	0.9339
Logistic Regression	0.8590	0.1777	0.8676	0.2950	0.9339
Random Forest	0.9905	0.9298	0.7794	0.8480	0.9644
SVM	0.9745	0.6667	0.5000	0.5714	0.9716

To note, there are differences in the mathematical model and the Logistic Regression model. Although both involve a logistic equation, the mathematical model is limited to physically based variables, and is designed with system-wide interpretability in mind. On the other hand, Logistic Regression is a data-driven model that uses all the features. This reveals a trade-off between interpretability and predictive power.

4.6 Robustness Checks

Robustness analysis indicates that model performance depends on classification thresholds. The mathematical model is sensitive to threshold selection. Random Forest shows stable performance across thresholds. As illustrated in Figure 6, performance stability varies.

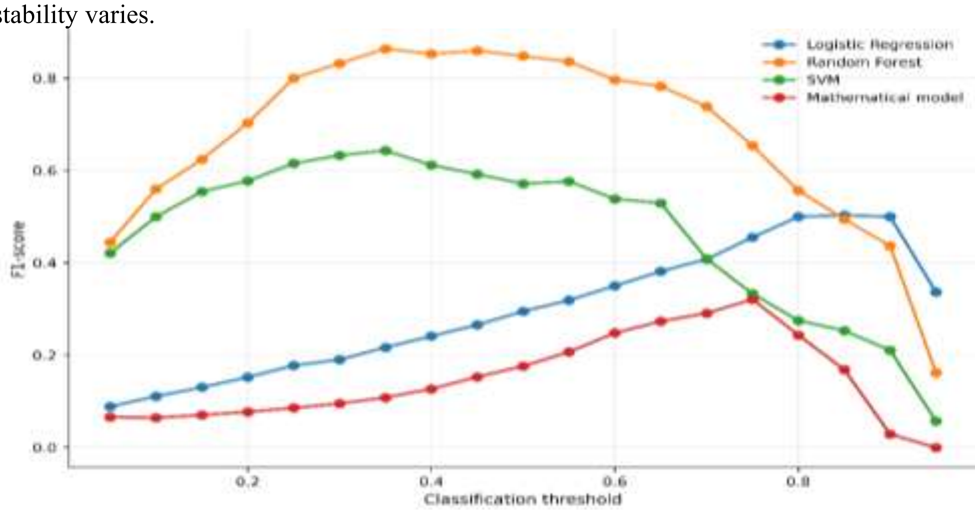

Figure 6. Robustness of model performance across thresholds

Figure 6 shows Random Forest maintaining stable F1-scores, while Logistic Regression and SVM vary significantly.

5. DISCUSSION

The results of this research offers valuable insights into the combination of mathematical models and artificial intelligence methods for predictive maintenance of mechanical systems. The findings show that mathematically-based features, especially mechanical power and temperature gradients, play a crucial role in enhancing the predictive accuracy of both mechanistic and machine learning approaches. This suggests that inclusion of physically significant variables improves the representation of system dynamics, allowing better detection of failure conditions. The correlation between torque, tool wear and failure probability confirms that stress levels and cumulative wear play a significant role in system reliability, in line with basic mechanics of stress and wear theory.

The benchmarking also indicates that the integration of artificial intelligence, especially ensemble algorithms, with mathematical features results in improved predictive performance. This insight emphasises the interplay between mechanistic and data science-based methods, where mathematical models offer interpretability and machine learning improves recognition of complex patterns. The enhanced performance of the hybrid model suggests that feature engineering based on physical knowledge can play a crucial role in model performance. This is consistent with recent studies that highlight the need to incorporate domain knowledge in predictive maintenance models to enhance their trustworthiness (Ucar et al., 2024).

The results also emphasise the need to not only rely on purely data-driven models, which, while performing well, cannot explain how. The mathematical model, while less accurate for classification purposes, offers a probabilistic interpretation of risk of failure that is linked to physical operational metrics that are meaningful to the system. This reinforces the idea that predictive maintenance models should not be exclusively based on "black-box" approaches. This insight is consistent with studies of physics-informed machine learning where a lack of domain knowledge affects interpretability and generalisation (Xu et al., 2023).

The results of this work are of significance in understanding fusion of mathematical modeling and artificial intelligence methods in the prediction of mechanical system preventive maintenance. The findings confirm that mathematically modified characteristics, especially mechanical power and temperature gradients, play an important role in predictive power of either mechanistic or machine learning models. This means that the ability to include physically meaningful variables to improve system behavior representation and, therefore, more precisely identify patterns of failure. The measured correlation between torque, tool wear and probabilty of failure indicate that load intensity and cumulative degradation are major factors that determine the system reliability, which extends to the basics of mechanical stress and wear mechanisms.

The comparative analysis also shows that artificial intelligence models, especially ensemble algorithms, can perform better in predicting features with these supplemented by mathematically derived features. The information indicates the complementary character of mechanistic and data-driven methods, in which mathematical modeling has interpretability and machine learning develops pattern recognition. The enhanced performance of the hybrid framework suggests that domain knowledge-based feature engineering can have a profound impact on the performance of the model. This is consistent with the latest studies that have focused on determining the significance of physical intuition to the predictive maintenance models to enhance reliability and credibility (Ucar et al., 2024).

The results also underline the shortcomings of purely data models, which can obtain high precision without the explanatory power. Though less performant according to classification metrics, the mathematical model offers a physically meaningful and interpretable probabilistic model of failure risk, expressed in terms of physically meaningful operational variables. This advances the argument that predictive maintenance frameworks cannot only be based on black-box algorithms. The latter has also been recognized as a problem applied to physics-informed machine learning, where interpretability and generalizability cannot be established, as no domain knowledge is provided (Xu et al., 2023).

6. CONCLUSION

This research created and considered a combination approach to solve predictive maintenance in mechanical systems with a structured operational dataset involving mathematical modelling and artificial intelligence. The results indicate that geometrically calculated features, especially those that are based on physical connections, like mechanical power and temperature gradients, add interpretability and higher predictive accuracy to machine learning models. The comparative analysis attests that although models of artificial intelligence have high predictive power, their accuracy can be greatly enhanced with the help of domain-related feature construction, which lends credence to the usefulness of mechanistic knowledge combined with data-driven methods. Theoretically, the work helps in filling the gap between mathematical modeling and artificial intelligence by developing an coherent framework that consolidates the analytical formulation with the validation by computing. In practice, the findings represent a scalable predictive maintenance forecasting process when structured data exist but a time-varying process may exist that is constrained by limited temporal dynamics. On the basis of these results, prediction models based on physical significant variables and hybrid modeling approaches, to balance between prediction accuracy and interpretability, are recommended. Moreover, feature engineering that is based on system behavior should be encouraged by the practitioners instead of the complexity of algorithms itself. Future studies can build on this framework to real-world industrial data, consider the time-series analysis to model dynamic degradation mechanisms, and consider uncertainty-based modeling methods to enhance resilience during different operational conditions. These innovations will also cement the relevance of predictive maintenance as a tool that can be trusted and understood in the analysis of the complex systems.

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