Machine Learning for Predictive Maintenance of Industrial Machines

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Abstract: This work presents a novel approach to constructing a predictive model using machine learning techniques for the early identification of machine faults for industrial maintenance purposes. The topic is justified by the importance of predictive maintenance in increasing operational efficiency, reducing costs, and improving the reliability of industrial equipment. The early identification of failures makes it possible to carry out preventive interventions, avoiding negative consequences and optimizing the use of industrial resources. Traditional maintenance techniques, such as corrective and preventive maintenance based on fixed intervals, cannot adequately predict unexpected events that could lead to equipment failure. The main objective is to develop and validate a predictive model capable of detecting patterns that indicate possible failures in industrial machinery before they occur. To this end, a hybrid algorithm combining fuzzy logic and machine learning will be applied compared to three traditional models widely used in the literature. The study includes a comparative analysis of the results obtained, evaluating the performance, accuracy, and effectiveness of each model. The advantages and limitations of the developed model will also be discussed, as well as suggestions for future research to improve predictive systems in the sector continuously. This article is divided into sections, starting with the introduction, with a general contextualization of the problem, the arguments, the justifications, the objective, and the structure of the work. The following section presents research into related work. Then the methodology used to develop the fault prediction and identification models will be presented, followed by the experimental results, and finally the conclusions.

Keywords: Machine learning. Predictive modeling. Fault identification. Decision making.

1. Introduction

Industrial maintenance is a critical activity for ensuring the efficiency, safety, and productivity of production processes in various economic sectors. Unexpected failures in machinery and equipment can result in unplanned downtime, compromising operational continuity, significantly increasing maintenance costs, and reducing equipment lifespan. In this context, the ability to identify these failures in advance becomes an important competitive advantage for companies. There are a variety of machine learning predictive models, and some hybrids, found in the literature. However, these traditional models need to be retrained when there is a significant change in the pattern of information. Combined with the fact that in industries, due to cybersecurity concerns, there are significant restrictions on the connection between automation devices and external networks, real-time monitoring becomes a significant challenge. Hybrid fuzzy models have been applied in industry in additive manufacturing and cybersecurity processes.

Early identification of failures enables preventive interventions, avoiding negative consequences and optimizing the use of industrial resources. Traditional maintenance techniques, such as corrective and preventive maintenance based on fixed intervals, are insufficient to adequately predict unexpected events that can lead to equipment failure. Therefore, the need for predictive maintenance arises, which uses advanced techniques to predict failures based on continuous analysis of the condition of machinery and equipment. Among the most effective techniques for this purpose are predictive models based on machine learning. These models are capable of learning complex patterns from operational data collected in real time, thus enabling accurate prediction of the conditions that precede failure.

The model that integrates Three-Way Decision (3WD) theory in Pythagorean Fuzzy environments excels in modern scenarios that require flexibility and behavioral realism, applying the concept of cognitive computing to emulate human behavior for decision-making under uncertainty.

The main objective of this paper is to develop a predictive model for machine maintenance failure identification that integrates 3WD theory within Pythagorean Fuzzy environments, leveraging cognitive computing principles to emulate human decision-making under uncertainty and thus deliver the flexibility and behavioral realism required by modern industrial scenarios. This paper is organized as follows: Section 2 presents the related work. Section 3 explains the design of the methodology for predicting and identifying failures. Section 4 presents experimental results. The conclusions section closes the paper.

2. Related Work

A systematized literature review was carried out to gather empirical evidence from studies related to this article. The search was conducted in March 2025 to identify relevant research addressing works using 3WD for industrial applications in academic portals such as Google Scholar, IEEE Xplore, and Research Gate. The keyword "Three-Way Decision-Making" was used without filters. Initially, 6,509 references were retrieved. After applying the inclusion criteria (titles related to the research scope) and exclusion criteria (duplicate works), 229 references were selected. In the eligibility phase, titles and abstracts of articles, dissertations, and book chapters were screened to identify those related to industrial applications. Nine related works were identified: three on material selection for additive manufacturing [1], [2], [3], one on aviation equipment [4], three on anomalies and threats in industrial networks [5], [6], [7], and one on air quality monitoring [8]. One of these studies [9] was read in full, and its concepts were incorporated into this article. The articles evaluated but not used presented sophisticated approaches to integrating 3WD fuzzy and advanced algorithms, but for specific applications, being adaptable to related problems of material selection and malware detection. The model chosen for further study presented a more transparent and precise structural and mathematical approach to problems with an uncertain context.

2.1. Three-Way Decision Models with Pythagorean Fuzzy Loss Functions

Using the theory of 3WD and previous studies, an improved decision-making model was developed to improve the accuracy of loss functions. Using real-value loss functions, the 3WD model in Pythagorean Fuzzy information systems aimed to classify regions of positive acceptance, negative acceptance, and hesitation as a differential in the third dimension. The advantages of 3WD fuzzy models over purely statistical approaches are the reduction of unnecessary calculations [10], the ability to deal with multiple decision-makers [10], a solid theoretical foundation [11], and cognitive advantages [12]. The main components of this model are the Pythagorean Fuzzy information system, the fundamental value loss functions, and the expected losses [9].

The structure of the information system is defined as:

$$S = (U, A, V_{PF}, f) \qquad (1)$$

Where U is the set of objects, A is the set of attributes, V_{PF} represents the Pythagorean Fuzzy values used to describe the attributes, and f is the function that associates each object with a Pythagorean Fuzzy value. In Pythagorean Fuzzy numbers, each object $u \in U$ is assigned as:

$$W(u) = l(l_{W(u)}, v_{W(u)}) \qquad (2)$$

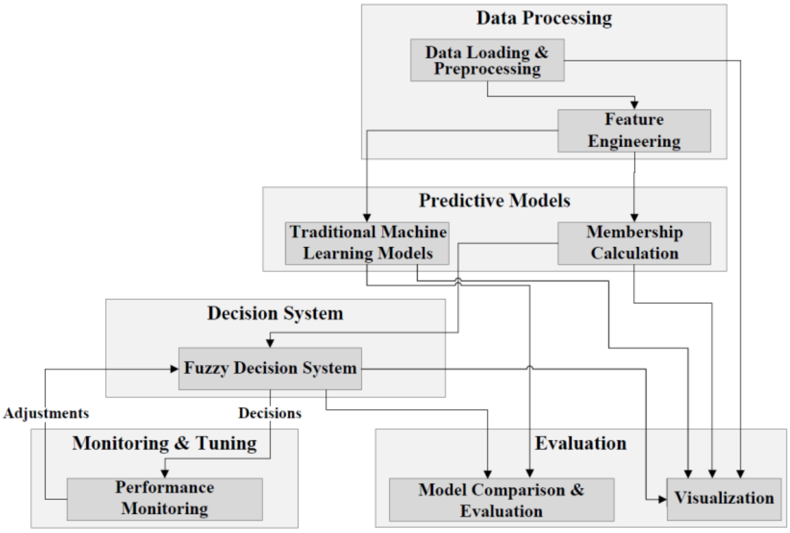
Where $l_{W(u)}$ is the aggregate degree of pertinence and $v_{W(u)}$ is the aggregate degree of non-pertinence. The degree of hesitation is:

$$\pi_{W(u)} = \sqrt{1 - l^2 + v^2} \qquad (3)$$

3. Methodology

Based on a concept presented in an article identified during the systematized review, a model was developed using the 3WD approach [9]. This concept involves a decision-making process considering three possible outcomes, which is particularly useful in our context. A synthetic dataset simulating machine telemetry [13], available online, was used to test the proposed model. The model was evaluated to check its viability in predicting anomalies based on signals from sensors connected to the machines using model efficiency indicators. It was then compared with traditional machine learning models using the same database. Finally, the results and discussions of the study were presented before the final considerations. The stages for the experiment were pre-processing for filtering, normalization, and selection of the variables derived from the database, modeling, training, validation, and comparison of the model, as shown in the diagram in Figure 1. This model actively monitors the decisions made and, through feedback from the results, feeds back the parameters to redefine the losses, engaging the readers in its operation. Three traditional machine learning models were also trained, validated, and evaluated for comparison with the decision model.

Figure 1. The predictive model for identifying machine failures for maintenance using machine learning.



The code was implemented using the theoretical 3WD concepts with Pythagorean Fuzzy numbers:

a. Pythagorean Fuzzy information system, with the equations (1), (2), and (3);
b. Loss functions with Pythagorean Fuzzy values, with losses represented as pairs $(\boldsymbol{l}, \boldsymbol{v})$;
c. Calculation of expected combination losses via Pythagorean Fuzzy operations;
d. Integration of hesitation $(\boldsymbol{\pi})$;
e. Three decision strategies $(\boldsymbol{s_1}, \boldsymbol{s_2}, \boldsymbol{s_3})$, for choosing between $\{\boldsymbol{a_P}, \boldsymbol{a_B}, \boldsymbol{a_N}\}$.

3.1 Predictive Model

Three algorithms based on the gradient boosting – recommended for continuous monitoring of imbalanced data in industrial fault prediction - were designed. The parameters of each machine learning model were adjusted to the features of the dataset, ensuring the minimization of false positives and negatives, reducing losses, optimizing performance, balancing speed and accuracy, and controlling stall and depth levels. The algorithms are XGBoost [14], LightGBM [15], and CatBoost [16]. Each algorithm has unique strengths that cater to different data types and needs.

3.2 Decision System

The fuzzy system algorithm was developed to combine the diverse perspectives of three experts, with inputs being the relevance values μ, $\boldsymbol{v}$, $\boldsymbol{\pi}$, and sensor data. Actions were defined as $\boldsymbol{a_P}$ for preventive, $\boldsymbol{a_B}$ for basic acceptance, and $\boldsymbol{a_N}$ for no action, reflecting the different viewpoints involved. Pythagorean Fuzzy numbers were used to calculate losses, which were then aggregated using weights assigned to the experts. The decision strategies were: $\boldsymbol{s_1}$, a conservative one that minimizes $\boldsymbol{v} - \mu$; $\boldsymbol{s_2}$, a moderate one which minimizes $\boldsymbol{\pi}$, which represents hesitation one, and $\boldsymbol{s_3}$, a dynamic one based on SHAP, which triggers $\boldsymbol{a_N}$ if $\boldsymbol{\pi > 0.7}$.

3.3 Monitoring and Optimization

The Optuna framework, a set of libraries designed explicitly for machine learning, was used to determine the optimal parameters for the fuzzy model in effective fault detection. The Matthews Coefficient (MCC) was used as the optimization metric. The optimization process consisted of generating initial parameters, configuring the decision model, evaluating temporal data, calculating the MCC, updating, and returning to the model configuration stage for 50 iterations to select the best parameters for the final result.

4. Experimental Results

This section presents the experiments with detailed explanations and valuable insights. We used the following execution environment:

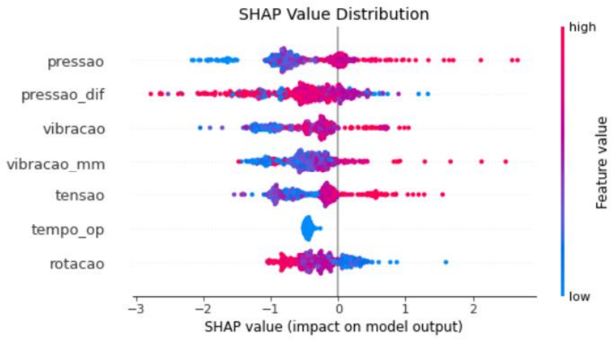
[System 1] Execution environment with 1 GPU. Comprises two Intel Xeons at 2.26 GHz and 24 GB DDR3 main memory. Each one is a quad-core processor with 12 MB of cache memory. It contains two NVIDIA Tesla C2050 GPUs, each with 14 Stream Multiprocessors (SM) and 32 Stream Processors (SP), totaling 448 cores.

In our experiments, we use a version of the proposed model, developed in Python using the Spyder IDE (Integrated Development Environment), which was designed with a robust feedback mechanism.

In the data evaluation phase, we found no null or infinite values, indicating a sound processing of the dataset, and we normalized the variables tension, rotation, pressure, vibration, age, and time_op. We identified 162 outliers, which may have come from real anomalies. Additionally, we found twelve outliers in binary_fault, confirming class imbalance.

In Figure 2, SHAP (SHapley Additive exPlanations) demonstrates the impact of each variable on the model output. The features are listed on the Y-axis on the left, in descending order of impact: *pressure,pressure_dif*, *tension*, *vibration*, *vibration_mm*, *time_op*, and *rotation*. The red features on the right side of the graph indicate that they help increase the prediction, while the blue features on the left side reduce it. The high-pressure values increase the output of the model - a positive SHAP contribution - while low values reduce it. The other features also have an impact, the intensity of which can be verified by the value and its associated color.

Figure 2. SHAP value distribution.



The fuzzy contribution was assessed according to the following indicators:

a. The pertinence impact of 99.17%, calculated as:

$$\boldsymbol{mu_{impact}} = \boldsymbol{mu \cdot class_{weights}[a_P]} \tag{4}$$

This indicator influences the decision to take preventive action ($\boldsymbol{a_P}$). The higher it is, the greater the risk detected and the higher the cost of preventive action;

b. The risk analysis indicator, calculated as:

$$\boldsymbol{nu_{impact}} = \boldsymbol{nu \cdot class_{weights}[a_B]} \tag{5}$$

It denotes confidence in the absence of failure and its impact on backup decision-making ($\boldsymbol{a_B}$). The higher the *nu_impact*, the lower the risk detected, and the less prioritized the action;

c. The impact of hesitation of 0.83% - which represents the degree of uncertainty – calculated as:

$$\boldsymbol{pi_{impact}} = \boldsymbol{\sqrt{1 - mu^2 - nu^2}} \tag{6}$$

As a conclusion of the contribution assessment, decision-making prioritized preventive action due to the high $\boldsymbol{mu_{impact}}$. In the context of Pythagorean Fuzzy logic, the three components $\boldsymbol{mu}$, $\boldsymbol{nu}$, and $\boldsymbol{pi}$ adhere to a specific constraint, ensuring a meticulous balance of impacts and comprehensively reflecting the nature of the three dimensions in the decision:

$$\boldsymbol{mu^2 + nu^2 + pi^2 = 1} \tag{7}$$

Table 1. Comparison between models.

Models	F1-Score	AUC-ROC
XGBoost	0.0579	0.7923
LightGBM	0.0015	0.6814
CatBoost	0.1689	0.7396
Fuzzy	0.3414	0.8798

XGBoost is an optimized algorithm for structured data and classification/regression problems. LightGBM is focused on computational efficiency and large volumes of data. CatBoost, however, excels in handling categorical data. The summary of the models evaluated is in Table 2.

Table 2. Summary of model results.

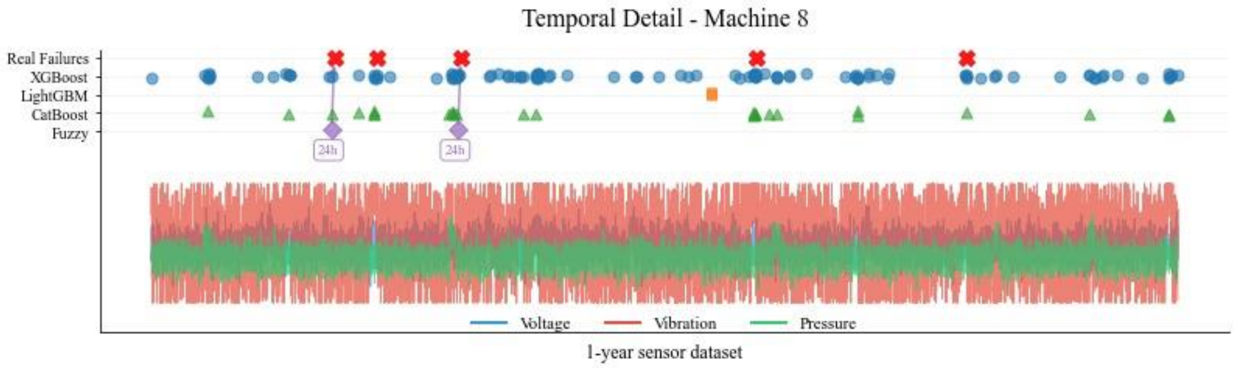
Models	Features	Limitations	Ideal Usage Scenario
Fuzzy	Best AUC	Low F1 in critical applications	Preventive maintenance
CatBoost	Best F1 between traditional	AUC lower than Fuzzy	When balanced precision/recall is critical
LightGBM	-	Poor overall performance	Not recommended for this problem
XGBoost	Medium-high AUC	F1 too low	When false negatives are tolerable

Fuzzy is the model developed based on logic, which deals with uncertainty and interpretable rules. With a high AUC-ROC, it performed well in ordering risks. However, its low F1-score indicated difficulties in correctly classifying borderline cases, which depend on the balance between precision and recall.

Figure 3 illustrates the predictions of each model in comparison with the actual faults of one machine. The purple diamonds represent the faults predicted by the fuzzy model. The numbers below the two occurrences indicate the elapsed hours between the prediction and the occurrence of the real fault, showcasing the models' predictive accuracy.

As practical results, the evaluation of the dataset containing sensor information from 100 machines over one year yielded 40% accuracy in predicting failures, indicating the conservative alerting behavior of the model. Of the alerts generated, 27.8% effectively predicted failures more than one hour in advance. The average time to early detection was 24.15 hours. The recall rate of 31.9% underscores the urgency of improving the model, as it reveals significant room for enhancement through refining the rules or incorporating new variables.

Figure 3. Actual failures versus predicted failures by models.



5. Conclusions

In conclusion, our proposed predictive model - anchored in three-way decision theory and implemented within a Pythagorean Fuzzy framework - achieved an AUC-ROC of 0.88, demonstrating superior risk-ranking capability by accurately prioritizing machines with the highest likelihood of failure. The model reliably detected subtle anomalies in pressure and vibration readings and complex non-linear sensor interactions, outperforming benchmark algorithms such as LightGBM and CatBoost. Its robustness to noisy or incomplete data further distinguishes it. At the same time, its inherently interpretable decision rules offer transparent failure-prediction criteria - an advantage that conventional models cannot match.

Moreover, our real-time self-tuning mechanism effectively reduced false alarms following peak events, and the higher standard deviation of the model in terms of AUC-ROC across cross-validation folds attests to its resilience against overfitting. From an operational standpoint, the fuzzy approach also facilitated more nuanced cost-weighting strategies, contributing to maintenance expense reduction.

However, we acknowledge certain limitations: classification ambiguity arises for cases near decision-boundary thresholds - reflected in an F1 score of 0.34 - which may constrain applicability in safety-critical contexts. Additionally, inference throughput under continuous streaming remains suboptimal, and the model depends on external preprocessing for feature engineering, manual weight calibration, and adaptation to shifting data distributions.

Overall, when the primary objective is to rank equipment by failure risk, our fuzzy decision-theoretic model provides a compelling balance of predictive performance, interpretability, and cost efficiency. Future work will focus on tests with other datasets with a larger volume of data, improving boundary discrimination using optimization algorithms or techniques such as fuzzy clustering, automating the adaptation of features and weights with automatic attribute selection algorithms or meta-learning, and improving real-time inference for large data streams with autoencoders.

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