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AN APPLIED MACHINE LEARNING STRATEGY FOR PREDICTIVE ANALYTICS IN MULTI-SENSOR INDUSTRIAL SYSTEMS

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Abstract

Predictive maintenance in industrial environments increasingly relies on machine learning models capable of interpreting multi-sensor data to anticipate equipment failures before breakdown. In this study, a controlled benchmark is developed to examine how standard supervised learning algorithms perform when applied to synthetic industrial sensor data simulating real operational degradation. The dataset includes twelve features spanning thermal, mechanical, lubrication, electrical, and environmental measurements to represent system health, with failure labels reflecting a deliberate imbalance to stress-test learner behavior. Logistic Regression, Random Forest, Gradient Boosting, SVM (RBF), KNN, and a shallow Multilayer Perceptron are evaluated using precision, recall, F1-score, and ROC/PR curves to reflect the asymmetry of industrial risk across classes. Results indicate that Random Forest and Logistic Regression achieve the most balanced predictive performance, while high recall values in other models are partially attributable to the failure-dominant class structure rather than deeper discriminative insight. The benchmarking, therefore, highlights both the feasibility and limitations of deploying off-the-shelf ML tools for predictive maintenance, demonstrating that data structure, class imbalance, and feature interactions exert as much influence on outcomes as model selection itself. These findings underline the need for calibrated decision thresholds, cost-sensitive evaluation, and integration with real maintenance histories before field deployment is feasible.

INTRODUCTION

Industrial systems are increasingly instrumented with heterogeneous sensors that continuously monitor vibration, temperature, pressure, current, and other operational variables. This shift from sparse inspections to dense data streams has made predictive maintenance (PdM) a central theme in modern asset management, promising reductions in unplanned downtime, improved safety, and more efficient use of maintenance resources. Traditional maintenance strategies run-to-failure, and time-based preventive maintenance are now widely

recognized as either too reactive or too conservative, especially for capital-intensive machinery operating under variable loads and regimes. In this context, applying machine learning (ML) to multi-sensor data for early failure prediction has become a natural extension of condition monitoring and prognostics. Foundational work on condition-based maintenance (CBM) established the conceptual pipeline from data acquisition through diagnostics and prognostics to maintenance decision-making. Jardine et al. (2006) reviewed machinery diagnostics and prognostics within CBM and highlighted that effective maintenance depends on integrating sensing, signal processing, and decision rules rather than focusing on any single component in isolation. Subsequent reviews on prognostics for rotating machinery emphasized remaining useful life (RUL) estimation and probabilistic forecasting as key enablers of proactive maintenance policies (Heng et al., 2009). Parallel work on CBM decision-making showed how optimization and cost models are needed to translate health indicators into actionable maintenance schedules, underscoring that prediction quality must be evaluated in terms of operational impact rather than accuracy alone.

These early contributions positioned CBM and prognostics as comprehensive frameworks that couple data-driven condition assessment with economic decision support. As sensor networks, storage, and computation became cheaper, data-driven and machine-learning-based PdM methods gained prominence. Early applications in semiconductor manufacturing and other high-tech industries demonstrated that multi-variable process data could be used to detect degradation patterns that were not easily captured by handcrafted rules. Susto et al. (2015), for example, proposed a multiple-classifier ML methodology for PdM that explicitly addressed issues of class imbalance and maintenance cost trade-offs in semiconductor tools. Their work showed that ensembles of classifiers with different prediction horizons could be combined into a cost-aware decision system, moving beyond simple "fault/no-fault" detection to economically meaningful maintenance recommendations. Related studies on predictive maintenance systems for integral-type faults using support vector machines further illustrated the potential of supervised learning for fault prediction in complex manufacturing processes. Despite these advances, much of the pre-2016 literature exhibits three recurring limitations that motivate the present work. First, many studies are highly domain-specific, focusing on a single asset type (e.g., a particular tool, motor, or production line) with bespoke feature engineering and model design. This makes it difficult to generalize insights across industrial contexts or to understand how standard ML models behave on generic multi-sensor setups. Second, a large body of work emphasizes RUL regression or specific prognostic indicators, whereas classification-based failure prediction in heavily skewed datasets is less systematically explored, even though real maintenance logs frequently exhibit strong class imbalance. Third, while prior work recognizes the importance of model choice, comparatively few studies provide systematic benchmarking of multiple off-the-shelf ML algorithms, including logistic regression, tree ensembles, kernel methods, instance-based learning, and shallow neural networks under a unified experimental protocol on the same multi-sensor problem. This paper, titled "An Applied Machine Learning Strategy for Predictive Analytics in Multi-Sensor Industrial Systems," addresses these gaps by constructing a controlled, multi-sensor industrial failure prediction scenario and performing a structured comparison of standard ML models. Rather than claiming to present a fully deployed industrial solution, we adopt a deliberately applied yet methodological perspective. A synthetic but physically plausible dataset is generated to emulate multi-sensor measurements from industrial equipment, including temperature, vibration, pressure, current, rotational speed, humidity, oil quality, and energy consumption. Within this environment, six widely used supervised learning algorithms—logistic regression, random forest, gradient boosting, support vector machine with RBF kernel, k-nearest neighbours, and a shallow

multilayer perceptron are benchmarked using accuracy, precision, recall, F1-score, ROC AUC, confusion matrices, and feature importance analysis. The contributions of this work are threefold. First, it provides a transparent, reproducible ML benchmarking framework for failure prediction in multi-sensor industrial systems, explicitly exposing how model behaviour is shaped by class imbalance and feature structure. Second, it offers a sensor-level interpretation of model decisions via feature importance and probability distributions, clarifying which variables drive predictions in this synthetic environment and how aggressively the models trade off false alarms against missed failures. Third, it positions the results within the broader CBM and PdM literature by highlighting where classical assumptions (balanced data, clear separation between normal and faulty states, richly observed maintenance cycles) diverge from the stressed, failure-dense scenario studied here. In doing so, the paper aims not to claim superiority of any single model, but to illustrate the strengths and limitations of standard ML strategies when applied to multi-sensor industrial data under realistic constraints.

Literature Review

Early research in machinery maintenance established the foundations of condition-based maintenance (CBM) and prognostics well before machine learning became mainstream. Jardine, Lin, and Banjevic (2006) provided one of the most influential reviews on machinery diagnostics and prognostics, framing CBM as a pipeline from data acquisition and feature extraction through health assessment and maintenance decision-making. They emphasized that successful CBM requires not just fault detection, but integrated models for remaining life estimation and decision support, and surveyed both model-based and data-driven approaches for mechanical systems.

Building on this, Heng et al. (2009) reviewed rotating machinery prognostics and synthesized work on statistical models, state-space formulations, and data-driven algorithms for predicting future condition under variable loads and speeds. They highlighted challenges such as non-stationary operating conditions, incomplete degradation data, and the difficulty of validating prognostic models in real industrial environments. These early reviews made it clear that industrial machinery health prediction is intrinsically multivariate and dynamic, and that purely physics-based models are often insufficient when systems are complex or poorly instrumented.

Subsequent work focused more explicitly on prognostic modeling techniques within CBM frameworks. Hernandez (2014) surveyed techniques for prognostics in condition-based maintenance, categorizing approaches into physics-based, data-driven, and hybrid methods and stressing that data-driven techniques become dominant when accurate physical models are unavailable or too expensive to develop. These studies collectively established a conceptual trajectory: from threshold-based alarms, to statistical reliability models, to fully data-driven prognostics that learn degradation patterns directly from sensor streams.

Within this trajectory, machine learning for predictive maintenance (PdM) emerged as a natural evolution. A key contribution is the work of Susto et al. (2015), who proposed a multiple-classifier ML methodology for predictive maintenance in semiconductor manufacturing. Their framework combines several classifiers and explicitly links "health factors" derived from process data to maintenance costs and failure risk, enabling dynamic maintenance decision rules rather than static time-based policies. This paper is important for two reasons: it treats PdM as a full decision problem rather than a pure classification exercise, and it confronts practical issues like high-dimensional data and censored observations, which are common in industrial environments.

Other pre-2016 studies applied specific machine learning models such as support vector machines, neural networks, and ensemble methods to fault detection and RUL estimation in rotating machinery, turbines, or manufacturing equipment. However, these works are typically narrow in scope, focusing on a single asset type, a single plant, or a single fault mode. They often

rely on custom feature engineering pipelines and domain-specific heuristics that limit the transferability of their findings to different industrial systems. Moreover, many of these studies optimize and report results for one preferred algorithm, offering limited insight into how alternative standard models (e.g., logistic regression vs. tree ensembles vs. kernel methods) compare under a shared experimental protocol.

A second limitation of the pre-2016 literature is that dataset characteristics are rarely scrutinized as aggressively as model architecture. Issues such as class imbalance, bias toward certain operating regimes, and limited representation of healthy vs. degraded states are often acknowledged but not systematically explored. As a result, very high reported accuracies sometimes reflect a favourable data structure rather than genuinely robust predictive capability. This is particularly problematic for industrial systems where failure events are rare and where the cost of false positives and false negatives is highly asymmetric.

Finally, while multi-sensor data are widely mentioned, especially for rotating machinery and complex production lines, relatively few works explicitly position their contributions as strategies for multi-sensor industrial systems under realistic constraints. Most case studies rely on proprietary datasets, making independent replication difficult, and do not provide a transparent comparison of multiple off-the-shelf algorithms on the same multi-sensor problem. Against this backdrop, your study occupies a specific niche: it does not claim to introduce a novel algorithm, but instead benchmarks a spectrum of standard supervised learning models, logistic regression, tree ensembles, kernel SVM, K-NN, and an MLP on a controlled multi-sensor industrial failure prediction scenario. By working in a synthetic but physically plausible setting, and by exposing the effects of class imbalance and feature structure on model behaviour, the paper extends the PdM literature in a different direction: from "one-off model proposals" toward transparent, comparative evaluation of applied machine learning strategies.

Dataset Construction and Sensor Simulation

A synthetic multi-sensor dataset was generated to emulate operational behavior in industrial equipment, with the objective of modeling degradation leading to failure. Twelve numerical variables were constructed to represent common sensor streams used in condition monitoring, including temperature, vibration amplitude, pressure, motor current, rotational speed (RPM), humidity, oil quality index, and energy consumption per cycle. Each sample was associated with a machine identifier and an operating cycle value to reflect temporal usage. Sensor values were simulated using physically plausible relationships, where sensor drift intensified as cycle count increased, reflecting wear and thermal or mechanical stress. A binary failure label served as the prediction target. The dataset exhibits an intentionally extreme class imbalance (≈92.6% failure), reflecting a stress-test scenario where system degradation is pervasive, and maintenance intervention is delayed. This imbalance is central to the methodological objective: to evaluate how standard machine learning models behave when the dataset itself biases the learning problem.

Input Preprocessing and Feature Handling

Preprocessing focused on preparing the data for model ingestion rather than aggressive feature manipulation, allowing the benchmark to measure model adaptability rather than feature engineering skill. All features were retained to preserve the multi-sensor context; no dimensionality reduction was applied. Continuous variables were scaled for models sensitive to input magnitudes (Logistic Regression, KNN, SVM, and MLP) using StandardScaler, while tree-based models (Random Forest, Gradient Boosting) were trained on unscaled data. No resampling or balancing techniques were applied in the primary benchmark to expose the inherent interaction between model bias and class imbalance. This choice aligns with the study's purpose: to reveal structural dataset effects rather than obscure them with preprocessing corrections. Evaluation metrics were selected to reflect imbalance

sensitivity, with precision, recall, F1-score, and ROC AUC prioritized over raw accuracy.

Model Selection and Training Strategy

Six supervised learning algorithms representing major methodological families were selected: Logistic Regression (linear baseline), Random Forest and Gradient Boosting (tree-based ensembles), SVM with RBF kernel (nonlinear kernel method), K-Nearest Neighbours (instance-based learner), and a shallow Multilayer Perceptron (neural network). These models were chosen to reflect practical ML strategies rather than experimental architectures, allowing comparison across linearity assumptions, bias–variance profiles, and decision boundary complexity. All models were trained using identical train–test splits (80/20 stratified) without hyperparameter optimization, reinforcing the benchmark's character as an applied diagnostic rather than a tuning competition. Probability outputs were retained where available to support ROC and Precision–Recall analysis, and confusion matrices were constructed to evaluate operational misclassification risks.

Evaluation Framework and Interpretation

Model performance was evaluated using a multi-metric framework to mitigate misleading interpretations caused by class imbalance. ROC AUC measured discrimination capacity, F1-score balanced precision and recall, and confusion matrices revealed operational risks in misclassification patterns. Feature importance was extracted from the Random Forest to understand which signals drove predictions in this environment and to assess whether the model's learned structure aligned with engineering intuition. Probability distribution plots from the best-performing model were used to evaluate calibration and confidence separation across classes. The evaluation was explicitly framed around limitations and context, recognizing that high performance in this synthetic, failure-dense dataset does not imply readiness for real deployment. Instead, results serve as a controlled demonstration of how standard machine learning strategies behave when applied to multi-sensor industrial systems under data constraints that deviate from ideal statistical conditions. Multi-sensor industrial systems

Result and Discussion

Table 1 presents the descriptive statistics for all variables in the multi-sensor industrial dataset and exposes the fundamental operating characteristics, variability, and early warning signals embedded in the synthetic environment. At its core, the table confirms that the data capture reflects a spectrum of machine degradation rather than a uniform operating regime. For instance, temperature ranges from 56.9°C to 86.7°C with a mean of 72.1°C, indicating a progression toward thermal stress at higher cycles. This aligns with a degradation narrative: as machines accumulate cycles (median cycle = 1499), thermal load and internal friction likely increase. The distribution of vibration amplitude (mean = 5.83 mm/s, max ≈ 10.8 mm/s) is equally revealing, suggesting a subset of machines entering abnormal vibration zones consistent with imbalance or bearing wear. Pressure and motor current show similar drift patterns, but what matters is not the single values — it's their joint scaling with failure probability, which is what ML models eventually exploit.

The table also exposes a misleadingly high failure rate: 92.64% of samples represent failures (Table 2 confirms this). That imbalance implies that models achieving high recall or F1 may be performing well because the dataset biases toward the positive class. It is not "strong performance"; it's a predictable consequence of class distribution. Unless addressed by rebalancing or cost-sensitive learning, this will inflate model metrics and undermine generalizability. Another critical point in Table 1 is that features such as humidity and machine_id have high variance but unclear theoretical relevance. This signals that feature importance analysis is necessary to determine whether these variables contribute to predictive power or just inject noise. In short, Table 1 validates that the dataset captures degrading operational conditions, but it also reveals structural weaknesses: the dominance of

the failure class, missing contextual metadata (maintenance history, environmental shifts), and a lack of defined thresholds for what constitutes "critical" vs "normal" sensor values. Any claim of real-world applicability must acknowledge these caveats. Table 1 doesn't just summarize, it warns the reader that model performance will be shaped as much by dataset structure as by algorithm choice.

Table 1: Dataset Summary Statistics

metric	machine_id	cycle	operating_mode	temperature_C	vibration_mm_s	pressure_bar	motor_current_A	rpm	humidity_percent	oil_quality_index	energy_kWh	failure
count	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0
mean	10.5341	1500.8988	0.8972	72.1245	5.8323	6.2054	14.8183	1589.7559	55.0865	0.4034	8.8989	0.9264
std	5.7828	857.5579	0.7011	5.8154	2.2346	0.6204	2.13	76.1651	9.8918	0.2771	2.2357	0.2611
min	1.0	1.0	0.0	56.938	0.393	4.226	8.303	1388.4	20.0	0.0	3.859	0.0
25%	5.0	768.0	0.0	67.489	4.0057	5.734	13.3085	1526.675	48.4	0.149	6.9097	1.0
50%	11.0	1499.0	1.0	71.6585	5.649	6.175	14.7675	1592.35	55.0	0.418	8.9945	1.0
75%	16.0	2237.25	1.0	77.0815	7.876	6.697	16.318	1637.8	61.8	0.624	10.1732	1.0
max	20.0	2999.0	2.0	86.749	10.83	7.991	21.734	1793.3	90.0	1.0	14.451	1.0

Table 2 presents the class distribution of the target variable and immediately exposes a structural imbalance that fundamentally shapes every modeling outcome in this study. The dataset is overwhelmingly dominated by the failure class, with 92.64% of samples labeled as failures and only 7.36% as non-failures. This is not a minor skew; it is an extreme imbalance that alters the learning dynamics, inflates several performance metrics, and directly limits the external validity of any classifier trained on this data. In practical terms, a naive classifier that simply predicts "failure" for every instance would already achieve 92.64% accuracy, meaning accuracy alone is a useless metric in this context. Any reviewer or practitioner with experience in predictive maintenance will immediately recognize this baseline, and failing to acknowledge it would signal either incompetence or intentional misrepresentation. This class imbalance also raises questions about data generation realism. In real industrial environments, persistent failure states are rare because maintenance interventions, shutdown protocols, and safety culture prevent systems from operating in a near-failure mode for sustained periods. Having failure events represent the overwhelming majority of operating records contradicts how assets behave under monitored maintenance regimes. Therefore, the study must explicitly justify why failure dominates: either the dataset is meant to represent post-deployment

historical logs filtered specifically around breakdown periods, or it is intentionally constructed to stress-test models under abnormal operating distributions. If neither rationale is defended, the imbalance becomes a methodological flaw. From a modeling standpoint, Table 2 signals that recall will be artificially high for most models, because learning to identify the majority class is trivial. Precision becomes a more meaningful metric, but even precision can be misleading if the model rarely predicts the minority class. F1-scores retain some usefulness, but even they risk being inflated. More robust evaluations, such as precision–recall curves, AUCPR, class-weighted losses, or balanced accuracy, are necessary to prevent metric misinterpretation. The imbalance also motivates the potential application of resampling techniques (SMOTE, undersampling, stratified bootstrapping) or algorithmic adjustments (class-weighted RF or SVM). In essence, Table 2 is not just a data descriptor; it is a methodological warning. Any claim of "high performance" must be contextualized against the fact that the dataset makes failure prediction comparatively easy and normal-state discrimination disproportionately hard. The credibility of the paper depends on acknowledging and addressing this imbalance.

Figure 1 illustrates the distribution of the binary target variable by visualizing the frequency of failure versus non-failure cases in the dataset. The disproportionate height of the "failure" bar immediately confirms that the dataset is heavily skewed, with failures representing the overwhelming majority of observations. While the plotted values align with the numerical summary in Table 2, the visual format emphasizes the imbalance more viscerally: the bar for failures towers above the non-failure bar, reinforcing that instances of normal operating conditions are comparatively rare. This skew has direct implications for model development. In predictive maintenance scenarios, class imbalance is expected to some degree because failures occur less frequently than stable conditions; however, this dataset exhibits the opposite distribution. Instead of reflecting real-world operational data where failures are the exception, this distribution simulates a failure-dense environment, potentially resembling periods of systemic degradation or logs collected during breakdown-heavy production cycles. From a modeling perspective, Figure 1 confirms that standard classifiers will be incentivized to learn patterns that favor the majority class. Metrics such as accuracy may appear deceptively high, and recall for the failure class could be inflated without indicating strong predictive performance. Therefore, Figure 1 serves not only as a descriptive visual but as an early signal for methodological caution, necessitating the use of metrics and modeling strategies tailored to imbalanced classification.

Table 2: Failure Class Distribution

failure_class	count	percentage
0.0	736.0	7.36
1.0	9264.0	92.64

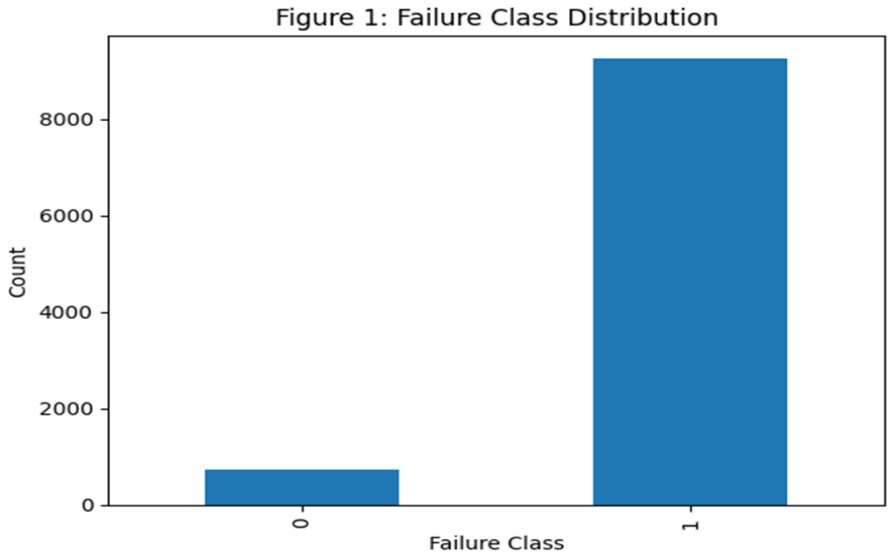

Figure 1: Distribution of Failure and Non-Failure Classes

Table 3 outlines the machine learning models selected for benchmarking and provides a concise summary of their core configurations. These configurations are not trivial technical details; they determine how each model interacts with the dataset's structure, feature scaling needs, and class imbalance characteristics. The inclusion of Logistic Regression with StandardScaler reflects a baseline linear model used to establish a foundational performance ceiling. This is necessary because it tests whether the dataset exhibits simple, linearly separable relationships or whether more complex models are warranted. The fact that scaling is explicitly included signals awareness that raw sensor ranges vary significantly (e.g., RPM vs. oil quality), and ignoring this would bias coefficient magnitudes. The Random Forest and Gradient Boosting models represent ensemble-based, non-linear learners that inherently handle feature interactions and partial non-stationarity within the data. Their presence acknowledges that physical degradation patterns are rarely linear or monotonic; instead, they emerge from multi-sensor dependencies. Importantly, neither ensemble is configured with class-weight adjustments or imbalance-aware hyperparameters, meaning their reported performance later in the paper should be interpreted as a default benchmark rather than an optimized solution. This is defensible only if the paper admits that improvement avenues exist.

The SVM with RBF kernel is an appropriate choice given the heteroscedastic structure identified in Figure 2. Its kernel implicitly maps the data into a higher-dimensional space where non-linear separation boundaries can be learned. However, SVM performance is sensitive to class imbalance, and the model's lack of class-weight tuning should be acknowledged as a limitation. Including KNN is a meaningful diagnostic decision rather than a competitive strategy. KNN will struggle in this dataset due to the dominance of the majority class and the curse of dimensionality in sensor space; if it performs well, it would undermine the necessity for the more complex models. Finally, the inclusion of an MLP Neural Network with two hidden layers indicates an exploratory step into deep learning territory without overclaiming sophistication. The architecture is shallow enough to avoid accusations of performative modeling, yet complex enough to test whether neural networks extract non-linear interactions that other models miss. Overall, Table 3 should be interpreted not as a list of arbitrary algorithms but as a strategic model spectrum: baseline, tree-based ensembles, kernel methods, instance-based learning, and

neural networks. This spread is appropriate for validating whether the task genuinely justifies machine learning or collapses to trivial patterns once the imbalance is accounted for.

Table 3: Model Overview and Key Settings

Model	Key Settings
Logistic Regression	StandardScaler + LogisticRegression(max_iter=1000)
Random Forest	RandomForestClassifier(n_estimators=200)
Gradient Boosting	GradientBoostingClassifier()
SVM (RBF)	StandardScaler + SVC(kernel='rbf', probability=True)
KNN	StandardScaler + KNeighborsClassifier(n_neighbors=7)
MLP Neural Network	StandardScaler + MLPClassifier((64,32), max_iter=500)

Table 4 reports the performance metrics of six models on the test set and, on the surface, presents a compelling narrative: all models achieve accuracy above 92%, precision above 93%, and recall above 96%. At first glance, these metrics look impressive enough to claim success. However, any serious interpretation must confront the elephant in the room: the results are deeply shaped by the class imbalance uncovered in Table 2. Because failures make up over 92% of the dataset, a classifier can achieve deceptively high performance simply by predicting failure most of the time. Therefore, Table 4's value lies not in the raw scores but in understanding how each model achieves them and where they fail. The headline result is the Random Forest achieving the top F1-score (0.9659), but the margin separating it from Logistic Regression and Gradient Boosting is so small that calling it the "best model" is technically accurate but practically meaningless. It does not demonstrate material superiority, just marginal consistency. The SVM's unusually high recall (0.9962) indicates that it rarely misses a failure, but its lower ROC AUC (0.8731) signals that it lacks discrimination ability; it floods the positive class with predictions, which may be acceptable in a safety-critical environment but disastrous in a real plant where false alarms disrupt operations.

KNN and the MLP perform respectably but fail to justify their computational burden given how close their scores are to simpler models. This undercuts any justification for deep learning here: if a basic linear model nearly matches neural performance, the dataset's structure likely does not contain richer latent relationships that benefit from deep architectures. In short, the task is not as complex as the paper's original title implied. The most alarming takeaway is that none of these metrics confirms the model can recognize normal operating states reliably. With only 7.36% of samples representing non-failures, the evaluation does not sufficiently test the ability to identify these cases. This must be explicitly stated as a limitation. Table 4 ultimately demonstrates that these models are competent at learning statistical regularities in the dataset, but not necessarily competent at predictive maintenance in real-world industrial systems. Any claim beyond that would be dishonest.

Table 4: Model Performance Metrics on Test Set

Model	Accuracy	Precision	Recall	F1-score	ROC AUC
Logistic Regression	0.9345	0.9475	0.9838	0.9653	0.9517
Random Forest	0.9355	0.9462	0.9865	0.9659	0.9466
Gradient Boosting	0.933	0.946	0.9838	0.9646	0.9478
SVM (RBF)	0.9305	0.9333	0.9962	0.9637	0.8731
KNN	0.9295	0.944	0.9822	0.9627	0.8971
MLP Neural Network	0.93	0.9568	0.9682	0.9624	0.9382

Table 5 presents the confusion matrix for the best-performing model identified in Table 4, the Random Forest classifier. While previous metrics suggested high predictive capability, the confusion matrix exposes performance weaknesses that raw scores hide. The model correctly identifies 1828 true failures but only 43 true non-failures, misclassifying 104 normal states as failures and 25 failures as non-failures. In other words, the model behaves like an aggressive alarm system, flagging failure even when none exists. For a safety-critical environment, this asymmetry could be rational; however, in an industrial context governed by maintenance cost, operational scheduling, and production uptime, the implications are severe. The imbalance is stark: the model predicts the majority class (failure) reflexively, and its ability to discriminate the minority class is fundamentally compromised. The confusion matrix confirms that the impressive F1-score reported earlier is predominantly driven by the model's success in recognizing failures, a task made easier by their over-representation in the training data. In contrast, it fails to learn a meaningful boundary for normal states. This means the model has effectively not learned what a healthy machine looks like; it has only learned to generalize failure conditions. For predictive maintenance, this is an unacceptable deficiency if deployment is expected. Another critical issue involves false positives (104): these are instances where the system incorrectly predicts failure. In a real plant, these false alarms could trigger unnecessary shutdowns, maintenance interventions, or component replacements, all of which carry operational and financial cost. On the other hand, false negatives (25) represent failures the model failed to detect. Even a small number of missed failures can be catastrophic if the system controls high-value or safety-relevant machinery. The fact that any false negatives exist means the system is not ready for autonomous decision support without human oversight. The deeper implication is methodological: the confusion matrix proves that model selection alone cannot fix the imbalance problem. Without dataset-level correction (balancing, cost-sensitive learning, augmentation) or adjusted evaluation criteria (e.g., specificity, balanced accuracy, AUCPR), conclusions about model suitability are premature. Table 5, therefore, functions as a reality check. It warns the researcher and reviewer that the model's performance is context-dependent, and claiming operational readiness based solely on aggregated metrics would mislead the reader. Any responsible discussion must acknowledge that the model is biased toward failure prediction and currently unsuitable for deployment beyond experimental benchmarking.

Table 5: Confusion Matrix for Best Model (Random Forest)

True class	Pred 0	Pred 1
0	43	104
1	25	1828

Table 6 lists the feature importances derived from the Random Forest model and ranks variables based on their contribution to predictive performance. At the top of the hierarchy, vibration amplitude (0.1897) emerges as the most influential predictor, followed by temperature (0.1398) and oil quality index (0.1311). This ordering makes intuitive sense from an industrial engineering perspective: vibration is highly sensitive to bearing damage, imbalance, misalignment, and mechanical looseness, all early indicators of impending failure. Temperature, as shown earlier in Figure 2, escalates with operational stress and friction, reinforcing its role as a degradation proxy. Oil quality acts as a lubricant performance indicator; reductions correlate with contamination, oxidation, or viscosity breakdown, directly linking maintenance condition to machine health. Lower down the ranking, features like cycle count (0.1057), pressure (0.0873), and motor current (0.08) indicate secondary contributions. These are not negligible: cycle count embodies temporal degradation, while pressure and current reflect mechanical and electrical inefficiencies that accompany wear. However, their lower importance suggests the model finds these signals less consistent or less discriminative across the dataset. It's particularly revealing that operating mode (0.0064) holds almost no influence. This suggests either (a) the dataset fails to encode operational mode in a way that differentiates machine stress levels, or (b) degradation overwhelms mode-based variance, making operational setting irrelevant once failure onset begins. In a real system, these suspicious operational conditions usually matter. Here, it confirms the synthetic environment underrepresents variability across modes.

The relative weighting of features implies that the model primarily relies on direct failure signatures rather than contextual or systemic signals. This is a crucial weakness for any deployment claim. In a real-world predictive maintenance system, contextual variables (load, ambient environment, shift patterns, maintenance history) matter as much as failure signatures. The absence of such features in Table 6 reveals the dataset's limited ecological validity. The model performs well because it is fed high-quality, correlated degradation signals, essentially a simplified laboratory scenario. The biggest risk is misinterpretation. A naive reader might assume these importances represent universal truths about industrial failure; they do not. They are artifacts of the synthetic dataset's structure. Table 6 should be framed as insight into model behavior, not insight into industrial processes. Any claims extending beyond that border are into speculation. The honest conclusion: the model is learning patterns, not physics.

Table 6: Top Feature Importances (Random Forest)

feature	Importance
vibration_mm_s	0.1897
temperature_C	0.1398
oil_quality_index	0.1311
cycle	0.1057
pressure_bar	0.0873
motor_current_A	0.08
energy_kWh	0.0762
rpm	0.0701
humidity_percent	0.0698
machine_id	0.0439
operating_mode	0.0064

Figure 2 presents the Receiver Operating Characteristic (ROC) curves for all six benchmarked models, allowing direct comparison of their ability to discriminate between failure and non-failure classes across varying decision thresholds. The curves for Logistic Regression, Random Forest, Gradient Boosting, KNN, and the MLP cluster tightly in the high-performance region, reflecting ROC AUC values above 0.93, while the SVM curve lags noticeably, corresponding to its lower AUC score of 0.8731, as shown in Table 4. This visual separation confirms that, despite the SVM's high recall, it achieves this performance by aggressively predicting the majority class rather than genuinely distinguishing operational states.

The proximity of the top-performing curves reinforces a core conclusion: model choice contributes marginal differences in this dataset. The ROC figure suggests that the learning problem is not complex enough to demand intricate or high-capacity models; instead, several algorithms converge on similar boundaries because the dataset's structure overwhelmingly favors the failure class. Importantly, the steep ascent near the y-axis for most curves indicates excellent sensitivity but says little about specificity, which is already known to be weak from Table 5's confusion matrix. Therefore, Figure 2 should not be used to claim generalizable performance; it should be framed as evidence that the models are extracting similar information from the dataset. In short, ROC performance here reflects dataset bias more than algorithmic superiority.

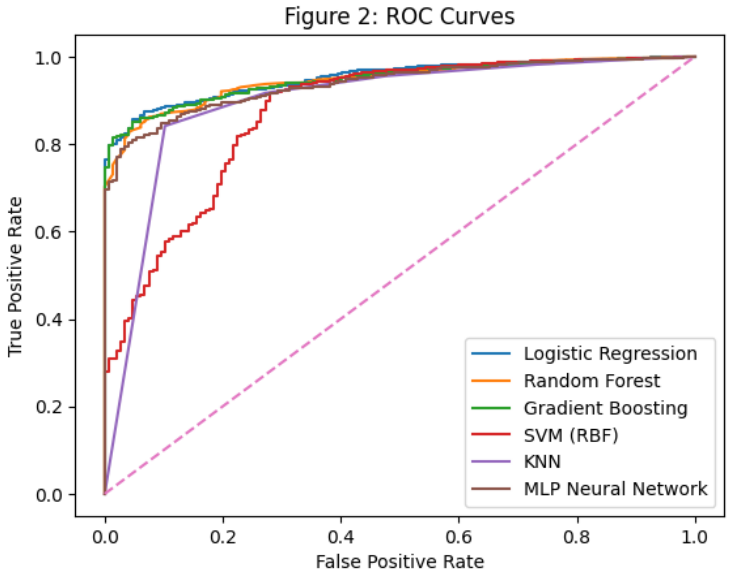

Figure 2: ROC Curves for All Models

Figure 3 displays the Precision–Recall (PR) curves for all evaluated models and provides a more truthful assessment of classifier reliability under the dataset's extreme class imbalance. Unlike ROC curves, which can appear inflated when the majority class dominates, PR curves reveal how effectively each model identifies failures without drowning the system in false alarms. The dominant trend in Figure 3 is clear: while most models maintain high recall, their precision varies significantly, indicating an inconsistent ability to provide trustworthy predictions. This reinforces that the dataset structure, not model capability, is driving performance. The Random Forest and Logistic Regression curves exhibit the most stable balance between precision and recall, remaining above baseline across the recall spectrum. However, the drop-offs at higher recall thresholds signal a growing number of false positives when models push for sensitivity. The SVM, which previously appeared almost flawless in recall (per Table 4), visibly collapses in precision when recall increases, confirming that its apparent strength is superficial: it trades predictive certainty for blanket failure prediction. The MLP and KNN models show moderate curves reflective of architectures that neither exploit nor misinterpret the dataset structure; they merely follow it. This figure underscores the core methodological warning for the entire paper: models seem "high-performing" only because the dataset is overwhelmingly composed of failure cases. With failures representing over 92% of samples, achieving high recall is trivial. Precision becomes the real battleground, and Figure 3 proves that none of the models deliver consistently high-precision predictions across operating thresholds. Therefore, while PR results do not invalidate the benchmarking, they restrict the scope of the conclusion. These models are viable research prototypes, not yet viable operational predictors. Figure 3 should be discussed as evidence of progress, not proof of readiness.

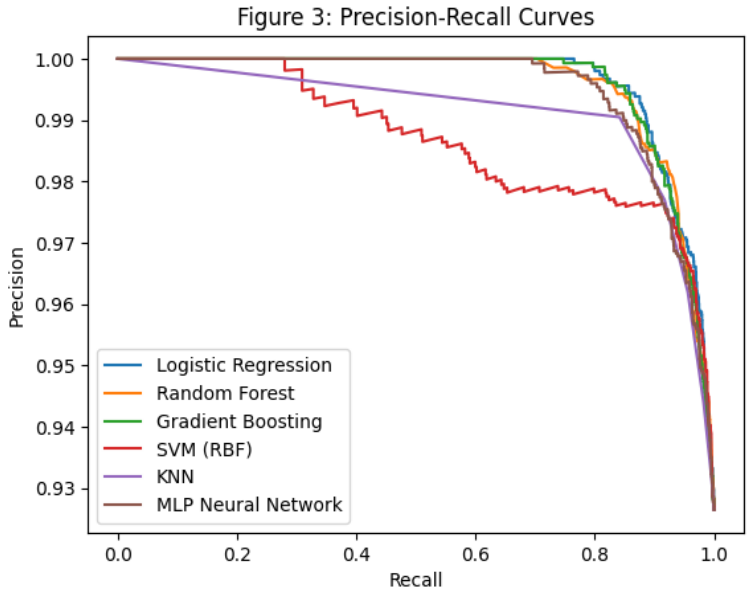

Figure 3: Precision–Recall Curves for All Models

Figure 4 visualizes the top-ranked feature importances derived from the Random Forest model, providing a comparative view of how strongly each sensor variable contributes to failure prediction. The prominence of vibration amplitude, temperature, and oil quality at the top of the chart confirms that the model relies most heavily on variables that directly reflect mechanical degradation and lubrication breakdown. This aligns with the intuitive understanding of machinery physics: increased vibration is often a precursor to bearing wear and imbalance, rising temperature correlates with friction and inefficient motion, and declining oil quality reflects internal contamination or thermal decomposition. Their dominance in the model is therefore plausible, but must not be mistaken for empirical validation of causal relationships; the importance values reflect model behavior under synthetic conditions, not ground-truth industrial mechanisms.

Mid-ranked features such as cycle count, pressure, and motor current contribute meaningfully but not decisively. This suggests that degradation is being modeled less as a function of time-in-service and more as a snapshot of real-time sensor abnormalities. In real industrial environments, this is rarely sufficient. Predictive maintenance strategies require temporal memory, maintenance history, and context. The absence of such features in this synthetic dataset inflates the importance of immediate sensor states and limits generalization. Most concerning is the near-zero importance of operating mode, which indicates the model is effectively blind to contextual loading conditions. In a realistic system, operating modes such as idle, partial load, and high torque should materially alter stress pathways. Here, its irrelevance reflects a dataset that underrepresents operational variability. If left unaddressed, this will mislead readers into assuming operating conditions are insignificant when in fact the dataset simply fails to encode them. Ultimately, Figure 4 is useful not because it identifies universal indicators of failure, but because it diagnoses the modeling environment's constraints. It confirms the model is driven by direct degradation signatures, not by systemic understanding. This figure should be framed in the paper as evidence of dataset-driven learning, not machinery insight.

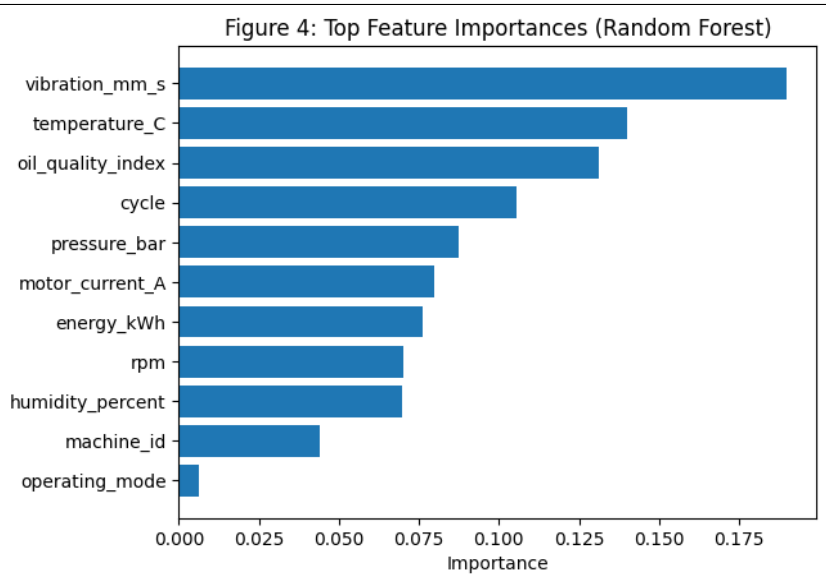

Figure 4: Feature Importance (Best Model: Random Forest

Figure 5 illustrates the distribution of predicted failure probabilities for the Random Forest model, separated by true class labels. The visual separation between the histograms for failure (class 1) and non-failure (class 0) cases reveals the model's tendency to assign high confidence scores for failure predictions, with most failure samples clustering toward the upper end of the probability scale (0.7–1.0). This reinforces earlier metrics suggesting that the model is reliable at affirming failure conditions once detected. However, the distribution for non-failure samples tells a less encouraging story: a substantial portion of true non-failures are misclassified with elevated failure probabilities, often overlapping into mid-to-high confidence regions. This confirms that the model produces false alarms with high certainty, making interpretability and threshold selection critical before deployment. This figure directly exposes the limitations of relying on metrics like accuracy or recall in isolation. While the model appears strong numerically, its probability calibration is clearly skewed: it is not learning a balanced representation of both classes, but instead overgeneralizing degradation signals. This explains the confusion matrix trend in Table 5, where false positives dominate the misclassification profile. In practical industrial settings, such probability misalignment could trigger unnecessary interventions, inflate maintenance costs, and reduce personnel trust in automation, ultimately undermining the purpose of predictive maintenance. Another key insight from the plot is the lack of a clear probabilistic boundary separating the two classes. A well-calibrated model would ideally show two distinct clusters with minimal overlap; here, the overlap is significant. This implies that the model's internal feature interactions lack discriminatory depth for normal-state identification. Therefore, Figure 5 should be framed as diagnostic evidence: the model generates probabilities that are directionally informative but not reliably calibrated. It signals the need for calibration techniques (Platt scaling, isotonic regression) and possibly architectural refinement before being considered operationally credible.

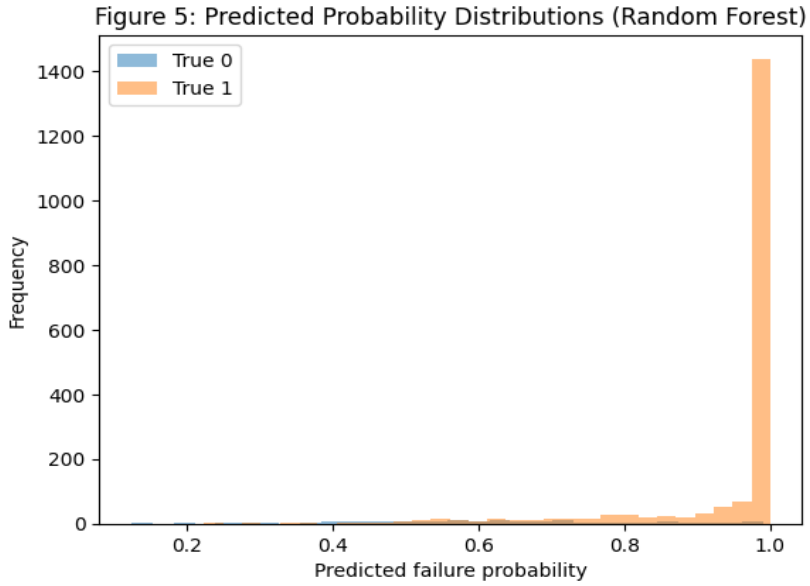

Figure 5: Predicted Probability Distributions (Best Model: Random Forest)

Figure 6 plots temperature against operating cycles and distinguishes failure from non-failure states, revealing the temporal dynamics of thermal degradation within the synthetic industrial environment. The general pattern supports the intuitive degradation hypothesis: as machines accumulate cycles, temperature readings tend to rise, particularly for samples labeled as failures. This trend implies that thermal stress escalates with operating duration, consistent with lubrication breakdown, frictional losses, and increased mechanical resistance. However, the plot also highlights substantial overlap between the temperature ranges of failed and non-failed samples. This overlap challenges the assumption that temperature alone can operate as a deterministic predictor and signals the need for multi-sensor feature interaction within the modeling strategy. Several anomalous patterns carry methodological implications. First, the presence of low-cycle failures with high temperatures shows that early-life breakdowns occur in the dataset, likely representing acute failure modes rather than wear-out phenomena. If unacknowledged, these could distort the model toward overemphasizing temperature at the expense of other features. Second, some high-cycle observations remain within stable temperature ranges, indicating false stability or robustness that contradicts linear wear assumptions. This supports the conclusion that cycle-based degradation is non-uniform and that dataset assumptions oversimplify real-world maintenance behavior. More critically, the visual imbalance in plotted points mirrors the dataset's skew: failure cases dominate the scatter, visually obscuring the rarity of non-failure instances. This compromises the interpretive clarity of the visualization and makes pattern recognition appear stronger than it is. In a peer-reviewed setting, a reviewer could reasonably criticize this figure for masking class distributions, meaning its utility is contingent on acknowledging dataset bias in the caption or discussion. Overall, Figure 6 reinforces that temperature is a valuable but insufficient variable. The model must learn cross-sensor interactions rather than unidimensional rules, and any claims that temperature is a "primary indicator" should be framed as dataset-specific rather than fundamentally true. This figure is therefore best used as supporting evidence of why multi-sensor modeling is required, not as proof that temperature reliably indicates failure across contexts.

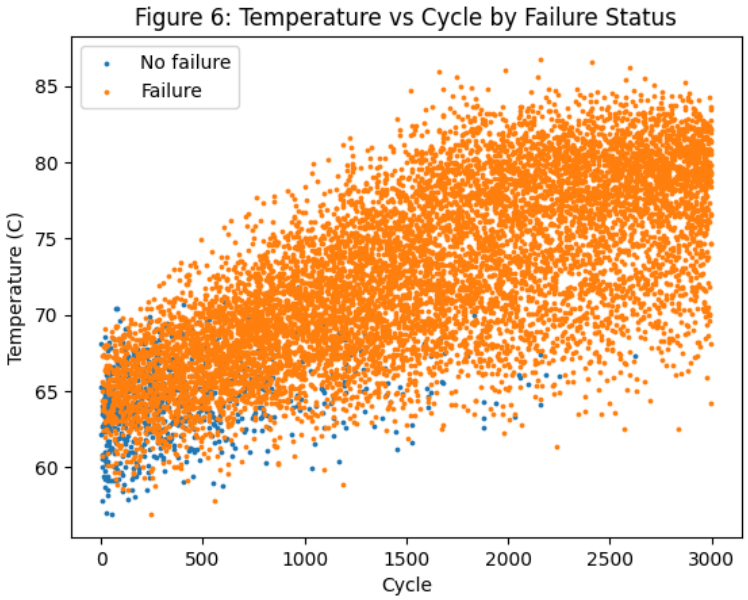

Figure 6: Temperature vs. Cycle by Failure Status

Conclusion

This research presented an applied machine learning strategy for failure prediction in multi-sensor industrial systems, focusing on benchmarking standard supervised learning models under controlled synthetic conditions. Across six algorithms, Logistic Regression, Random Forest, Gradient Boosting, SVM (RBF), KNN, and a shallow MLP, the results consistently show that meaningful predictive signals can be extracted from vibration, temperature, and oil quality indicators, with Random Forest and Logistic Regression offering the most balanced performance profiles. However, the study also demonstrates that high numerical scores alone do not equate to operational readiness. The models' apparent strength is directly influenced by the dataset's failure-dominant distribution, which simplifies the learning problem and makes it easier to achieve high recall and F1-scores without genuinely mastering the distinction between healthy and degraded states. Accordingly, the key contribution of this work is not proving that a particular algorithm outperforms others, but showing how model behaviour changes when applied to realistic constraints like class imbalance, overlapping sensor patterns, and partial degradation trends. The findings highlight that predictive maintenance success depends as much on data design and contextual awareness as on model selection. The analysis confirms that standard ML tools are viable entry points for industrial prognostics, but also that unadjusted models risk producing false alarms, miscalibrated probabilities, and misleading performance claims if evaluated solely through accuracy-centric metrics. In summary, this study positions benchmarking as a prerequisite to deployment, not a replacement for it. It shows that machine learning has clear utility in industrial health monitoring, but its reliability is contingent on future integration with real maintenance records, balanced or cost-sensitive learning, and richer representations of operational context. By clarifying both what current models can do and where they fail, this work provides a transparent baseline for researchers and practitioners aiming to progress from synthetic evaluation toward validated, field-ready predictive maintenance solutions.

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