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TOWARDS RELIABLE PREDICTIVE MAINTENANCE USING HYBRID MACHINE LEARNING

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Abstract: Unexpected machine failures in modern industrial environments remain a critical challenge, leading to production downtime, increased operational costs, and safety risks. Traditional maintenance strategies based on fixed schedules often fail to capture complex degradation patterns present in sensor data. This paper presents a predictive maintenance (PdM) framework that leverages supervised machine learning to classify machine health states and detect potential failures.
The proposed system utilizes the AI4I 2020 Predictive Maintenance Dataset, which consists of multivariate sensor data including Air temperature, Process temperature, Rotational speed, Torque, and Tool wear. Three supervised learning models—Support Vector Machines (SVM), Random Forest (RF), and XGBoost—are trained and evaluated on this dataset. A hybrid ensemble approach using a Voting Classifier is implemented to improve prediction robustness and overall classification performance.
To enhance interpretability, feature importance analysis derived from the Random Forest model is used to identify key contributing factors. The analysis highlights Torque and Tool wear as the most significant indicators of machine failure, providing actionable insights for maintenance decision-making.
Furthermore, a Streamlit-based graphical user interface (GUI) is developed to enable interactive and near real-time prediction using user-provided inputs. Experimental results demonstrate that the hybrid model outperforms individual models in terms of accuracy, making the proposed system a practical solution for predictive maintenance in Industry 4.0 environments.

Index Terms **-** Predictive Maintenance, Hybrid Learning Framework, Fault Diagnosis, Feature Engineering, Supervised Learning, Model Evaluation, F1-Score

I. INTRODUCTION

The rapid transition toward Industry 4.0 has fundamentally transformed industrial automation by integrating Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), and Artificial Intelligence (AI)[1]. This digital transformation enables the collection of massive multivariate sensor streams, allowing factories to move beyond traditional maintenance paradigms toward intelligent, data-driven strategies[2]. Within this landscape, Predictive Maintenance (PdM) has emerged as a critical technology for maximizing the availability and efficiency of industrial assets.[3]
Unplanned machinery downtime remains one of the most significant challenges in modern manufacturing, often consuming between 5% and 20% of annual productive capacity [4]. In high-stakes sectors, the costs of unexpected failures can be staggering; the International Energy Agency (IEA) estimates that unplanned outages cost energy-intensive industries nearly USD 50 billion annually [5]. Furthermore, machinery downtime can account for up to 60% of total operating expenses in certain industrial environments. Traditional maintenance approaches generally fall into three categories: reactive maintenance, which repairs equipment only after a failure occurs; preventive maintenance, which follows fixed, time-based

schedules; and condition-based maintenance, which triggers actions when measurable indicators cross preset thresholds[6]. However, reactive strategies lead to costly disruptions, while preventive schedules often result in "over-maintenance"—unnecessary servicing of healthy components that leads to significant resource waste.[7]

To overcome these limitations, supervised machine learning models are increasingly utilized to identify subtle degradation patterns within sensor data before they escalate into catastrophic breakdowns.[8] By analyzing parameters such as temperature, torque, and rotational speed, these models can classify equipment health states and detect incipient faults.[9] While individual algorithms like Support Vector Machines (SVM), Random Forest (RF), and XGBoost have demonstrated success in fault diagnosis, researchers are increasingly turning to hybrid ensemble approaches to improve prediction robustness and classification performance.[10]

Despite the high predictive accuracy of advanced models, their adoption on the shop floor is often hindered by their "black-box" nature, which can limit the trust of maintenance engineers.[11] Consequently, providing interpretable diagnostics through feature importance analysis is essential for identifying the root causes of failure, such as excessive Torque or Tool wear.[12] Furthermore, for PdM systems to be practically applicable, they must be integrated into user-friendly interfaces that support real-time decision-making for non-expert operators.

This study presents a comprehensive PdM framework implemented on the AI4I 2020 Predictive Maintenance Dataset. The work contributes a robust hybrid ensemble framework that integrates SVM, RF, and XGBoost to achieve superior health-state classification. Furthermore, the framework bridges the gap between theoretical modeling and shop-floor practice by deploying the model via a Streamlit-based Graphical User Interface (GUI), providing an interactive tool for near real-time machinery health monitoring in smart manufacturing environments.

II. Literature Review

Recent research in Predictive Maintenance (PdM) has shifted from theoretical modeling toward practical, data-driven frameworks integrated within the Industry 4.0 paradigm.[13] This section explores the transition from traditional maintenance to intelligent diagnostics, the efficacy of supervised machine learning architectures, and the critical necessity for model interpretability and real-time deployment.

2.1. Paradigm Shift in Maintenance Strategies

Industrial maintenance has evolved from reactive and preventive models toward proactive, data-centric strategies.[14] Reactive maintenance (RM) repairs equipment only after failure, leading to unplanned downtime that can cost hundreds of thousands of dollars per hour.[15] Conversely, preventive maintenance (PM) relies on fixed schedules, which often result in "over-maintenance" and the waste of functional components.[16] Predictive Maintenance (PdM) addresses these inefficiencies by leveraging the Industrial Internet of Things (IIoT) to collect multivariate sensor streams—such as temperature, torque, and rotational speed—enabling the detection of subtle degradation patterns before failure occurs.[17]

2.2. Supervised Learning for Industrial Fault Classification

Supervised machine learning is established as the most effective paradigm for PdM because it maps historical failure patterns to future occurrences. Research consistently highlights three core algorithms:

- Support Vector Machines (SVM): SVMs are widely utilized for defining high-dimensional decision hyperplanes that separate "normal" from "failure" states. They are particularly effective for binary classification in vibration and thermal analysis.[18]
- Random Forest (RF): As an ensemble of decision trees, RF is cited as one of the most frequently used methods due to its robustness against overfitting and its inherent ability to provide feature importance measures.[19]
- XGBoost: This gradient-boosting framework has demonstrated exceptional proficiency in managing time-series data, often achieving superior accuracy and speed compared to traditional classifiers in industrial benchmarks[20].

2.3. Hybrid Ensemble Frameworks and Voting Classifiers

While individual models offer high accuracy, researchers are increasingly adopting hybrid ensemble approaches to enhance prediction stability.[21] Implementing a Voting Classifier allows a system to aggregate the unique decision logic of multiple architectures (e.g., SVM, RF, and XGBoost), effectively reducing the variance and bias associated with a single-model approach.[22] These frameworks are particularly beneficial when dealing with imbalanced industrial datasets, where failure events are rare compared to normal operating cycles.

2.4. Model Interpretability and Human-Centric Interfaces

A critical barrier to PdM adoption is the "black-box" nature of complex models, which can hinder operator trust in safety-critical settings. To build transparency, modern research emphasizes model-intrinsic interpretability, such as the feature importance rankings provided by tree-based models like RF and XGBoost.[23] Recent studies indicate that mechanical parameters like Torque and Tool wear are the most influential indicators of impending failure.[24] Furthermore, the emergence of Industry 5.0 necessitates human-centric interfaces. Streamlit-based Graphical User Interfaces (GUIs) and interactive dashboards are increasingly used to provide real-time decision support, transforming predictive insights into actionable maintenance work orders for non-expert operators.[25]

2.5. Comparative Summary and Research Gaps

The proposed framework addresses recurring limitations in deployment readiness and interpretability by combining a robust hybrid ensemble with a serialized model for low-latency inference via a Streamlit GUI.

Table 1 summarizes the main methodological trends and identifies the gaps that motivate the proposed framework.

Table 1. Categorized Comparison of PdM Methods and Identified Gaps.

Category	Core Methods	Strengths	Limitations	Gap Addressed by This Work
Statistical	Regression, ARIMA	Interpretable	Sensitive to noise and shift	Handles complex sensor transients.
Tree-Based ML	Random Forest, DT	High precision, feature ranking	Requires extensive feature engineering	Uses automated feature attribution.
Deep Learning	CNN, LSTM, TCN	Captures temporal dependencies	High training cost, "Black Box"	Implements interpretable ML logic.
Proposed Hybrid	Ensemble + GUI	Robustness and real-time accessibility	Requires labeled data	Bridges the gap between theory and shop-floor deployment.

III. Methodology

The proposed methodology as shown in fig 3.1 follows a modular, end-to-end workflow designed to transform raw industrial sensor streams into actionable maintenance decisions. The system is implemented in Python and is structured into four distinct phases: data preprocessing, exploratory correlation analysis, hybrid model development, and real-time deployment via a Streamlit interface.

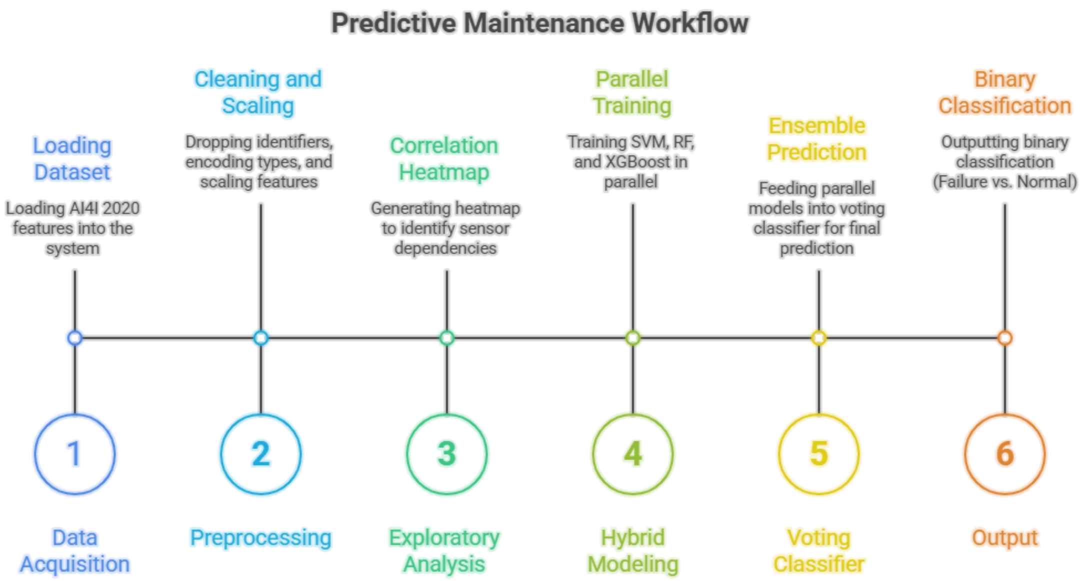

Fig 3.1 Predictive Maintenance Workflow

3.1. Data Preparation and Preprocessing

The framework utilizes the multivariate AI4I 2020 Predictive Maintenance Dataset, a recognized benchmark for industrial condition monitoring. The preprocessing pipeline ensures data integrity through the following steps derived from the project code:

- Feature Filtering: Non-predictive identifiers, including UDI and Product ID, are discarded to prevent the models from learning arbitrary indices.
- Categorical Encoding: The machine Type (representing L, M, or H quality levels) is transformed into numerical values using LabelEncoder.
- Target Refinement: Specific fault indicators (e.g., TWF, HDF, PWF) are removed, leaving a single binary Machine failure target variable to facilitate discrete health-state classification.
- Data Normalization: To prevent features with larger scales (like Rotational Speed) from dominating the models, Z-score standardization is applied to ensure a mean of 0 and a standard deviation of 1.

Equation (1): Z-score Normalization

$$z = \frac{x - \mu}{\sigma}$$

Where x is the original sensor value, μ is the feature mean, and σ is the standard deviation.

3.2. Exploratory Data Analysis (EDA) and Feature Attribution

To identify electromechanical couplings, a correlation heatmap is generated using the seaborn library. This quantifies associations between the primary features: Air temperature, Process temperature, Rotational speed, Torque, and Tool wear.

To enhance model transparency, the framework utilizes model-intrinsic feature importance derived from the Random Forest model. By calculating the relative contribution of each sensor to the reduction in Gini impurity, the framework identifies Torque and Tool wear as the primary indicators of degradation, providing engineers with actionable diagnostic evidence rather than opaque alarms.

3.3. Hybrid Ensemble Model Architecture

The core of the framework is a hybrid predictive system that integrates three distinct supervised learning architectures into a Voting Classifier:

3.3.1. Support Vector Machine (SVM): Utilized to define optimal high-dimensional decision hyperplanes that separate "Normal" from "Failure" states.
Equation (2): SVM Decision Function

$$f(x) = \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b\right)$$

Where αi are Lagrange multipliers, yi are class labels, and K(x,xi) is the kernel function.

3.3.2. Random Forest (RF): Employs an ensemble of *B* decision trees {*T*1,…,*TB*} to provide robustness against noise and non-linear transients.
Equation (3): RF Majority Voting

$$\hat{y} = \text{argmax}_j \sum_{b=1}^{B} I(T_b(x) = j)$$

Where I(⋅) is the indicator function and j∈{0,1} represents the health state.

3.3.3. XGBoost: A scalable gradient-boosting library utilized for its high computational efficiency and accuracy in processing structured sensor data.
3.3.4. Hybrid Integration: The individual predictions are aggregated using a Hard Voting strategy to reduce individual model bias and improve overall classification stability.
Equation (4): Hard Voting Mechanism

$$\hat{y}_{final} = \text{mode}\{C_{RF}(x), C_{XGB}(x), C_{SVM}(x)\}$$

Where Ci(x) is the predicted class from each standalone classifier.

3.4. Real-Time Deployment (Streamlit GUI)
To bridge the gap between theoretical modeling and industrial practice, the finalized hybrid model is serialized into a .pkl file using the joblib library. This model is integrated into a Streamlit-based Graphical User Interface (GUI).
The interface allows operators to input real-time sensor readings through interactive widgets. Upon clicking the "Predict Machine Failure" button, the system performs low-latency inference and provides an instantaneous status update—either "Machine Operating Normally" or "Machine Failure Detected!!". This deployment path ensures that predictive insights are accessible on the shop floor without requiring data science expertise.

IV. Results and Analysis

This section evaluates the performance of the developed machine learning architectures and the hybrid ensemble framework. The experimental findings are derived from testing on 2,000 samples of the AI4I 2020 Predictive Maintenance Dataset. The analysis focuses on overall accuracy, fault-specific detection metrics, and the diagnostic insights provided by graphical outputs.

4.1. Comparative Performance of Models
The overall classification accuracy was consistently high across most architectures, confirming the effectiveness of supervised learning for industrial condition monitoring.

- XGBoost achieved the highest overall accuracy of 0.985.
- The Hybrid Model (Voting Classifier) and Random Forest both reached a robust accuracy of 0.984.
- The Support Vector Machine (SVM) reported the lowest overall accuracy at 0.97.

4.2. Failure Detection Analysis (Class 1)

In industrial predictive maintenance, overall accuracy can be misleading due to class imbalance; in this study, the test set contained 1,939 normal instances and only 61 failure events. Therefore, this study prioritizes metrics for the "Failure" class (Class 1):

- SVM Reliability Gap: While the SVM showed a perfect precision of 1.00, its Recall was only 0.02, indicating it failed to detect nearly 98% of actual machine failures. This yields a critical F1-score of 0.03, proving it unsuitable for standalone deployment.
- XGBoost Sensitivity: XGBoost emerged as the most sensitive model for fault identification, achieving the highest recall of 0.62 and an F1-score of 0.72 for Class 1.
- Hybrid Model (Ensemble) Robustness: The Hybrid Ensemble achieved a precision of 0.91 for failures, the highest among all functional models. This signifies that when the hybrid system predicts a failure, it is correct 91% of the time, effectively minimizing the risk of costly false alarms on the shop floor.

Table 2: Performance Summary for Machine Failure Detection (Class 1)

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.97	1.00	0.02	0.03
Random Forest	0.984	0.85	0.57	0.69
XGBoost	0.985	0.84	0.62	0.72
Hybrid Ensemble	0.984	0.91	0.52	0.67

4.3. Interpretation of Graphical Results

The following interpretations provide a deeper understanding of the system's performance and the underlying physical relationships within the sensor data.

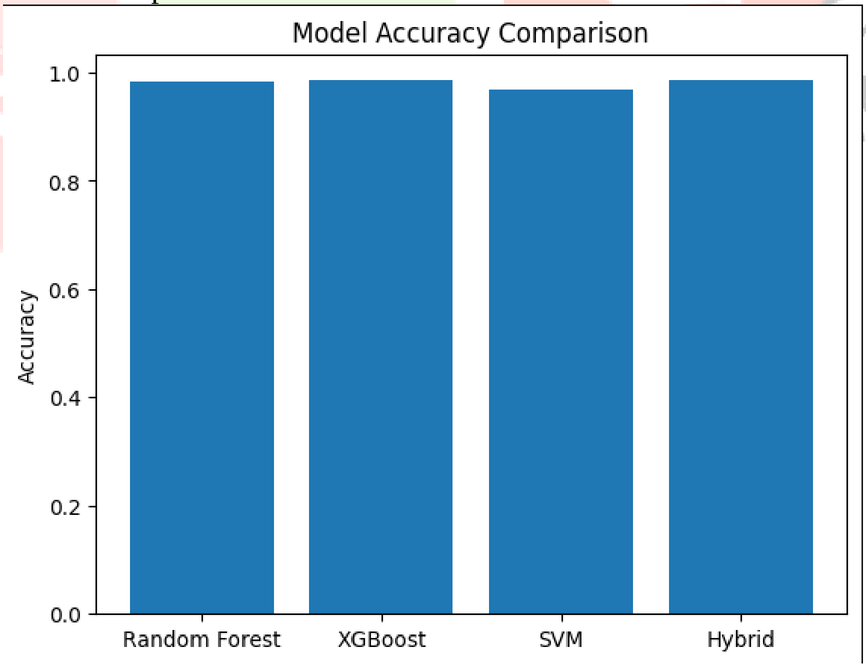

Fig 4.3.1 Model Accuracy Comparison

4.3.1. Model Accuracy Comparison The Model Accuracy Comparison bar chart confirms that ensemble methods (XGBoost, RF, Hybrid) provide a consistent performance advantage over the SVM baseline. While the SVM bar appears competitive at 97%, the graphical representation masks its inability to detect rare faults, emphasizing that high-precision ensemble models are required for industrial reliability.

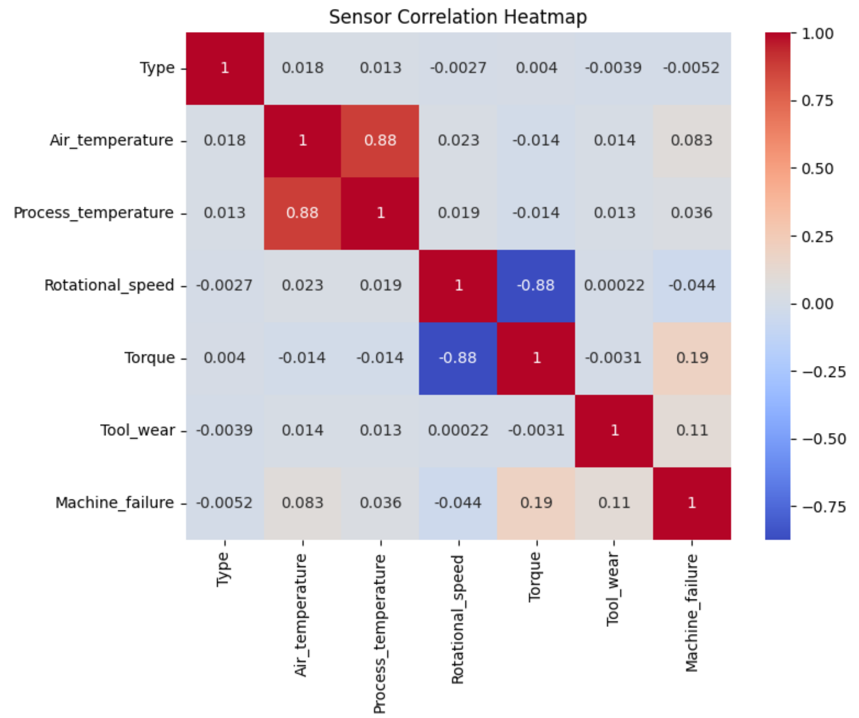

Fig 4.3.2. Sensor Correlation Heatmap

4.3.2. Sensor Correlation Heatmap: The Sensor Correlation Heatmap visualises the electromechanical couplings between parameters such as Air temperature, Process temperature, Rotational speed, Torque, and Tool wear. A strong positive correlation is observed between Air and Process temperatures, indicating that ambient heat is a significant factor in internal thermal load. Conversely, mechanical features like Torque and Rotational speed exhibit independence, providing the models with diverse physical signals to verify failure states.

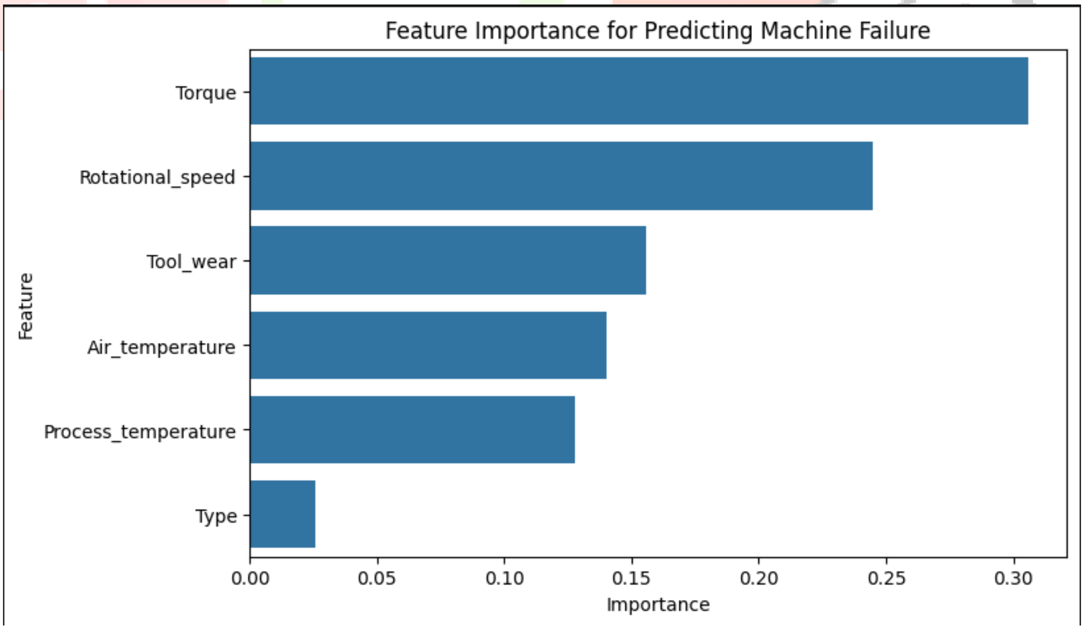

Fig 4.3.3. Feature Importance for Predicting Machine Failure

4.3.3. Feature Importance for Predicting Machine Failure: This chart, derived from the Random Forest component, ranks features based on their contribution to identifying failure. Torque and Tool wear are prioritized as the most significant drivers. This confirms that mechanical strain and cumulative degradation are the primary precursors to machine failure in this context, providing engineers with actionable diagnostic evidence rather than "black-box" alerts.

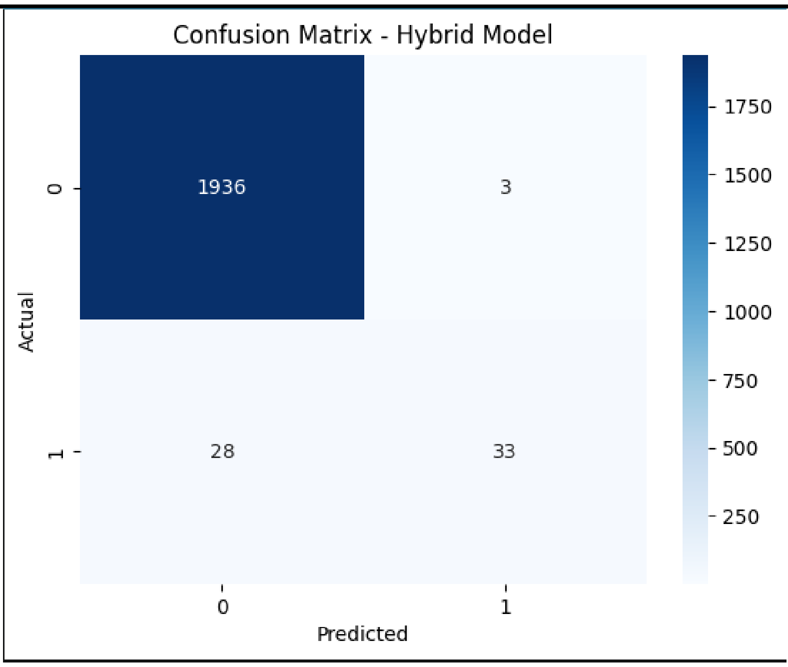

Fig 4.3.4. Confusion Matrix - Hybrid Model

4.3.4. Confusion Matrix - Hybrid Model The Confusion Matrix provides a granular breakdown of the Hybrid Model's 2,000 predictions. It shows near-perfect identification of the 1,939 normal instances while highlighting the model's high precision—generating only three false positives. This visual proof of reliability is essential for building operator trust when the model is deployed via the Streamlit GUI.

V. Discussion

The experimental results demonstrate the critical role of ensemble learning in addressing the complexities of industrial condition monitoring. The findings highlight several key themes regarding model selection, data challenges, and physical diagnostic drivers.

5.1. The Accuracy Paradox in Predictive Maintenance

A central observation in this study is the deceptive nature of overall accuracy when dealing with highly imbalanced industrial data. While the SVM achieved an accuracy of 0.97, its recall of 0.02 for the failure class indicates it was practically unable to detect machine breakdowns, correctly identifying only 1 out of 61 actual failures. This confirms that in a dataset with 1,939 normal instances versus 61 failure events, high accuracy is achieved simply by predicting the majority class. Consequently, the F1-score, which balances precision and recall, is a more vital metric for determining the operational effectiveness of a PdM system.

5.2. Balancing Sensitivity and Reliability

The comparative analysis reveals a trade-off between the sensitivity of XGBoost and the reliability of the Hybrid Model:

- Safety-Critical sensitivity: XGBoost achieved the highest recall (0.62) and F1-score (0.72) for failures, making it the most effective tool for environments where missing a failure is catastrophic.
- Operational Reliability: The Hybrid Model achieved a precision of 0.91, the highest among all functional models. In an industrial context, this high precision is crucial as it ensures that 91% of the maintenance alarms are valid. This significantly reduces "alarm fatigue" and prevents unnecessary production downtime caused by false positives.

5.3. Physical Significance of Feature Indicators

The Feature Importance analysis and Sensor Correlation Heatmap provide a physical justification for the model's predictions. The identification of Torque and Tool wear as the primary drivers for failure detection aligns with mechanical engineering principles, where torque fluctuations signal motor strain and tool wear represents cumulative degradation. Furthermore, the strong correlation between Air and Process temperatures confirms that the dataset captures realistic thermal couplings, allowing the models to utilize temperature trends to identify overheating conditions.

5.4. Deployment and Industry 4.0 Readiness

Beyond algorithmic performance, the successful serialization of the hybrid model into a Streamlit-based GUI addresses the gap between theoretical data science and shop-floor application. By allowing operators to input parameters such as Rotational Speed (RPM) and Tool Wear (min) to receive instantaneous predictions, the framework provides a human-centric interface for real-time decision support. This transition from "black-box" results to an interactive tool—which alerts users with "Machine Failure Detected!!"—demonstrates the system's readiness for integration into modern Smart Manufacturing ecosystems.

Ultimately, while standalone models like XGBoost offer high sensitivity, the Hybrid Ensemble framework provides the most balanced and trustworthy solution. By combining the strengths of multiple architectures, the system achieves the high precision necessary to sustain operational efficiency while maintaining the diagnostic depth required to prevent machine downtime.

VI. Conclusion and Future Work

This research successfully developed and validated a hybrid machine learning framework for predictive maintenance, demonstrating high efficacy in identifying impending industrial equipment failures. By integrating Random Forest, XGBoost, and Support Vector Machines (SVM) into a unified Voting Classifier, the system achieved a robust overall accuracy of 0.984.

While individual models like XGBoost showed high sensitivity with a recall of 0.62, the Hybrid Model proved most effective for industrial deployment by achieving the highest precision of 0.91 for the failure class. This high precision is critical for reducing "alarm fatigue" on the shop floor by ensuring that triggered maintenance alerts are highly reliable. Furthermore, feature importance analysis identified Torque and Tool wear as the primary diagnostic drivers, providing engineers with physical indicators to guide their maintenance strategies. Finally, the deployment of this model via a Streamlit GUI bridges the gap between complex data science and practical shop-floor operations, allowing for near real-time decision support.

Future Work

Despite the high accuracy achieved, several avenues for future research remain to enhance the system's robustness:

- Addressing Class Imbalance: The dataset utilized was heavily imbalanced, with only 61 failure instances out of 2,000 test samples. Future work should explore oversampling techniques like SMOTE or generative models to improve the recall rate, which currently sits at 0.52 for the hybrid system.

- Granular Failure Classification: The current framework focuses on binary classification (Normal vs. Failure). Future iterations could incorporate multi-class classification to predict specific failure modes—such as Tool Wear Failure (TWF) or Heat Dissipation Failure (HDF)—which were excluded in the initial preprocessing phase.

- Real-time IoT Integration: While the Streamlit GUI provides a user-friendly interface for manual data entry, the next phase of development should focus on automated data ingestion from live IoT sensor streams for truly continuous machine health monitoring.

- Deep Learning Exploration: Future studies could compare the performance of this hybrid ensemble against Recurrent Neural Networks (RNNs) or LSTMs, which may be better suited for capturing the temporal dependencies and long-term degradation patterns within sensor data.

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