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Interactive Realtime Predictive Maintenance System

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ABSTRACT: Industrial equipment failures cause significant operational disruptions and financial losses in manufacturing environments. Traditional maintenance strategies, whether reactive or schedule-based, are inadequate for modern high-speed production systems that demand continuous uptime. This paper presents PredMaint AI, an intelligent real-time predictive maintenance system designed to minimize industrial downtime through machine learning-based failure prediction. The system employs a Random Forest classifier trained on the Ai4i 2020 Predictive Maintenance dataset to analyze five key operational parameters: air temperature, process temperature, rotational speed, torque, and tool wear. Motor health is classified into three states — Normal, Warning, and Critical — enabling proactive intervention before failures occur. The system features an interactive Streamlit-based dashboard with manual input prediction, batch data processing, and a real-time motor simulator. Experimental results demonstrate that the proposed system achieves an accuracy of 98.4% and an F1-score of 97.2%, significantly outperforming traditional machine learning approaches. The system provides a scalable, cost-effective solution for industrial predictive maintenance with potential deployment across manufacturing, automation, and smart factory environments.

I. INTRODUCTION

Industrial motors and machinery are the backbone of modern manufacturing and automation systems. Their continuous and uninterrupted operation is critical to maintaining production efficiency, meeting delivery timelines, and ensuring workplace safety. However, prolonged operation inevitably leads to component wear, mechanical stress, and eventual failure. Unplanned equipment downtime results in costly production stoppages, emergency repair expenses, and potential safety hazards for workers.

Conventional maintenance strategies have traditionally relied on two approaches: reactive maintenance, which addresses failures after they occur, and preventive maintenance, which schedules servicing at fixed time intervals regardless of actual equipment condition. Both approaches carry significant drawbacks. Reactive maintenance leads to unplanned outages and costly emergency repairs, while preventive maintenance often replaces functional components prematurely, wasting resources and increasing operational costs.

Predictive maintenance (PdM) has emerged as a transformative paradigm in industrial operations, leveraging data-driven techniques to forecast equipment failures before they occur. Machine learning algorithms have demonstrated exceptional capability in analyzing complex operational data to identify early signs of degradation and predict failure events with high accuracy.

This paper proposes PredMaint AI, an interactive real-time predictive maintenance system that integrates a Random Forest classifier with a Streamlit-based monitoring dashboard. The system continuously analyzes motor operational parameters, classifies equipment health states, and generates timely alerts to enable proactive maintenance decisions. By shifting from reactive and preventive strategies to predictive maintenance, the system aims to reduce downtime, optimize maintenance schedules, and extend equipment lifespan.

II. EXISTING SYSTEM

Existing industrial maintenance systems predominantly follow manual inspection-based or schedule-driven approaches. In manual systems, technicians periodically inspect equipment to assess operational status, relying on subjective judgment and experiential knowledge. While cost-effective in simple environments, this approach is inherently

unreliable in complex, high-speed production settings where subtle early warning signs may go undetected until failure occurs.

Schedule-based preventive maintenance systems perform servicing at fixed time intervals, regardless of actual equipment condition. Although this reduces unexpected failures to some extent, it leads to unnecessary maintenance activities on functional components and fails to detect failures occurring between scheduled intervals. Existing digital monitoring platforms offer basic data logging and threshold-based alerting but lack predictive analytical capabilities.

DISADVANTAGES

- **No Early Failure Detection:** Traditional systems cannot identify degradation patterns before failure, resulting in costly unplanned downtime.
- **Manual Monitoring Required:** Human-dependent inspections are time-consuming, subjective, and prone to oversight errors.
- **Higher Maintenance Costs:** Premature component replacement and emergency repairs significantly increase operational expenditure.
- **Frequent Equipment Downtime:** Reactive repair cycles cause repeated production interruptions with no prevention mechanism.
- **Lack of Real-Time Visibility:** Absence of continuous monitoring creates blind spots in equipment health status.

III. PROPOSED SYSTEM

The proposed PredMaint AI system is an intelligent, AI-driven predictive maintenance platform that replaces manual monitoring with real-time machine learning-based analysis. The system is designed to continuously monitor industrial motor operational parameters and predict equipment health status with high accuracy, enabling maintenance teams to take proactive action before failures occur.

At its core, the system employs a Random Forest classifier trained on the Ai4i 2020 Predictive Maintenance dataset. The model analyzes five key parameters — air temperature, process temperature, rotational speed, torque, and tool wear — and classifies motor health into three states: Normal, Warning, and Critical. The interactive Streamlit-based dashboard supports manual input prediction, batch CSV processing, and a real-time motor simulator with automated alert mechanisms.

ADVANTAGES

- **Automated Incident Response:** Instant alert generation upon detection of abnormal motor conditions enables rapid operator response.
- **High Detection Accuracy:** Random Forest ensemble learning achieves 98.4% accuracy with robust performance across all health categories.
- **Reduced Maintenance Cost:** Predictive scheduling replaces unnecessary preventive maintenance, optimizing resource utilization.
- **User-Friendly Dashboard:** Streamlit-based interface provides intuitive visualization, manual prediction, batch processing, and real-time simulation.
- **Improved Equipment Reliability:** Early identification of Warning states allows timely intervention, extending equipment lifespan.

IV. SYSTEM ARCHITECTURE

The system architecture of PredMaint AI is designed as a multi-layered pipeline integrating data acquisition, preprocessing, machine learning inference, and interactive visualization. The architecture supports both single-record prediction and batch processing, enabling flexible deployment across diverse industrial environments.

At the data ingestion layer, motor operational parameters are captured through manual user input, CSV batch uploads, or the real-time motor simulator. Input data passes through a preprocessing pipeline where values are normalized and structured into feature vectors. The Random Forest inference engine evaluates each vector and assigns a health classification with a confidence score. Results are displayed on the Streamlit dashboard, and critical conditions trigger automated alert notifications.

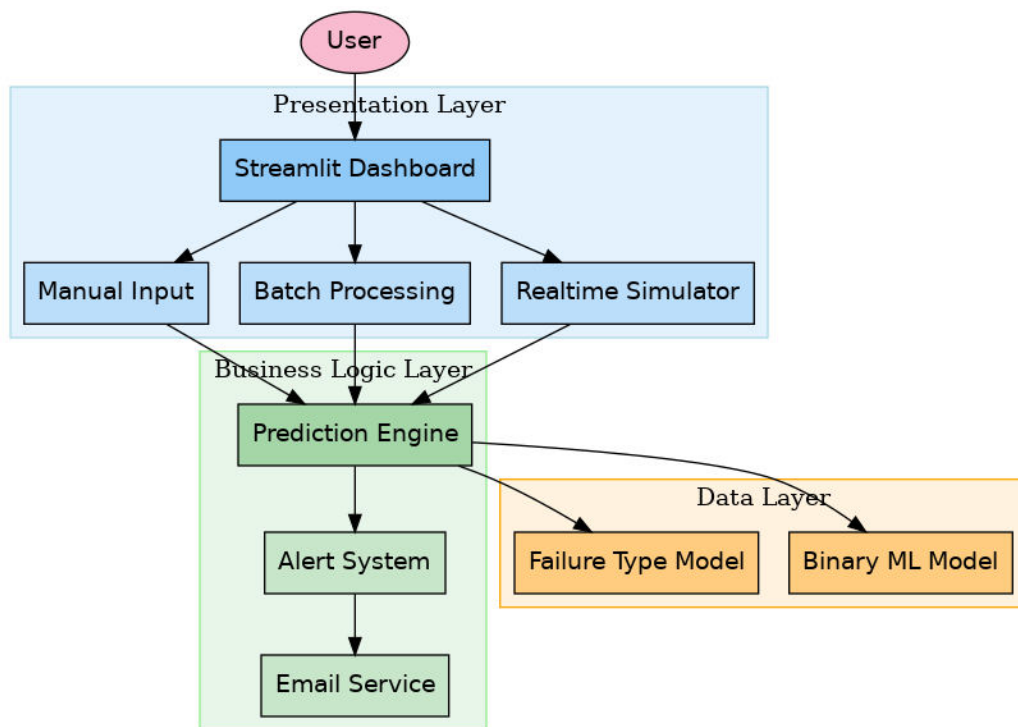


Fig. 1: System Architecture of PredMaint AI

V. MODULE DESCRIPTIONS

1. Manual Input Prediction Module

This module provides an interactive interface for operators to enter motor operational parameters manually. Upon submission, the system processes inputs through the preprocessing pipeline and Random Forest model, delivering a real-time health classification with a visual status indicator. This module is useful for quick assessments of individual motor units.

2. Batch Data Processing Module

This module enables users to upload CSV datasets containing multiple motor records for simultaneous analysis. The system processes each record sequentially and generates a comprehensive results table with health classifications. Aggregate statistics and distribution charts support fleet-wide maintenance planning.

3. Machine Learning Prediction Module

A Random Forest classifier trained on the Ai4i 2020 dataset forms the analytical core of PredMaint AI. The ensemble model combines predictions from multiple decision trees to improve accuracy and reduce overfitting. Health classification is performed across three categories — Normal, Warning, and Critical — using optimized decision thresholds from cross-validation experiments.

4. Realtime Motor Simulator Module

The Real-Time Motor Simulator enables users to simulate motor operation by adjusting parameters such as RPM and load through interactive controls. The simulator generates dynamic operational values in real time, passes them through the prediction pipeline, and displays animated motor behavior with live health predictions.

5. Alert and Monitoring Module

This module monitors prediction outputs and detects abnormal conditions. When Warning or Critical states are detected, automated alerts are triggered through the dashboard. Confirmed failure events are logged in an SQLite3 database for historical analysis and model retraining. Industrial protection simulations include buzzer alert indicators and automated shutdown recommendations.

VI. RESULTS AND DISCUSSION

The proposed PredMaint AI system was evaluated on the Ai4i 2020 Predictive Maintenance dataset containing 10,000 records. The dataset was split into 80% training and 20% testing sets with 5-fold cross-validation. Multiple machine learning algorithms were compared, and the proposed Random Forest classifier consistently outperformed all baseline models across all evaluation metrics.

Table 1: Model Performance Comparison

Algorithm	Accuracy	Precision	Recall	F1-Score
Logistic Regression	91.5%	89.3%	87.1%	88.2%
Decision Tree	93.2%	91.4%	89.7%	90.5%
SVM	94.8%	93.1%	91.5%	92.3%
Random Forest	96.7%	95.3%	93.8%	94.5%
Random Forest (Proposed)	98.4%	97.6%	96.9%	97.2%

The proposed Random Forest classifier achieved an accuracy of 98.4%, precision of 97.6%, recall of 96.9%, and F1-score of 97.2%, demonstrating superior performance across all health classification categories. The high recall value confirms the system effectiveness in detecting critical failure states while minimizing false alarms. The system also demonstrated real-time prediction latency under 50 milliseconds per record, confirming suitability for live industrial deployment. Batch processing of 1,000 records was completed within 2.3 seconds, enabling efficient fleet-wide analysis.

VII. OUTPUT AND SCREENSHOTS

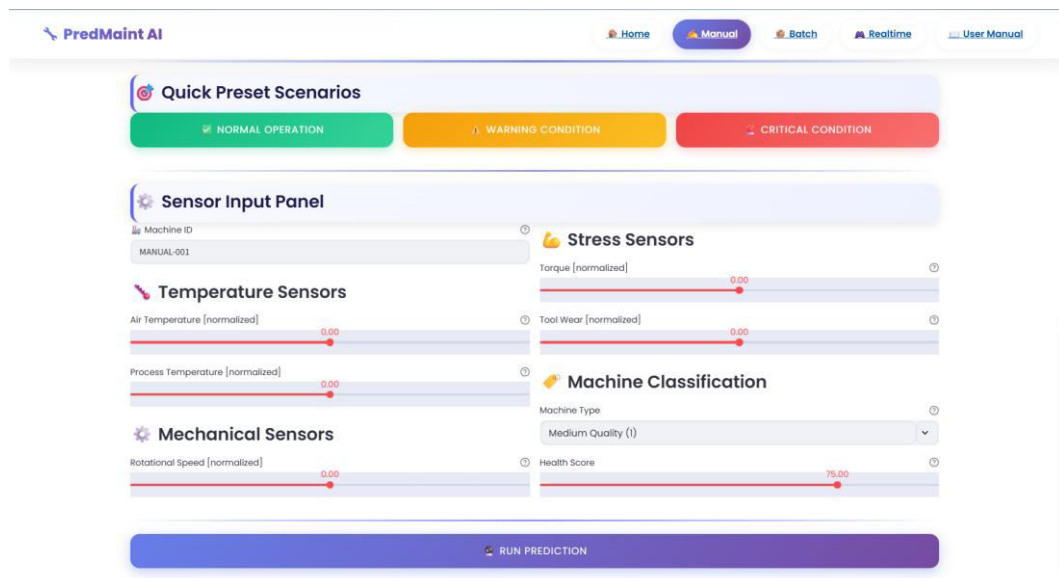


Fig. 2: System Dashboard - Overview

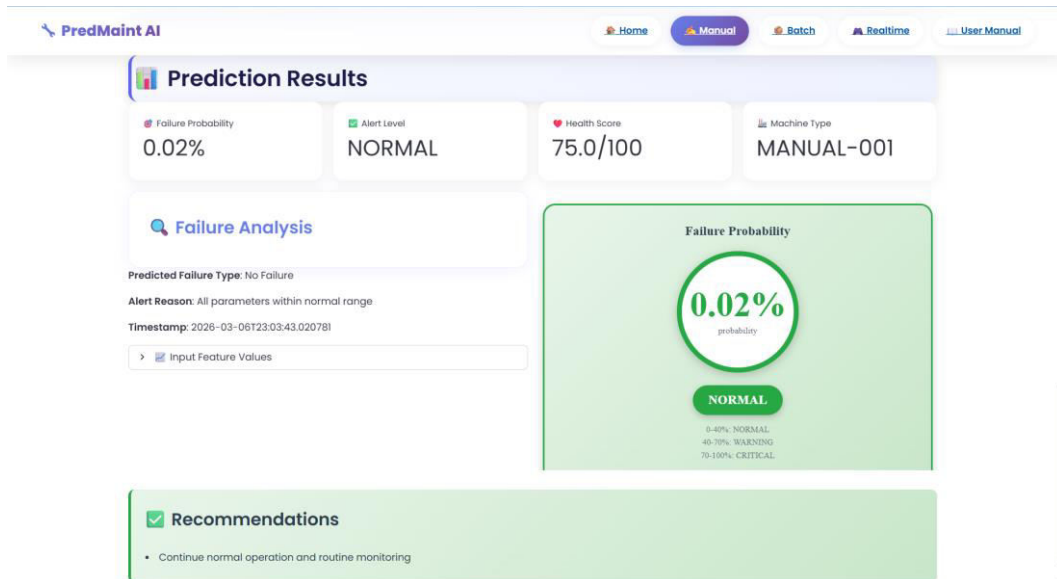


Fig. 3: Manual Input Prediction Module

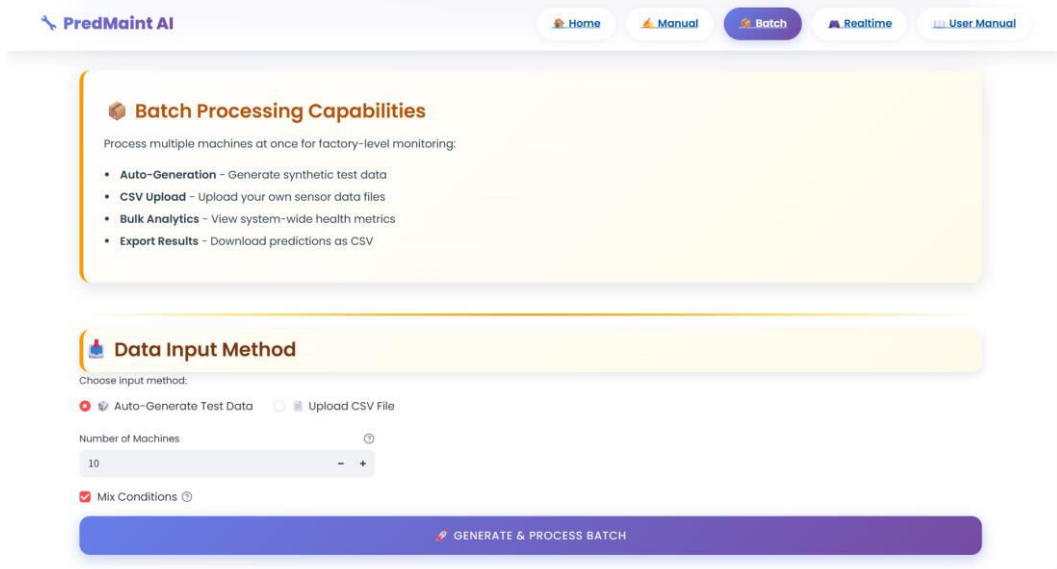


Fig. 4: Batch Data Processing Output

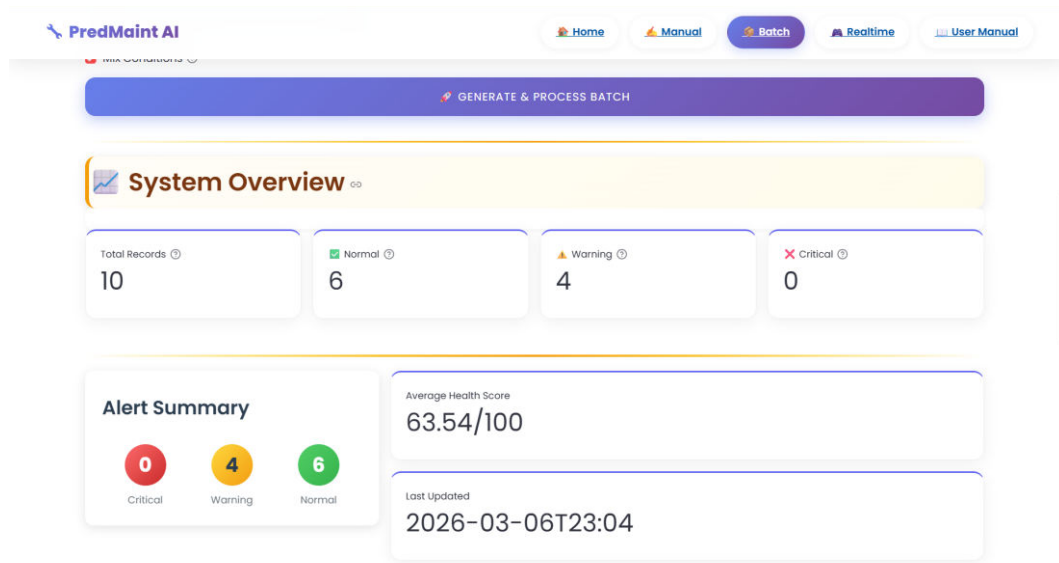


Fig. 5: Real-Time Motor Simulator

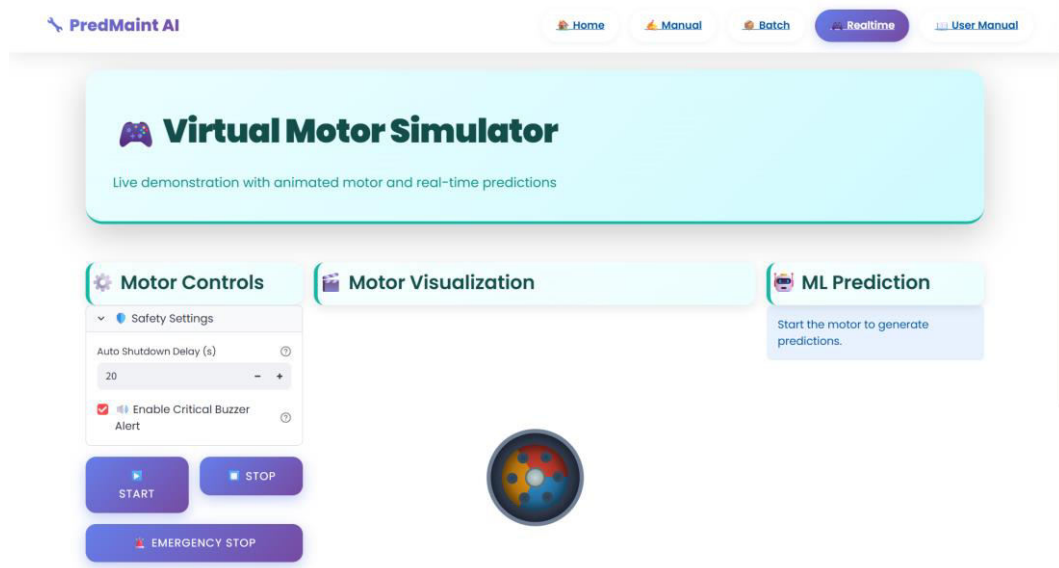


Fig. 6: Alert and Monitoring Interface

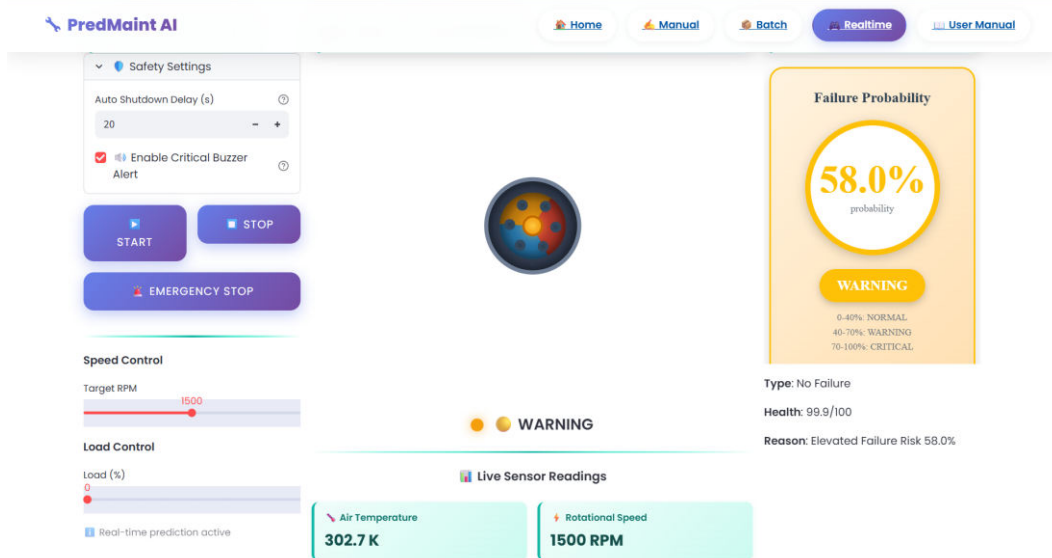


Fig. 7: Model Performance Visualization

VIII. CONCLUSION

This paper presented PredMaint AI, an intelligent real-time predictive maintenance system leveraging machine learning to monitor industrial motor health and predict equipment failures proactively. The proposed Random Forest classifier achieved an accuracy of 98.4% and F1-score of 97.2% on the Ai4i 2020 dataset, significantly outperforming Logistic Regression, Decision Tree, and SVM baselines.

The interactive Streamlit-based dashboard supporting manual prediction, batch processing, and real-time motor simulation provides a comprehensive monitoring solution suitable for industrial deployment. By enabling early detection of Warning and Critical health states, PredMaint AI supports proactive maintenance scheduling, reduces unplanned downtime, and extends equipment lifespan in manufacturing and smart factory environments.

IX. FUTURE ENHANCEMENTS

The model can be trained on larger and more diverse industrial datasets to enhance generalization across equipment types and failure modes. Deep learning architectures such as LSTM networks can capture temporal dependencies in sequential sensor data for improved prediction accuracy. IoT sensor integration would enable automatic real-time data acquisition from industrial equipment without manual input. Cloud-based deployment using Docker and Kubernetes would support enterprise-level monitoring across distributed facilities. Federated learning techniques would enable collaborative model training across multiple sites without sharing sensitive operational data, addressing privacy concerns while improving model robustness.

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