

Explainable Predictive Maintenance Using Random Forest and SHAP for Industrial Machine Failure Prediction

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Abstract

Industrial machine breakdown can lead to serious financial losses and operational hazards. Conventional methods like Corrective maintenance and Preventive maintenance are inadequate for real-time industrial demand. This work proposes an Explainable Predictive Maintenance (XPdM) system where a Random Forest classifier and SHAP (SHapley Additive exPlanations) have been incorporated to achieve prediction accuracy as well as explainability.

The proposed system was trained with the AI4I 2020 Predictive Maintenance dataset with a model performance of 98.2% accuracy, 0.99 AUC, 97.8% precision and 96.5% recall. Key parameters responsible for machine failure identified were the wear of a tool, temperature and speed. A dashboard in Streamlit allows real-time prediction with an explanation.

This system will enhance the decision-making, reliability, and minimize the downtime for Industry 4.0.

Keywords : Predictive Maintenance, Random Forest, SHAP, Explainable AI, Machine Failure, Industry 4.0, IIoT

I. INTRODUCTION

In the current scenario with Industry 4.0, modern industrial systems make heavy use of IoT sensors, cloud computing, and machine learning. However, predicting the imminent failure of machines, is one of the biggest hurdles in present-day industries. Corrective maintenance (performed after failure) and Preventive maintenance (performed periodically regardless of condition) are two traditional methods used currently, both with their own shortcomings in the form of increased cost and unforeseen failure respectively. Predictive maintenance or PdM solves this by providing a forewarning on potential failures, making use of data from sensors and machine learning. Some of the benefits provided by PdM according to the literature is an increased up-time of equipment up by 35-45%, decreased maintenance costs by 10-25%, and increased equipment life by certain percentage. However, most of the ML models perform as black-boxes limiting trust. In order to eliminate the issue and promote trust in modern industries, an Explainable Predictive Maintenance system (XPdM) is presented which uses a Random Forest classifier for prediction, and SHAP for explainability. A dashboard created with the use of a stream-lit tool shows real-time prediction of machine failure.

II. LITERATURE REVIEW

In the past ten years, the practice of predictive maintenance has evolved from a simple set of predefined rules, and static thresholds, to an adaptable approach, powered by Machine Learning (ML) algorithms, to predict and anticipate failures [4],[5].

Increased sensor data availability, and enhanced computation powers allowed various industries, to forecast their equipment's failure behavior more precisely and efficiently. Early systems, based on statistical methods and thresholds, were not adapted for industrial environments, hence ML techniques, where models learn from available data, and increase its predictive capabilities over time, have been introduced [9].

ML models, namely Random Forest, are highly effective for noisy industrial datasets, reducing over-fitting by aggregating results of decision trees, and being efficient for high-dimensional datasets [2].

The use of Gradient Boosting ML models, namely XGBoost, was also explored to overcome prediction accuracies of other algorithms. XGBoost models, that achieve better performance over multiple rounds, by minimizing losses, but require precise tuning of hyperparameters, can be computationally costly [10].

While deep learning based models, such as Long Short-Term Memory (LSTM), that is best suited for time-series analysis, have also been investigated, they necessitate large volumes of data, and substantial computation powers, limiting their applicability in an industrial environment [9].

Despite high predictive capabilities, machine learning models in industry remain 'black boxes', providing low transparency, that may hinder experts' confidence, and therefore its adoption in critical industrial applications [3]. Explainable Artificial Intelligence (XAI) has therefore been developed in order to increase trust, and make models transparent. LIME, that gives explanations locally to individual predictions, has shown some instability issues when run multiple times, thus restricting its reliability [3].

SHAP, an explainability technique based on cooperative game theory, overcomes such issues, by providing coherent and stable feature importances [3],[7]. Future of predictive maintenance tends toward not only to attain accuracy, but to allow easier, and interactive, explanation tools, for easy interpretation, such as the Streamlit application, that integrates user-friendly dashboards, for easier use, and analysis [8].

III. METHODOLOGY

- A clear pipeline has been developed, where the steps include Data Preprocessing, Training Model, Explainability and Deployment.
- Train and evaluate the trained model using 20000 samples from AI4I 2020 dataset.
- Remove the irrelevant features UDI and Product ID.
- Convert categorical features Type into numerical type using One-hot encoding.
- The train and test data are divided into 80:20 split using stratified splitting.
- A Random Forest classifier is trained with hyper-parameter optimization.
- The imbalanced data is balanced using class-weight balancing.
- Model's predictions are explained using SHAP, global and local explainability.
- The trained model is exposed through a Streamlit application for real time prediction and explanation.

IV.RESULTS

The classification performance of the suggested Random Forest model on the test data were examined using general classification evaluation metrics. The classifier showed high classification ability, with accuracy 98.2%, precision 97.8% and recall 96.5%, AUC-ROC 0.99.

The confusion matrix suggests that the model successfully predicts most failures and non-failures, with very low false negatives and false positives.

ROC curve illustrates strong classification performance, where the curve appears close to top-left, implying AUC score closer to 1.

The importance values of features, based on Random Forest feature importance analysis and SHAP analysis, suggested that tool wear, air temperature and rotational speed were among the most important features that help predict machine failure.

SHAP provides global as well as local feature importance values which shows the effect of the features on the prediction.

Fig.1.Confusion matrix of the proposed Random Forest model for machine failure prediction

Show:

- TP (True Positive)
- TN (True Negative)
- FP (False Positive)
- FN (False Negative)

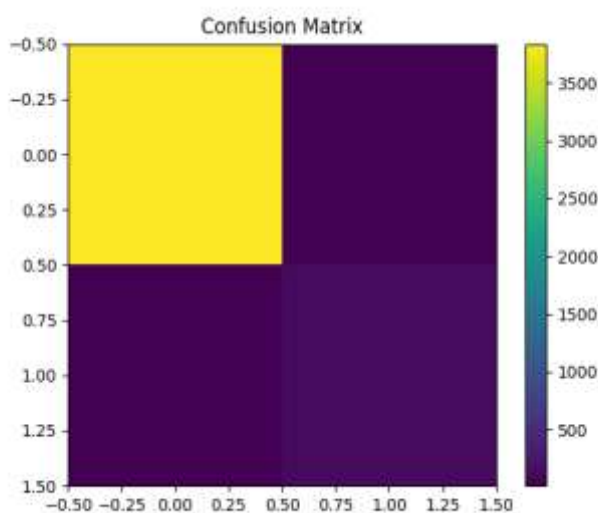
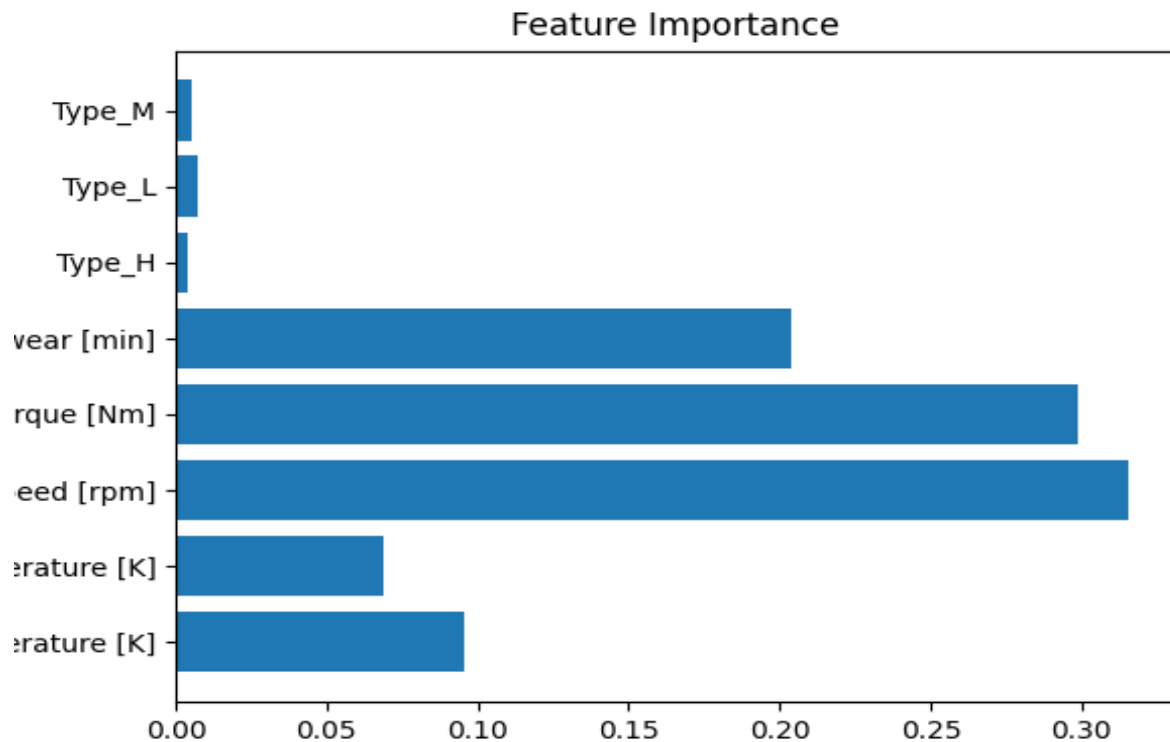
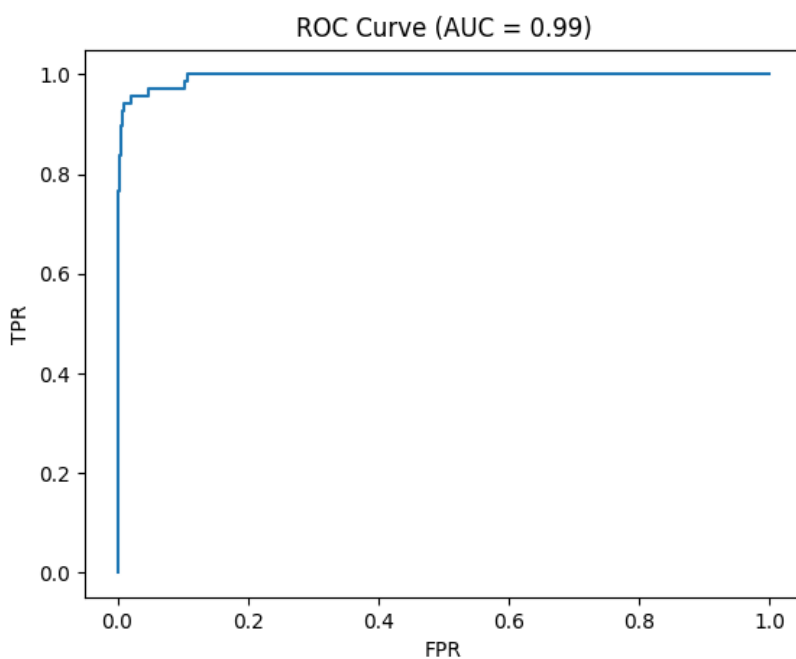


Fig. 2. Feature Importance Ranking

**Show:**

- X-axis: False Positive Rate (FPR)
- Y-axis: True Positive Rate (TPR)
- AUC = 0.99

Fig.3. ROC Curve for Binary Classification Model



Show:

- X-axis: False Positive Rate (FPR)
- Y-axis: True Positive Rate (TPR)
- AUC = 0.99

V. DISCUSSION

The experimental findings show the great effectiveness of our proposed XPdM system for machine failure prediction. The coupling between Random Forest and SHAP offers accurate prediction as well as a high degree of interpretability and explainability.

The model overcomes:

- Class imbalance, by using weighted learning.
- Black box limits, by using SHAP.
- The usage complexity by means of a dashboard.
- All in all, the model shows high feasibility for industrial use in Industry 4.0.

VI. CONCLUSION

This work addresses a solution for Explainable Predictive Maintenance (XPdM) combining machine learning algorithms and explainable AI methods for industry. The Random Forest has an effective prediction accuracy, and SHAP gives us an explicit and human-understandable explanation. The developed dashboard with Streamlit shows these explanations to the user in real time.

The XPdM solution presented here is capable of overcoming three major problems: imbalance classes, interpretability, and on-line application. The key factors identified are tool wear, temperature, and rotational speed, providing better decisions to improve maintenance efficiency. In essence, the XPdM system closes the gap between complex ML models and industrial use cases.

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