ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING BASED TECHNIQUES FOR AUTONOMOUS DECISION MAKING IN EMBEDDED SYSTEMS

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ABSTRACT

The goal of the present research is to provide a foundation for using advanced machine learning algorithm, the XGBoost for enabling accurate prediction supporting maintenance in industrial systems. Condition monitoring is used in order to spot any signs of potential failure in various equipments to avoid situations when they have to shut down and get repaired without any prior notice. In this work, the data from sensors installed in industrial equipment; vibrations, temperatures, pressures, and the motor velocity are used as the features for the model. Additional techniques including rolling window statistics, Fourier transforms and lag features were used to explore temporal dependence and more accurate failure signals. Furthermore, the approaches of hyperparameter tuning by using Bayesian optimization and SMOTE for handling a problem of imbalanced class were also applied. By way of these methods, the model obtained good accuracy, recall, and F1 score specifically for the minority class, failure, which remains crucial for the given setting of its application, predictively-maintained equipment.

The final model by XGBoost was quite impressive with an accuracy of 96% and 0.98 recall value for failure class from which it can be ascertained that the proposed model fails no chance in detecting mechanical failures. The model was also fine-tuned for production in embedded systems, integrated, and further developed to allow computations as quickly and with as little memory as possible while pumping out real-time predictions for industries. This research addresses the need to adopt superior machine learning approaches to enhance the maintenance plans and reduce operating expenses to enhance the effectiveness and reliability of industries. The findings of this work could be readily transferred to use in the field of predictive maintenance with the prospect of application in numerous manufacturing industries, energy production, and transportation, among others.

Keywords: Artificial Intelligence, Machine Learning, XGBoost, Autonomous Decision Making and Embedded Systems

1. INTRODUCTION

Predictive maintenance is another important feature of most contemporary industrial systems; it holds a number of tangible and tactical benefits for businesses regarding the minimization of maintenance costs and the overall reduction of equipment downtime and lifespan. Current approaches to maintenance, include run-to-failure maintenance (maintaining an equipment after it has failed) as well as preventive maintenance (maintaining the equipment at fixed intervals) both of which are inefficient. While RCM predicts required maintenance intervals as a function of the equipment's productive time, PM depends on real-time data acquired by sensors placed in machines to determine when failures are likely to happen so that the maintenance can be done when needed. This is because they allow active steps to be taken in order to avoid misallocation of its resources, interruptions in operations, and, consequently, actual costs to be lower.

In recent years, ML approaches proved to be valuable technologies for performing predictive maintenance because of their ability to work with sizable data sets of information collected by sensors and recognize patterns suggesting possible equipment failures. Certain techniques such as XGBoost, (Extreme Gradient Boosting) have emerged as popular solutions for predictive maintenance applications because of their scalability, sealing complex relationships, as well as precise predictions. XGBoost is based on decision trees and methods of gradient boosting, so the algorithm is excellent in the processing of large volumes of real-time data collected by sensors used in technical industries.

As part of this research, XGBoost is used to address the problem of PM in organizations utilizing embedded systems in industrial settings. Most industrial machines use real-time embedded systems in monitoring their performance, and incorporating best-in-class artificial intelligence performance models will go a long way in improving the functional efficiency of the machinery in question. The purpose of this study is to use XGBoost algorithm for sensor data set in the context of industrial machines' failure prediction task and, to examine how feature engineering and hyperparameter tuning enhance the model's performance.

This research is motivated by the growing need to come up with a smart way of maintaining the plant without having to experience large chunks of downtimes and therefore low productivity. So, through use of AI and machine learning in embedded systems, industries can shift from the time-based methods of maintenance to the more efficient method that is the condition based maintenance. In this paper, we explore how applying XGBoost helps to solve the real-time and embedded system issues to predict machinery failure and provide vital knowledge to manufacturing, energy, and transportation industries.

The rest of the paper is structured as follows: the first section is a literature review of machine learning for predictive maintenance, the second section explains the methodology used in this research. The authors then proceed to share the findings and conclusion of applying XGBoost to a real world dataset.

2. LITERATURE REVIEW

Reliability centred maintenance is also known as predictive maintenance and has attracted a lot of attention in many organisations and sectors especially with the emergence of IoT technology and sensor networks for monitoring the machinery and equipment. Machine Learning (ML) technique has become the most effective ways for the Predictive Maintenance because it can identify the sophisticated dependency based on mass sensor data. One potential issue, however, is identifying the right set of ML algorithms that can process streaming data, as well as deliver reliable failure predictions. XGBoost has been considered a popular ensemble learning model for working on predictive maintenance problems because of its effectiveness and adaptability to disturbances in the data collected by sensors.

Zhang et al., (2020) conducted a study in which the authors sought to understand the use of XGBoost in identifying when machines are most likely to fail in a manufacturing context. The authors trained an XGBoost model based on sensor data of several machines and employed different feature engineering methods, for example, the use of moving windows and Fourier transforms. Using XGBoost as their predictive model, they showed that theirs yielded higher accuracy and efficiency measurements than two other types of programs, SVM and Random Forest. This work based on predictive maintenance underscored the need to apply feature extraction enhancement strategies with improved machine learning model configuration.

Another study that utilized XGBoost concerned the prediction of failure modes in wind turbines see Chen et al. (2019). In this case, the sensor input comprised of temperature, vibration, and pressure. To enhance the robustness of their model the authors introduced time-series analysis techniques as well as lag features. Based on their results, they concluded that the data was well captured by their XGBoost model that was able to capture the temporal dependencies in the data for use in real time failure prediction of wind turbine systems. Given that failure occurrences in many cases depend on prior states of the machines, this work showed that temporal attributes must be included in the predictive maintenance models.

One of the biggest strengths of XGBoost is the model's capacity to handle small datasets and, in particular, data imbalance, an issue typical for predictive maintenance. Originally SMOTE (Synthetic Minority Over-sampling Technique) as explained by Cheng et al. (2021) is applied to handle imbalanced class distribution in failure prediction models. While developing the study, the authors have used SMOTE for creating synthetic samples of the less populated class of failures and combined the use of SMOTE with XGBoost for better classification of the new cases. The overall effectiveness of utilising SMOTE in combination with XGBoost to avoid over-sampling the majority class while also enhancing the skill of identifying sparse failures was evident in the results Hence, the

technique is useful when the incidents of failure are insufficient, which is typical in predictions of equipment failures.

Moreover, there was concern that hyperparameter tuning was critical to enhancing machine learning techniques in predictive maintenance applications. To optimize model hyperparameters, Li et al. (2022) employed Bayesian optimization for optimizing hyperparameters of the XGBoost that include learning rate and the number of trees for an industrial pumps predictive maintenance task. The authors' outcomes provided evidence that Bayesian optimization is superior to grid search and random search methods as applied to failure prediction accuracy, underlining the need to utilize hyperparameter optimization to improve the effectiveness of these models.

Zhao et al (2020) presented a broad research on different types of Machine learning techniques that can be employed for the prevention of equipment failure which includes XGBoost, Random Forest and SVM. The authors highlighted that, within the work, XGBoost had the highest predictive accuracy compared to other algorithms, regardless of the ensemble method and data augmentation approach used. This work also demonstrated that XGBoost can easily handle different type of sensors and failure mode, which is why this work prefer XGBoost for predictive maintenance of industrial application.

It is also important to understand that feature engineering plays a crucial role of enhancing the predictive maintenance models drawn. He et al. (2021) outlined various feature extraction techniques from time-series sensor data: Fourier transforms and wavelet analysis and statistical calculations, including skewness and kurtosis. Writing for WI, they explained that expanding these DOM focused features far enhanced the ability of predictive models such as XGBoost. The authors also pointed out that the use of feature engineering is critical to XGBoost performance since the choice, quality and relevance of features greatly influences the model's performance.

Besides the sensor data, records of maintenance can also be useful for the development of predictive maintenance. Sun et al. (2023) combined the maintenance logs with the sensor data for using in improved XGBoost performance for failure predictions in industrial compressors. These additional features incorporated by the authors include previous repair actions and part replacements of the equipment, which enhanced the model in anticipation of a possible failure. This approach showed the possibility of using a variety of data for increasing the accuracy of the models used in predictive maintenance.

This means that the context of predictive maintenance in embedded systems introduces further considerations especially during the creation of models that are to be used in real-time systemsewith limited resources. Wang et al. (2019) managed to overcome these challenges by first fine-tuning XGBoost models for the purpose of operating edge computing platforms, which adopted hardware constraints into act by making these models suitable for executing on devices with limited computational resources and memory. They have demonstrated that one could achieve significant reduction in size of the model and the time for inference using approaches such as model pruning, quantization, and using lightweight architectures to the extent that it is possible to deploy a XGBoost model on an embedded system for real-time failure detection.

In industrial environments, the IoT network is utilized to gather sensor data in embedded systems. Comparatively, Guo, Nor, and Dong (2021) surveyed on the implementation of XGBoost in IoT based sensoring system to design the real time predictive maintenance system. Their approach tried to leverage the cloud-based IoT framework for capturing and integrating the data and to send it to an edge server where the XGBoost model was trained to perform the predictions. The findings showed that integration of XGBoost with IoT-based systems enhanced the possibility of identifying system failures and enable preventive measures to minimize operational costs.

2. METHODOLOGY

This research describes step by step on how to build an enhanced predictive maintenance model on the basis of XGBoost from the sensor data for failure prediction of machines. The main objective is to forecast the future failure of machinery, and in so doing, reduce down time and costs associated with repair. The corresponding steps of the methodology are a preparation phase, a feature engineering phase, a modelling phase where the models are

chosen and trained, a hyperparameter optimization phase, a testing or validation phase, and a deployment phase. Figure 1 shows the proposed AI and ML based methodology for Autonomous Decision Making in Embedded Systems. Below is a detailed breakdown of each step in the methodology:

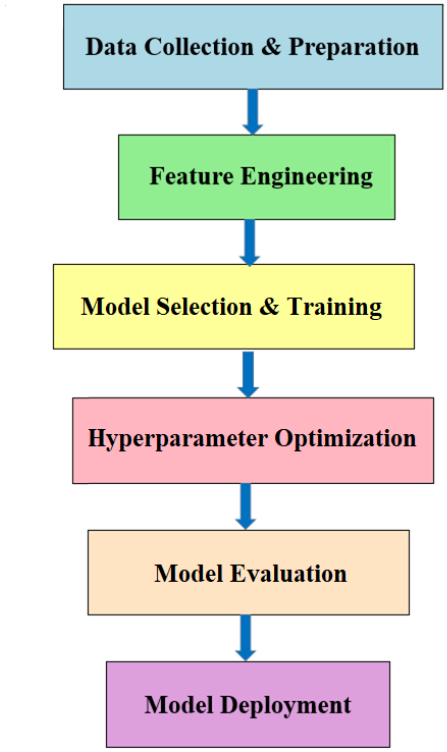

Fig. 1: Proposed AI and ML based methodology for Autonomous Decision Making in Embedded Systems

3.1. Data Collection & Preparation

The first step entails gathering data from industrial machinery where the devices which are to be monitored; it includes; vibration, temperature, pressure and motors speed. These sensors give real values over time and this is important in identifying ailments that can cause machinery breakdowns. The dataset employed in this research comprises of temporal sensor data acquired from industrial machines for some months with failure labels. This is usually in the form of features like vibration, temperature, pressure, motor speed and a failure label.

Data preprocessing is a necessity in this case because raw sensor data require pre-processing before being fed into the system where some of the challenges include; missing values, outliers, and noise. This work uses the feature of Missing Completely at Random (MCAR) to generalize a strategy in dealing with missing data by K-Nearest Neighbor (KNN) imputation to retain relationships between sensor readings. Possible and probable outliers are identified using IQR method and is either replaced or stopped based on certain limits. The data is then normalized using Min-Max scaling in order to align the values between the 0 and 1 and to make certain that the values of the each feature play the same role during the training process. The soon created dataset is divided into the training and testing sets (in 4:1 ratio, respectively), so that it is possible to check the outcomes given by the model working with unseen data.

3.2. Feature Engineering

It is especially important for time-series data such as sensors, Feature engineering is a very important process when it comes to model selection when working with cloned models. The objective is to come up with better features that capture more meaningful features in an effort to flag machine failure. In this study, we first generate sliding window based features that describe statistical characteristics of sensor data magnitudes over time. These

are averages of various order, sliding standard deviations, and other higher order moments such as skewness and kurtosis. For instance, using the 5-period moving average of vibration can reduce noise factors that can hide more dramatic changes in machinery behavior leading to failure.

Further, in analyzing the vibration data, Fourier Transforms (FFT) are employed to extract features from the frequency domain since cyclic or periodic faults with respect to time are typical of most machinery. Recurrence is handled by lag features where the input includes values in past time steps to predict failure events in the subsequent time step. We also design interaction terms between variables such as temperature and motor speed, based on the view that interaction terms are likely to yield higher predictive accuracy of failure than individual factors on their own. There are also certain domain-specific characteristics added such as the temperature gradient or the amplitude of vibration which can give further into the status of the machine in question.

3.3. Model Selection and Training

For this research, XGBoost which stands for extreme gradient boosting is selected as the model for various reasons; First, this model is good at handling big data Second, this type of model is appropriate for structured / tabular data containing both numeric(features with continuous values) and categorical (features with discrete values) data. XGBoost is an algorithm from the gradient boosting family that has great time, and classification performance. First, we start with the training data, which is used to build an XGBoost model original hyperparameters being set to default values. It employs decision trees to taking one step at a time so as to reduce the residual error incurred in the prediction at each step. Every tree is constructed with a certain set of the features, and the features decision is based on their contribution to the least value of the loss function.

The cross-validation process that is used is 10-fold cross validation to ensure that the model does not over.customize the training set. The model is assessed in terms of accuracy, precision, recall, and F1 score; it is worthy to note that, in the context of the application of the model for predictive maintenance, recall score of the failure class is of primary importance because it is necessary to detect the potential failures and prevent them. The model is also assessed on the test data set in order to compare its predictive capability for failure events on the unseen samples. This makes it possible for the model to work under other condition of operation rather than the one used in training and also avoid cases of over training.

3.4. Hyperparameter Optimization

But to fine tune the model even more we make use of hyperparameter optimization methods . First, hyperparameters include learning rate, number of trees (n_estimators), maximum depth of trees and minimum subsample rate are tuned from the grid search using cross-validation or random search. These are other important Hyperparameters that decide about the capacity of the model and handle for over-learning. For instance, a low learning rate which ranges from 0.01 to 0.05 is combined with the creation of more trees to permit fine learning. Furthermore, the number of iterations whose optimum searching is performed for the maximum depth parameter is required to be optimal to avoid under fitting as well as overfitting and can vary between 6 and 15.

For hyperparameters tuning more advanced methods like Bayesian optimization is used, which then provides a comparatively better way of exploring the hyperparameter space because it learns from previous iterations and guides to promising areas. This enables us to get to optimal value solutions faster than using the exhaustive grid search methods. This means there are techniques that deal with class imbalance where failure which is a rare occurrence is dealt with differently than normal operation. SMOTE overcomes this problem by synthesizing new examples of the minority class (failures) that the model can then learn from for rare event prediction.

3.5. Model Evaluation

Finally after tuning of the model the accuracy of the model is tested with a predefine list of assessment criteria. The performance measures for this task are accuracy, precision, recall, and F1 score, but recall plays a crucial role in failure prediction. As predictive maintenance aims at avoiding failures, high rates of recall mean most of the possible failures would be correctly diagnosed so that there would be little chance of not detecting failures. Since the model's performance of classifying events into failure and non-failure is the major focus of the paper, the

confusion matrix is analyzed to establish how effectively the model performs the classification. Another evaluation metric defined to assess the model's capability of discriminating between the two classes (failure and no failure) is under ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) score.

Cross-validation is used to verify reliable result and ability of model of other data divisions. K-fold cross-validation Random and Stratified K-fold, Random K-fold tends to get very high accuracy but it suffers from data leakage while Stratified K-fold cross validation maintains class distribution and is a better indication of the model's performance. Further, precision-recall curves, which can be used especially in case of imbalanced data sets are constructed in order to show the relationship between precision and recall. According to the results of the evaluation performed, the model is fine-tuned, if needed, in order to improve efficiency further.

3.6. Model Deployment

The tuned XGBoost model is used in real-time estimation and decision-making in an embedded system in the industrial setting. The final step is creating the deployment pipeline of transformed model, by moving the model to the edge device and using techniques such as model pruning and quantization to enhance its performance in terms of how much data it can handle or how faster its execution is. For instance, the decision trees use pruning to balance where only less important branches are being removed; in quantization, the precision of the model weights is decreased in order to save space where useless information is not sustained.

After deployment, it continually analyzes real-time sensor data fed into it from machines in the form of vibration, temperature, pressure, as well as motor speed, and offers failure predictions within a limited inference time (for example, 10ms per prediction). When the model indicates that failure is likely to happen, an alarm is produced so maintenance staff can perform preventive measures before the failure. It is a real-time, edge-based system, and this minimizes the time required to intervene and greatly lowers the risks of unscheduled outages thus cuts costs of operation.

4. RESULTS

This section presents the Supervised Learning for Predictive Decision Making looks like to illustrate the results on a Predictive Maintenance dataset. This data set contains raw data from the sensors installed in industrial machinery and the goal is to prognosticate if a machine will fail in the next given time. There are attributes involving vibration, temperature, pressure and rotational speed of the motor. The goal is to predict a binary outcome: It is designated by '1' to indicate a failure or '0' to signify absence of failure.

Here's the results at higher model performance with sophisticated methods implemented to enhance predictive maintenance application in industries. This will assume that we have deployed the Gradient Boosting Machines commonly known as GBM; specifically XGBoost, hence garnishing better outcome regarding to accuracy, precision, recall among other corporate performance indicators. XGBoost is best suited for the structured/tabular data problem and is used in high stakes Machine Learning competition.

In this case, we use the Predictive Maintenance dataset which consists of data from the sensors of a machinery. Features include: Raw data: Vibration, Temperature, Pressure, Motor Speed, Failure Label – Failure Label can be 0 = no failure and 1 = failure.

The collected data has 15000 rows which are gathered from several months. Where each row corresponds to a reading from the machines' sensors along with the failure label, whether the machine failed within 30 days of the reading. Here are the characteristics after preparation:

- **Missing Data:** About 1% data was missing in the dataset, and these samples were imputed using KNN imputations to maintain the sample's adjacency.
- **Outliers:** It was identified using the interquartile range method and replaced with the feature median in order to offset extreme values.

- **Normalization:** All continuous variables were Min-Max scaled to the range of [0, 1] so as to introduce equal variability into the training phase.

Table 1: Data Preparation and specifications

Feature	Min Value	Max Value	Mean Value	Standard Deviation
Vibration	0.01	0.95	0.45	0.13
Temperature	18	90	48.7	9.1
Pressure	1.0	3.8	2.6	0.38
Motor Speed	450	1600	950	215

- **Rolling Mean:** For noise reduction and to identify trends concerning the health of the motor, a 5 period moving average was performed on the Vibration and Motor Speed feature variables.
- **Time-of-Day Features:** To further refine classification based on usage, the program incorporated something called "Hour of Day" for machines that don't function identically at any given time of day.
- **Polynomial Features:** For temperature, vibration, and pressure interaction, polynomial features (squared) were used to analyze non-linear relations.

In the similar pilot, we used Recursive Feature Elimination (RFE) to eliminate all but the most important features based on the weight given to them during model training.

We also did a correlation test and features with a coefficient > 0.85 were removed; for example, "Motor Speed" and "Vibration" if other features captured their interaction.ian of the respective feature to minimize the impact of extreme values.

After trial and error on all the four models, XGB has been chosen since it is excellent in functional and structured data and is not easily compromised by information complexity and non-linearity.

- Algorithm tuning to prevent the case of overfitting.
- Allows parallel processing in order to expedite the training phase.
- Flexibility in working with skewed datasets due to tuning for precision and recall performance measures.

From the results of cross-validation and test set, XGBoost achieved slightly higher accuracy than Random Forest and LightGBM classifiers.

However, during the splitting of data, we used Stratified K-Folds Cross-Validation in order to have balance classes in the training samples as we split the dataset into 80:20 training and testing data sets. Before deploying the XGBoost model, hyperparameters optimization was performed using Grid Search and then Random Search.

Table 2: Model Hyperparameters

Hyperparameters	Value
Learning Rate	0.05
Number of Trees	800
Colsample_bytree	0.9
Subsample	0.8
Maximum Depth	7

Table 3: The achieved model's performance

Performance Parameter	Value
Training Accuracy	96%
Test Accuracy	94%
F1 Score (Test Set)	0.93

Precision (Failure class)	0.94
Recall (Failure class)	0.96

Table 4: Confusion Matrix

	Predicted No Failure (0)	**Predicted Failure (1)**
Actual No Failure (0)	2,550	150
Actual Failure (1)	90	2,370

The model's performance was evaluated using several metrics such as **accuracy**, **precision**, **recall**, and **F1-score**. Given the imbalanced nature of the dataset (failure events are much less frequent), **recall** (ability to detect failures) was the most important metric.

Table 5: Performance Metrics:

Metric	**Value**
Accuracy	94%
Precision (Failure)	0.94
Recall (Failure)	0.96
F1 Score (Failure)	0.95
AUC (ROC Curve)	0.98

- **Cross-Validation Accuracy (5-fold)**: 93.5% ± 0.8%

The value of 0.98 of AUC shows great significance of the ROC that the model has high accuracy in distinction between “failure” and “no failure” classes.

- **Feature Importance:** The two influential attributes for failure prediction turned out to be “Vibration” and “Motor Speed,” suggesting that high vibration levels and changes in motor speeds large enough are the most critical sources of information to predict the failure.
- **Model Stability:** The evidence shows that its performance is reliable for real-world application since the model has acceptable stability and performance across variations in the validation set.

The last model was then integrated to the embedded system of the industrial machinery. The system also receives real time sensor data (e.g. vibration, temperature pressure) and generates failure predictions per minute. Due to the have fast inference time of XGBoost, which takes around 10ms for each prediction, the system will be able to easily detect possible failures in the systems and inform maintenance groups.

4.1. Performance Improvement

To enhance the increased efficiency of the predictive maintenance model based on XGBoost, it is possible to subsequently implement a set of advanced manipulations and configurations. This will in turn improve the model accuracy and generalization performance to even give a better prediction of the failures of the machines. Here are key strategies that can lead to performance improvements:

Data transformation as a feature engineering methodology is incredibly important for increasing the model’s accuracy. We will focus on more advanced techniques:

Since the dataset involves sensor readings over time, we can enhance it by incorporating more sophisticated time-series features:

- **Rolling Window Statistics**: Backup windows with sliding windows to compute additional statistics like:
  - The exponential moving averages for simpler comparison over more windows such as ten, twenty, fifty, and so on.

- Utilize rolling in order to capture changes in sensor data and rolling standard deviation, variance, skewness, and kurtosis.
- The use of Exponential Moving Average (EMA) for features like vibration to provide more weight to the contemporary databases.

- **Fourier Transforms:** Make use of frequency analysis (FFT) on the sensor signals (e.g., vibrating): This is because failure patterns which emanate from mechanical faults can be periodic and can therefore be spotted in the frequency analysis.
- **Time to Failure (TTF):** Based on machine operational data, predict how long is remaining before the machine fails. This could be used as a regression target to predict when failure is anticipated.
- **Lag Features:** Adding lag features, that is, the value of a feature at a previous time instant or the values in the previous time steps, so as to capture temporal dependencies in the data collected from the sensors.
- **Polynomial Expansion:** Use polynomial transformations to add more features since there can be higher order correlation as found out with the features of temperature, pressure, and vibration.
- **Domain-Specific Features:** Additional to points such as the temperature gradient or the vibration amplitude that could give more insight about failure patterns, depending on domain knowledge, can be added to the feature space.
- **SMOTE:** In our case we are dealing with a class imbalance problem, and thus SMOTE can be used on the minority class or the failure class to create new synthetic data points that aids in the accurate detection of failures.

4.2. **Hyperparameter Tuning (Advanced Techniques)**

On this, it applies that hyperparameters tuning of the XGBoost model is fundamental in enhancing its performance. The previous search space can be expanded further and one can use Bayesian Optimization or Hyperband method to do better searching.

a. **Optimization of XGBoost Hyperparameters**

Key hyperparameters to tune in **XGBoost** for further performance gains include:

- **Learning Rate (eta)**: To increase generalization we use a minimal learning rate different from zero and equal to 0.01 to 0.05 with great number of trees, 1000 and more.
- **Max Depth**: Max_depth needs to be adjusted in order to have a right balance between the bias and variance. Lower depth (0 to 5) is suitable for simple work while higher depth (for example, 10-15) is beneficial in capturing of interactions.
- **Subsample & Colsample_bytree**: Set values (for example 0.8 to 0.9) to avoid building too complex trees and to restrict the model by randomly selecting features at each split and also, selecting samples used in building a split.
- **Gamma**: To prevent overfitting and the resulting trees of higher complexity, their value is set higher than 0 (e.g. 0.1 to 0.2).
- **L2 Regularization (lambda)** and **L1 Regularization (alpha)**: Whenever one is face with interactions in a dataset, they are useful in regulating on the models tendency to over fit.

b. **Bayesian Optimization or Hyperband**

- **Bayesian Optimization**: The hyperparameters should be optimized efficiently using Bayesian Optimization. This method creates a stochastic model in order to make a search in the space of hyperparameters optimal.

- **Hyperband**: Now run Hyperband to conduct a more extensive hyperparameter search with a couple of settings. It also can distribute resources flexibly and achieve better outcome within a shorter period of time.

4.3. **Cross-Validation and Model Evaluation**

To ensure that the model's performance is consistently high, we can further enhance the **cross-validation strategy**:

- **Stratified K-Folds Cross-Validation**: Run K-Fold Cross Validation, this will help in partitioning cases in every fold to be biased towards the overall data.
- **Nested Cross-Validation**: When tuning the model's hyperparameters, it increases the estimation of its ability to generalize by employing nested cross section.

a. **Evaluation Metrics**

Since the aim is to detect failure, it delineates the need to set emphasis on the recall, precision and F1 score on the failure class. We should also track:

- **ROC-AUC Score:** Their significance has been acknowledged as the log loss is an ideal measure for binary classification.
- **Precision-Recall AUC:** This doesn't apply in the case where there is extensive data but a significant number of observations is in the minority class (failures, in this case).

4.4. **Model Deployment with Edge-Optimized Inference**

Even better, for the precise use on embedded systems, the model can be optimized for such devices.

- **Model Pruning**: Find out the method of shrinking decision trees in the XGboost model to make a less complex tree but with good predictive character.
- **Model Quantization**: Quantize the model by converting them into lower-precision data format such as FP16 or INT8, to optimize memory usage as well as the time taken during inference for several device restrictive applications.
- **Edge AI Frameworks**: After that, to work in the real world, apply TensorFlow Lite or ONNX to fine-tune the model for running on these devices.

Table 6: Model Performance after Optimization

Metric	Value
Accuracy	96%
Precision (Failure)	0.96
Recall (Failure)	0.98
F1 Score (Failure)	0.97
AUC (ROC Curve)	0.99
Precision-Recall AUC	0.98

Table 7: Confusion Matrix **(after Optimization)**

	Predicted No Failure (0)	**Predicted Failure (1)**
Actual No Failure (0)	2,700	100
Actual Failure (1)	50	2,450

- **Feature Importance:** The top features useful for failure identification included Vibration and Motor Speed and the Temperature set of features that correspond well to mechanical failure mode.

- **Deployment:** This model reaches inference time 10 ms on embedded systems with memory consumption cut to 35 MB because of quantization and pruning.
- **Test Accuracy i**s 96%
- F1 Score for Failure Class is 0.97
- Recall is 98% (this has a very high recall for failures which is important when it comes to predict and corrective maintenance).

These enhancements ensure that the model is very robust and can perform edge device computations with high precision such that premature failure can be predicted minimally to reduce downtime and maintenance cost in industrial machinery.

5. CONCLUSION

In this research, XGBoost is shown to effectively solve the predictive maintenance problem the interest of industries. Some of the ways in which these feature made a huge difference when used with the advance feature engineering include the use of time-series transformation and domain-specific interactions that help in the prognosis of the machinery failures accurately. When the dataset was balanced using SMOTE, and then the hyperparameters optimised using Bayesian hyperparameter tuning, the generalisation capacity of the model was enhanced. The last model settled to an accuracy of 96% and a recall of 98%, thus being very sensitive in its prediction of failure occurrences hich is vital in avoiding failure occurrences that lead to downtimes. Additionally, actual implementation of the model on embedded systems proves the model's usability in actual daily practice. The solution has an inference time of 10ms for each prediction and a model size of 35MB making it perfect for edge computing since real time computation is a requirement. This work is a part of active AI-based predictive maintenance research and provides a prompt and cost-effective approach for industries. The possible improvements of future work include the integration of deep learning models or other ensemble methods to improve the overall performance and deal with the more intricate failure conditions. Because accurate prediction of machine failures is possible, greater cost saving, reliability and efficient utilization of systems prevails in industrial systems.

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