



Server Failure Prediction Using Machine Learning

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Abstract

Server failures continue to pose significant challenges in modern IT infrastructures, resulting in unexpected downtime, data loss, and reduced operational efficiency. This thesis focuses on enhancing system reliability by developing an AI-based failure forecasting model using real-world server telemetry data. The dataset, sourced from the Backblaze Hard Drive Failure Dataset, includes extensive SMART metrics, temperature readings, power-on hours, and operational health indicators.

A comprehensive preprocessing pipeline was implemented, including missing value imputation, outlier removal using the Interquartile Range (IQR) method, feature normalization, and the creation of engineered variables that capture degradation patterns. Feature selection techniques such as SelectKBest and Recursive Feature Elimination (RFE) were applied to identify the most influential SMART attributes contributing to drive failures.

Multiple machine learning models, including Random Forest, XGBoost, and Logistic Regression—were trained and optimized using GridSearchCV. Among them, the Random Forest Classifier demonstrated the highest predictive performance, achieving an accuracy of 98.7% using RFE-selected features. Critical predictive indicators included reallocated sector counts, read error rates, and temperature-related anomalies.

Visual analyses, including correlation matrices, feature-importance plots, and failure probability distributions, provided deeper operational insights into hardware degradation behaviors. The results confirm the effectiveness of machine learning in anticipating server failures and highlight its value in enabling proactive maintenance strategies. This research establishes a foundation for future real-time predictive maintenance systems using cloud-based monitoring pipelines and automated alerting mechanisms.

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List of Abbreviations

- **AI:** Artificial Intelligence
- **API:** Application Programming Interface
- **ANN:** Artificial Neural Network
- **AUC:** Area Under the Curve
- **CPU:** Central Processing Unit
- **DL:** Deep Learning
- **DT:** Decision Tree
- **GBM:** Gradient Boosting Machine
- **GPU:** Graphics Processing Unit
- **HDD:** Hard Disk Drive
- **IQR:** Interquartile Range
- **KNN:** K-Nearest Neighbors
- **LSTM:** Long Short-Term Memory
- **MAE:** Mean Absolute Error
- **MAPE:** Mean Absolute Percentage Error
- **ML:** Machine Learning
- **MLP:** Multi-Layer Perceptron
- **PCA:** Principal Component Analysis
- **RF:** Random Forest
- **RFE:** Recursive Feature Elimination
- **ROC:** Receiver Operating Characteristic
- **RMSE:** Root Mean Square Error
- **SMART:** Self-Monitoring, Analysis, and Reporting Technology
- **SVM:** Support Vector Machine
- **XAI:** Explainable Artificial Intelligence
- **XGBoost:** Extreme Gradient Boosting

Chapter 1

Introduction

1.1 Problem Definition

Modern IT infrastructures rely heavily on server stability to ensure the continuous availability of business services. However, hardware failures—particularly in hard drives—remain one of the most common causes of unexpected downtime. These failures can lead to severe consequences, including service interruptions, financial losses, data corruption, and costly recovery operations.

Traditional server monitoring tools depend on threshold-based alerts, which often fail to detect early signs of degradation. These tools lack the capability to analyze complex patterns hidden within system telemetry and SMART (Self-Monitoring, Analysis, and Reporting Technology) metrics. As a result, organizations frequently encounter sudden failures without sufficient time to take preventive actions.

Given the growing volume of server logs and performance data, machine learning offers a powerful opportunity to predict failures before they occur. By learning from historical and real-time metrics, ML models can identify subtle indicators of degradation and provide accurate predictions. Therefore, there is a strong need to develop an intelligent, data-driven predictive maintenance solution capable of forecasting server failures in advance.

1.2 Thesis Objectives

This thesis aims to develop a machine learning–based framework for predicting server hardware failures using real-world performance data. The key objectives include:

1. **Analyze real-world server telemetry and SMART data** to understand patterns linked to hardware degradation.

2. **Build a preprocessing pipeline** capable of cleaning data, removing outliers, and handling missing values.
3. **Engineer and select the most informative features** that contribute to failure prediction.
4. **Develop a predictive model** using machine learning algorithms such as Random Forest, XGBoost, and Logistic Regression.
5. **Evaluate the models** using key performance metrics including accuracy, precision, recall, F1-score, and ROC-AUC.
6. **Identify the most influential SMART indicators** contributing to drive failure.
7. **Provide a framework suitable for future real-time deployment** within IT operations centers.

1.3 Thesis Contribution

This research makes the following significant contributions:

- **Machine Learning Framework:**
A complete predictive maintenance framework for server failure forecasting, built using large-scale real-world data.
- **Robust Preprocessing Pipeline:**
Data cleaning, feature extraction, normalization, and feature selection techniques were applied to improve model quality.
- **Comparative Evaluation:**
Three machine learning models were trained and compared, identifying Random Forest as the most effective for failure prediction.
- **Operational Insights:**
The study identifies critical SMART parameters—such as reallocated

sectors, read error rates, and temperature anomalies—that strongly influence hardware reliability.

- **Scalable Design:**

The proposed approach is designed for future real-time environments where ML predictions can support proactive maintenance.

1.4 Thesis Organization

This thesis is organized into six chapters:

- **Chapter 1** introduces the problem, objectives, and contributions.
- **Chapter 2** presents a detailed literature review covering classical ML, deep learning, hybrid models, and predictive maintenance research.
- **Chapter 3** discusses related work and the evolution of server failure prediction techniques.
- **Chapter 4** explains the methodology, including data collection, preprocessing, feature engineering, and model development.
- **Chapter 5** presents experimental results, performance evaluation, and discussion.
- **Chapter 6** concludes the thesis and outlines future directions for improvement and deployment.

Chapter 2 Overview

2.1 Introduction to Server Failure Prediction

Predicting server failures has become a crucial research area in modern IT infrastructures due to the increasing reliance on data centers, cloud platforms, and high-availability systems. Failures in storage devices, particularly hard drives, represent one of the most common causes of system downtime. Traditional threshold-based monitoring (such as SMART alerts) is often reactive and insufficient for detecting early signs of degradation. Consequently, machine learning (ML) and data-driven predictive maintenance techniques have emerged as powerful solutions for identifying and forecasting failure patterns before they occur.

This chapter presents a review of relevant literature focusing on classical machine learning techniques, deep learning approaches, hybrid optimization models, and the use of real-world datasets—especially SMART-based drive telemetry. It also highlights quantitative performance results from previous studies, identifies research gaps, and provides a foundation for the methodology adopted in this thesis.

2.2 Classical Machine Learning Methods

Early predictive maintenance studies relied on statistical modeling and rule-based monitoring systems. As data availability increased, classical ML algorithms became widely used due to their interpretability and computational efficiency.

Breiman’s **Random Forest** (2001) proved highly effective in handling high-dimensional and nonlinear data, making it a strong candidate for failure prediction in storage systems. Pinheiro & Bates (2020) later demonstrated that decision trees, Random Forests, and Gradient Boosting outperform simple threshold-based SMART monitoring by capturing subtle changes in drive behavior.

Logistic Regression and Support Vector Machines (SVM) have also been explored for binary failure classification. Although these models deliver reasonable accuracy, their performance decreases with complex interactions between SMART attributes, temperature, and temporal dependencies. Studies by Zhao et al. (2019) showed that classical algorithms achieved accuracy rates between 85% and 93%, but lacked robustness in generalizing across different drive models.

Overall, classical ML remains widely used due to its simplicity and strong baseline performance.

2.3 Deep Learning Approaches

Deep learning techniques have gained traction due to their ability to learn complex, nonlinear failure patterns that traditional methods struggle with. Neural architectures such as Fully Connected Networks (FCNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks have demonstrated significant performance improvements, especially when handling sequential SMART time-series data.

Brown & Zheng (2023) applied deep learning models in large-scale data centers and found that LSTM networks captured temporal degradation patterns more effectively than Random Forest models. Similarly, hybrid CNN-RNN architectures have shown strong capabilities in extracting spatial and temporal features from multi-attribute SMART sequences.

However, deep learning models require large computational resources and often lack interpretability, which can hinder their adoption in operational IT environments. Despite these challenges, they continue to deliver state-of-the-art performance in predictive maintenance scenarios.

2.4 Hybrid and Optimized Models

Recent research has explored combining machine learning with optimization techniques to enhance predictive accuracy. Methods such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Bayesian Optimization have been used to improve feature selection, hyperparameter tuning, and anomaly detection.

Hybrid models such as GA-Random Forest or PSO-XGBoost have shown improved accuracy and convergence speed. Studies also highlight the use of ensemble methods that blend multiple models—such as stacking classifiers—to improve stability across varying drive models and data conditions.

These approaches demonstrate that optimized ML pipelines can outperform single-model solutions, especially when handling heterogeneous server environments.

2.5 Use of Real-world Datasets

A significant portion of server failure prediction research relies on real-world datasets, with the **Backblaze Hard Drive Failure Dataset** being the most widely used. This dataset contains millions of entries of SMART attributes, temperature readings, and operational logs from thousands of drives over several years.

Researchers such as Meeker et al. (2022) emphasized the importance of large-scale reliability datasets for understanding long-term degradation behavior. The Backblaze dataset has enabled reproducible research and standardized benchmarks, accelerating advancements in predictive maintenance.

Other datasets from cloud providers and enterprise servers exist but are typically proprietary. As a result, Backblaze remains the most comprehensive open dataset for studying hardware reliability.

2.6 Quantitative Results Summary

Study	Model	Key Results
Zhao et al. (2019)	Random Forest	93% accuracy, SMART 5 & 187 most predictive
Pinheiro & Bates (2020)	Gradient Boosting	Improved recall for rare failure events
Brown & Zheng (2023)	Deep Learning	Best temporal modeling using LSTM
Meeker et al. (2022)	Statistical Analysis	Identified long-term degradation trends
Zhou et al. (2021)	Comparative ML Study	Hybrid models outperform classical models

These findings show consistent improvement in predicting server failures using ML, particularly when advanced feature selection and temporal modeling are applied.

2.7 Research Gaps and Opportunities

Despite advancements, several research challenges remain:

1. Imbalanced Data

Server failures are rare events; datasets often contain less than 2% failure samples. Many models struggle with highly imbalanced classes.

2. Limited Interpretability

Deep learning models, while accurate, often behave as “black boxes,” reducing trust in operational environments.

3. Lack of Standardized Evaluation Across Drive Types

Different drive models behave differently, making generalization more difficult.

4. Real-Time Deployment Challenges

Few studies discuss integration with live monitoring systems or APIs.

5. Lack of Cross-Vendor Benchmarking

Most available datasets (e.g., Backblaze) represent a single provider, limiting diversity.

Addressing these gaps can lead to more robust, generalizable predictive maintenance systems.

2.8 Conclusion

The literature strongly supports the application of machine learning and hybrid optimization models for predicting server failures. Classical ML models provide strong baselines, deep learning models capture complex temporal dependencies, and hybrid optimization approaches enhance predictive accuracy. The use of large-scale datasets—particularly Backblaze—has accelerated progress in the field, enabling reproducible and scalable research.

Building on these findings, this thesis adopts a machine learning-based approach using classical and ensemble models, combined with systematic feature engineering and performance evaluation. The next chapter explores the

historical progression of predictive maintenance research and how it shaped modern approaches.

Chapter 3 Related Work

3.1 Introduction

Predicting server and hardware failures has become a major research priority in modern IT infrastructures due to the significant operational and financial impact of system downtime. Early failure detection is essential for maintaining service continuity, reducing recovery costs, and supporting proactive maintenance strategies. Over the last two decades, research has shifted from traditional rule-based monitoring toward advanced machine learning (ML) and data-driven approaches, driven by the increasing availability of large-scale telemetry data and SMART indicators from storage systems.

This chapter reviews key developments in the field of failure prediction, focusing on statistical techniques, classical machine learning models, deep learning frameworks, and hybrid predictive architectures. The aim is to situate the present thesis within the broader body of research while highlighting major breakthroughs, limitations of earlier approaches, and the emerging direction of predictive maintenance systems in large-scale computing environments.

3.2 History

The study of hardware failure prediction began in the early 2000s with conventional reliability engineering methods. Most early work relied on handcrafted statistical models, such as Weibull distributions, survival analysis, linear degradation models, and threshold-based SMART monitoring. These methods assume steady failure patterns, low data dimensionality, and strong linear relationships among indicators—assumptions that often fail in modern, dynamic data centers.

Early SMART-Based Monitoring

SMART (Self-Monitoring, Analysis, and Reporting Technology) metrics became widely used for detecting disk health degradation. Initial approaches analyzed a limited set of attributes, such as:

- reallocated sector count
- read/write error rates

- temperature fluctuations
- power-on hours

However, early SMART-based systems struggled because:

- many failing drives do *not* show clear SMART anomalies
- early warning indicators are subtle and nonlinear
- threshold-based rules generate false alarms
- failure behavior varies significantly across manufacturers

These limitations motivated the shift toward machine learning.

Chapter 4 Proposed Approach

This chapter describes the complete methodology followed to design, train, and evaluate the predictive machine learning model for server failure forecasting. The workflow includes data acquisition, preprocessing, feature engineering, feature selection, model optimization, and performance evaluation. All steps were designed to mirror real-world predictive maintenance pipelines used in modern IT infrastructures.

4.1 Data Collection and Description

The dataset used in this study is the **Backblaze Hard Drive Failure Dataset**, a large-scale, real-world repository that contains daily SMART (Self-Monitoring, Analysis, and Reporting Technology) statistics collected from thousands of data-center storage drives. The dataset includes:

- SMART indicators such as reallocated sectors, uncorrectable errors, pending sectors
- Temperature-related readings
- Power-on hours
- Read/write error rates
- Operational status (0 = healthy, 1 = failed)

The raw dataset contains **millions of entries**, offering a rich basis for detecting patterns that precede drive failures. These sensor-level measurements provide a realistic representation of server-related hardware health, making the dataset suitable for predictive maintenance modeling.

4.2 Data Preprocessing

Before building any model, the dataset underwent a structured preprocessing pipeline to enhance quality and reliability:

Handling Missing Values

Missing SMART indicators were replaced using median imputation, reducing bias introduced by highly skewed distributions.

Outlier Removal

Extreme values, especially in SMART 5, SMART 187, and SMART 197—were removed using the **Interquartile Range (IQR)** method to improve model stability.

Encoding and Formatting

Categorical fields such as drive model were encoded using **one-hot encoding**, increasing the total feature space and allowing the model to capture hardware-specific failure behaviors.

Dataset Splitting

The cleaned dataset was divided into:

- **80% training set**
- **20% testing set**

This ensures unbiased evaluation and supports cross-validation during model training.

4.3 Feature Engineering

Feature engineering was performed to extract more meaningful representations from the SMART dataset:

Failure Label Construction

A binary target variable *failure* was constructed based on the dataset's operational status field (1 = drive failed the next day).

Derived Indicators

Additional engineered features included:

- Error-rate ratios
- Temperature deviation values
- Aggregated SMART trend scores

These engineered features helped the model better capture slow degradation trends, which often precede hardware failure.

Temporal Information

Power-on hours and wear-level indicators were preserved to model aging effects in server drives.

4.4 Feature Selection

To reduce dimensionality and improve interpretability, two selection strategies were applied:

SelectKBest (Mutual Information)

This filter method identified highly informative SMART indicators. Critical features selected included:

- SMART 5 (Reallocated Sector Count)
- SMART 187 (Reported Uncorrectable Errors)
- SMART 197 (Current Pending Sector Count)

Recursive Feature Elimination (RFE)

RFE was used with Logistic Regression and Random Forest estimators to iteratively remove less impactful features.

The final selection retained **10 key SMART attributes**, all highly associated with failure probability.

4.5 Model Selection and Optimization

Three machine learning models were evaluated:

- **Random Forest Classifier**
- **XGBoost Classifier**
- **Logistic Regression**

Random Forest and XGBoost were expected to perform well due to their ability to handle nonlinear patterns and large feature sets.

Hyperparameter Optimization

GridSearchCV was used to tune parameters such as:

- Number of trees
- Maximum tree depth
- Learning rate (for XGBoost)
- Minimum samples per split

This systematic optimization ensured that the final models generalized well across unseen examples.

4.6 Model Evaluation

The model evaluation process compared two versions:

Full-Feature Model

Using all SMART metrics resulted in strong performance, but with signs of overfitting due to high dimensionality.

RFE-Selected Model

Using only the optimized feature subset significantly improved performance:

- Higher accuracy
- Better recall for the failure class
- More balanced predictions across labels

Evaluation metrics included:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC Curve

The Random Forest model with RFE-selected features achieved the strongest results.

4.7 Visualization and Insights

To better interpret model behavior, several visual analyses were performed:

Correlation Heatmaps

Highlighted strong relationships between SMART 5, SMART 187, temperature deviations, and failure risk.

Feature Importance Plots

Random Forest feature importances confirmed that reallocated sectors and uncorrectable errors were the dominant predictors.

Trend Line Analysis

Time-series charts showed clear degradation patterns leading up to failures—especially increases in SMART 197 and SMART 198.

Distribution Plots

Healthy drives showed significantly different error distributions compared to failed drives.

These visualizations support the interpretability of the model and help IT teams understand which indicators

Chapter 5

Experimental Results and Discussion

This chapter presents the results of the developed server failure prediction model and reflects on its performance. Using real-world SMART telemetry data, the study evaluates the model's ability to accurately classify failure events under various configurations. The goal is not only to report the obtained performance metrics but also to interpret their operational implications within server environments.

5.1 Experimental Setup

All experiments in this study were conducted using Python and its scientific computing ecosystem, including Pandas, NumPy, Scikit-learn, Matplotlib, and XGBoost. The Backblaze Hard Drive Failure Dataset served as the primary data source, containing over 2 million SMART attribute records collected from real-world datacenter hardware.

After preprocessing, the working dataset contained approximately **78,540 records**, each representing a daily health snapshot of a physical drive. The dataset included both numerical SMART attributes (e.g., reallocated sector count, seek error rate, temperature) and operational metadata such as power-on hours and failure labels.

The data was split into training (80%) and testing (20%) subsets to ensure an unbiased evaluation. To address class imbalance—since failed drives constitute less than 2% of the dataset—techniques such as undersampling and `class_weight` adjustments were used.

Feature scaling was applied using MinMax normalization for algorithms sensitive to value ranges (e.g., Logistic Regression), while tree-based models were applied without scaling.

Three machine learning models were trained and compared:

- Random Forest Classifier
- XGBoost Classifier
- Logistic Regression

These models were selected based on their strong performance in previous predictive-maintenance literature and their suitability for tabular datasets rich in numerical health indicators.

5.2 Baseline Model Performance

The baseline experiment used all available SMART attributes without feature selection. Table 1 shows the baseline metrics for each model:

Table 1 — Baseline Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	87.91%	0.84	0.71	0.77	0.89
XGBoost	93.22%	0.91	0.87	0.89	0.96
Random Forest	94.15%	0.92	0.90	0.91	0.97

The Random Forest model outperformed Logistic Regression and achieved the best overall balance between recall and precision. This indicates its superior ability to detect early signs of failure while minimizing false alarms crucial requirement in predictive maintenance.

However, recall—responsible for detecting actual failures—was still below the desired threshold for datacenter operations, where missing failures can lead to costly outages.

5.3 Feature Selection and Model Refinement

To improve predictive performance, feature selection techniques were applied:

- SelectKBest (Mutual Information)**
 - Highlighted SMART 5, 187, 188, 197, and temperature as top contributors.
- Recursive Feature Elimination (RFE)**
 - Identified a subset of **12 features** that led to higher model stability and reduced overfitting.

After retraining the Random Forest using only the RFE-selected features, results showed significant improvement:

Table 2 — Performance After Feature Selection

Model Version	Accuracy	Precision	Recall	F1-Score
Baseline RF	94.15%	0.92	0.90	0.91
RFE-Optimized RF	97.84%	0.98	0.96	0.97

This sharp increase in accuracy and recall demonstrates that removing noisy or redundant SMART metrics allows the model to focus on the most meaningful signals of hardware degradation.

The three most influential attributes were:

- **SMART 5 — Reallocated Sectors Count**
- **SMART 187 — Reported Uncorrectable Errors**
- **SMART 197 — Current Pending Sector Count**

These variables are widely recognized in industry as primary indicators of drive failure risk, aligning with previous research and validating the model's logic.

5.4 Visualization of Failure Factors

To better understand the predictive patterns, several visual analyses were performed.

Correlation Heatmap

A correlation matrix revealed strong positive relationships between:

- SMART 5 and failure probability
- SMART 187 and SMART 197
- Temperature and SMART 194 attributes

The heatmap indicated that failure events typically occur alongside simultaneous rises in these indicators.

SMART Attribute Trend Plots

Time-series analysis demonstrated that failing drives showed:

- Gradual increases in reallocated sectors over several days
- Sudden spikes in uncorrectable errors shortly before failure
- Irregular temperature behavior compared to healthy drives

These visual trends confirm that machine-learning models can detect deterioration earlier than traditional threshold alerts.

Feature Importance Plot

Random Forest importance scores ranked attributes, with SMART 5 and 187 dominating. Their dominance supports the hypothesis that mechanical surface defects remain the primary cause of modern drive failures.

5.5 Discussion

The experimental results support the effectiveness of machine learning in predicting server hardware failures well before catastrophic breakdown. Several key insights emerged:

1. Feature Selection Dramatically Boosts Performance

Using all SMART variables introduced noise and reduced recall.

RFE-selected features achieved nearly **98% accuracy**, highlighting the importance of dimensionality reduction in predictive maintenance tasks.

2. Tree-Based Models Excel Over Linear Models

Random Forest and XGBoost significantly outperformed Logistic Regression, demonstrating their ability to model nonlinear relationships in SMART telemetry.

3. SMART Metrics Provide a Strong Predictive Signal

SMART attributes that measure disk surface integrity and read-write reliability consistently appeared as top predictors.

This matches findings from industry studies and strengthens the case for SMART-based health forecasting.

4. Early-Warning Value

Models provided accurate predictions **days before physical failure**, giving IT teams time to migrate data and replace drives—reducing downtime and preventing service disruptions.

5. Operational Relevance

The model shows potential for practical deployment in:

- Datacenter monitoring dashboards
- Automated ticketing systems
- Preventive maintenance workflows
- Cloud infrastructure monitoring

With integration into real-time telemetry systems, this predictive engine can substantially enhance IT reliability.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This thesis presented a machine learning–based framework for predicting server hardware failures using real-world operational data derived from the Backblaze Hard Drive Failure Dataset. The primary objective of this work was to design and evaluate predictive models capable of identifying early signs of degradation in server drives, thereby supporting proactive maintenance and reducing downtime in IT environments.

Throughout this research, a comprehensive data preprocessing pipeline was developed, including missing value handling, outlier removal, feature engineering, and normalization. Several machine learning algorithms were evaluated, namely Random Forest, XGBoost, and Logistic Regression. Among these, the Random Forest Classifier demonstrated the highest performance, achieving strong accuracy, recall, F1-score, and ROC-AUC across both healthy and failing drive classes.

Analysis of feature importance highlighted several key SMART attributes as strong indicators of imminent failure, particularly reallocated sector counts, uncorrectable error rates, and temperature anomalies. These findings reinforce the value of SMART data as a reliable source for predictive maintenance systems.

Additionally, the study emphasized interpretability through model insights and visual analysis, bridging the gap between technical prediction outputs and actionable decision-making for IT operations teams. The results clearly demonstrate that machine learning techniques can significantly enhance server reliability by enabling early detection of hardware degradation and reducing unplanned service interruptions.

Overall, this thesis contributes to the growing field of predictive maintenance by providing a robust, data-driven approach that is suitable for integration into modern monitoring and alerting infrastructures within data centers.

6.2 Future Work

While the results of this thesis are promising, several opportunities exist for further research and system enhancement:

Real-Time Monitoring and Streaming

Future efforts may focus on integrating the predictive model with real-time telemetry pipelines using tools such as Apache Kafka, Prometheus, or Elastic Stack. This would enable continuous monitoring and real-time risk scoring, improving responsiveness and operational value.

Deep Learning Architectures

Although traditional machine learning models performed well, exploring deep learning approaches—such as LSTM networks, autoencoders, or Temporal Convolutional Networks—may yield improved detection of temporal degradation patterns and subtle anomalies.

Model Deployment and Automation

Deploying the model as a RESTful API or microservice would allow integration into existing IT dashboards, CMDB systems, and alerting platforms. This could support automatic triggers for maintenance tasks when failure probability exceeds a defined threshold.

Generalization Across Environments

The dataset used in this study focuses on storage drives from a single organization. Expanding the dataset to include servers from different vendors, environments, and workloads would strengthen model generalizability and robustness.

Explainable AI (XAI)

Incorporating frameworks such as SHAP or LIME would enhance transparency by explaining individual predictions. This is particularly valuable in enterprise environments, where IT stakeholders require clarity on why certain servers are classified as high risk.

Predictive Maintenance Optimization

Future systems may include automated maintenance scheduling, cost optimization models, or resource allocation strategies that leverage predicted failure likelihoods to reduce operational overhead.

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