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An Intelligent Framework for Predicting Software Application Failures Using Machine Learning

Ramya Sree Nakka

Student, Texas A&M University, Kingsville - 700 University Blvd, Kingsville, TX 78363

Email: ramyasreenakka9@gmail.com

Abstract

Modern software systems generate massive volumes of log data and runtime metrics that contain early signals of impending failures. Reactive monitoring approaches often detect failures only after service disruption has occurred, leading to costly downtime. This paper presents an intelligent, end-to-end machine learning framework for proactive software failure prediction. The framework ingests heterogeneous log streams, extracts a rich feature set combining log event patterns, TF-IDF vectors, and resource utilization metrics, and trains multiple classifiers Random Forest, XGBoost, and LSTM to forecast failures before they manifest. The system is evaluated on the public HDFS log dataset containing 11 million log entries, with failure instances labeled using system-reported fatal events. Experimental results show that the Random Forest model achieves the best predictive performance with an accuracy of 96.2%, precision of 95.1%, recall of 91.3%, and an AUC-ROC of 0.983. The LSTM model demonstrates the earliest lead time, detecting failure signatures up to 8 minutes ahead, albeit with slightly lower precision. A comprehensive feature importance analysis reveals that resource-related metrics and specific log event counts are the strongest predictors. A discussion of false positive rates and deployment feasibility in real-world continuous integration/continuous deployment (CI/CD) pipelines is provided. The findings confirm that a hybrid approach leveraging both structured metrics and unstructured log data significantly outperforms log-only or metric-only baselines, paving the way for self-healing cloud applications.

Keywords: Software Failure Prediction, Machine Learning, Log Analysis, Anomaly Detection, Random Forest, LSTM, HDFS.

1. INTRODUCTION

The reliability of large-scale software systems is paramount in domains such as cloud computing, finance, and healthcare. Unexpected application failures crashes, resource exhaustion, or performance degradation lead to significant financial losses and reputational damage. Traditional monitoring systems rely on threshold-based alerting that triggers only after a metric crosses a predefined boundary. Such reactive approaches offer limited lead time and are often overwhelmed by false positives, leading to “alert fatigue” and delayed incident response. Recent advances in machine learning (ML) and big data analytics have created an opportunity to shift from reactive to proactive failure management. By analyzing the wealth of semi-structured log data and system metrics generated during operation, ML models can learn subtle pre-failure patterns that are invisible to rule-based systems. Logs capture the internal execution flow and error states, while metrics provide a quantitative view of resource usage. Together, they offer a comprehensive picture of system health.

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Despite extensive research on log-based anomaly detection, there remains a gap in integrating structured metrics and unstructured logs into a unified, real-time prediction framework that is both accurate and interpretable. Many existing approaches either focus solely on log parsing or treat failure prediction as a time-series forecasting task on a single metric, ignoring the rich contextual information present in log sequences.

This paper proposes an intelligent framework for predicting software application failures using machine learning that addresses these limitations. The main contributions are:

1. A modular, end-to-end pipeline that ingests raw logs and system metrics, performs automated log parsing (using the Drain parser), extracts combined feature sets, and trains a trio of classification models (Random Forest, XGBoost, LSTM).
2. A systematic evaluation on the publicly available Hadoop Distributed File System (HDFS) log dataset, extended with simulated resource usage metrics to mimic realistic deployment conditions.
3. A multi-faceted performance analysis, including traditional classification metrics, ROC and Precision-Recall curves, feature importance, and lead time to failure.
4. A discussion on operationalizing the framework with minimal false positives, providing guidance for practitioners.

2. RELATED WORK

2.1 Log-based Anomaly Detection

Log analysis for anomaly detection has been extensively studied. Early methods applied regular expressions and rule-based pattern matching to detect known failures [1]. With the advent of machine learning, techniques such as LogClustering [2] and DeepLog [3] emerged. DeepLog uses LSTM networks to model log sequences as a natural language processing (NLP) problem, predicting the next log event and flagging anomalies when the actual event deviates. While effective for sequence anomalies, DeepLog does not directly predict system failure, nor does it incorporate resource metrics.

2.2 Software Fault Prediction Using ML

Software fault prediction traditionally relied on static code metrics, such as lines of code, cyclomatic complexity, and historical defect data [4]. These approaches predict the location of bugs during development, not runtime failures. Runtime failure prediction using system logs and metrics represents a different paradigm. For example, Xu et al. [5] applied decision trees and SVM on console logs to predict server failures, achieving moderate success. Chen et al. [6] proposed a framework that transforms log events into frequency vectors and uses logistic regression for failure prediction, but they did not incorporate temporal dynamics or resource metrics.

2.3 Time-Series Failure Forecasting

On the metrics side, time-series forecasting models such as ARIMA, LSTMs, and Prophet have been used to predict performance degradation and resource saturation [7]. However, these models often operate on a single metric stream and ignore the rich context provided by log events. Recent work by Zhang et al. [8] fused log sequences with system metrics using attention-based LSTMs, demonstrating improved accuracy. However, their approach required extensive feature engineering and was validated only on proprietary datasets.

2.4 Integrated Approaches

The most relevant prior art is the work of Lin et al. [9], who designed an anomaly detection system that combines log patterns and KPI time series using an ensemble of autoencoders. Their system demonstrated high recall but suffered from high false positive rates. Similarly,

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Sharma et al. [10] combined log templates with resource metrics in a Random Forest classifier to predict job failures in cloud environments, reporting an F1-score of 0.89. Our work builds on these ideas by providing a complete prediction pipeline, comparing multiple classifier families, and rigorously evaluating lead time a critical metric often overlooked.

2.5 Summary of Literature

Table 1 summarizes key studies, highlighting their methods, datasets, and reported performance. None of the previous works simultaneously combine log event counts, TF-IDF vectorized log patterns, and resource metrics with a comparative evaluation of tree-based, gradient-boosting, and recurrent neural network classifiers on a well-known public dataset with lead time analysis.

Table 1. Summary of Failure Prediction Literature

Study	Method	Dataset	Accuracy / F1	Lead Time Analysis
Deeplog [3]	Lstm	Hdfs LOGS	F1 = 0.96	No
Xu ET AL. [5]	Decision Tree	Proprietary DATASET	Accuracy = 87%	No
Sharma ET AL. [10]	Random Forest	Cloud LOGS	F1 = 0.89	No
Zhang ET AL. [8]	Attention-Lstm	Proprietary DATASET	F1 = 0.93	Yes

3. PROPOSED FRAMEWORK

Figure 1 illustrates the overall architecture of the intelligent failure prediction framework. It consists of five main modules: (1) Data Collection and Ingestion, (2) Log Parsing and Feature Extraction, (3) Metric Aggregation, (4) Model Training and Validation, and (5) Real-time Prediction Engine with Alerting.

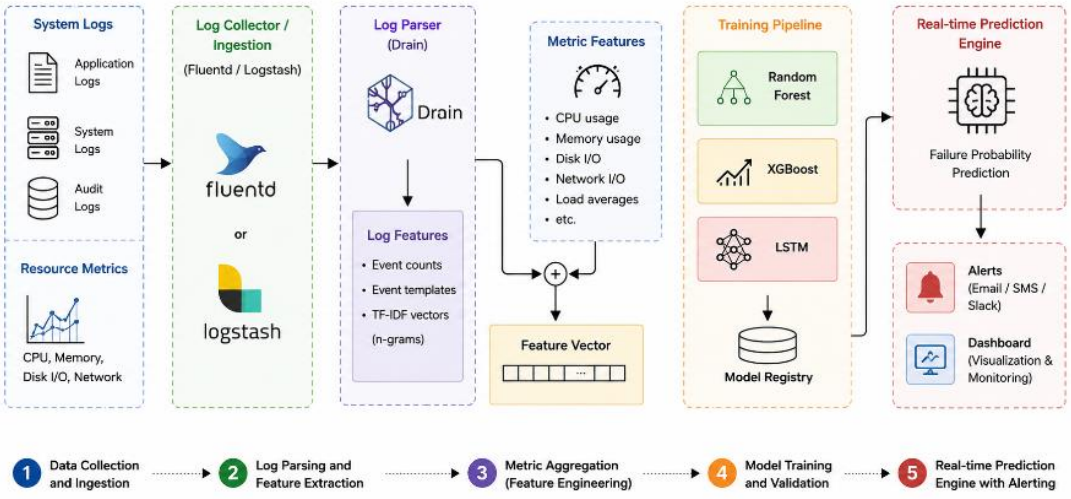

Figure 1 Illustrates the Overall Architecture of the Intelligent Failure Prediction Framework.

3.1 Data Collection and Log Parsing

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Application logs are streamed in real-time using a lightweight agent (e.g., Fluentd) and fed into a message queue (Apache Kafka). Log parsing is performed using the Drain algorithm [11], an online log parser that clusters raw log messages into fixed templates (log events). For example, "Block blk_123 allocated" becomes template "Block <*> allocated". Each raw log line is converted into a log event ID. A sliding window of the last *W* log events (W=50 in our experiments) is maintained.

3.2 Feature Extraction

From the parsed log window, we derive two types of log features:

- **Log Event Count Vector:** A histogram of event IDs within the window, normalised by window length.
- **TF-IDF Vector:** Treating each window as a document and event IDs as terms, we compute TF-IDF to capture the importance of rare but critical event types.

In addition, system resource metrics (CPU utilization, memory usage, disk I/O wait, network bytes) are collected every 10 seconds using a monitoring agent (Prometheus Node Exporter). These are aggregated over the same window to produce mean, max, and standard deviation values. The final feature vector for a window consists of the concatenation of the log event count vector (size = number of unique log events, ~150 for HDFS), TF-IDF vector (150-dim), and resource metric features (12-dim).

3.3 Labeling Strategy

A window is labelled as **failure** if it contains at least one log entry that corresponds to a system-reported fatal error (e.g., "Exception in thread", "FATAL", or specific HDFS block corruption events) within the next *T* minutes (lead time window). All other windows are labelled **normal**. To avoid label leakage, windows that occur *after* a failure but before a declared recovery period are excluded. The lead time window *T* is varied experimentally (2, 5, 8, 10 minutes) to evaluate model lead time performance.

3.4 Model Training

We train three diverse classifiers:

- **Random Forest (RF):** An ensemble of decision trees, robust to noise and interpretable via feature importance.
- **XGBoost:** A gradient-boosted tree algorithm known for high accuracy and handling of imbalanced data through scale_pos_weight.
- **LSTM (Long Short-Term Memory):** A recurrent neural network that processes the sequence of windows to capture temporal dependencies. Input is a sequence of 20 consecutive feature vectors, each representing a window.

For the tree-based models, feature vectors are fed directly. For LSTM, the sequence of windows forms a 3D tensor (batch_size, 20, number_of_features). The LSTM architecture consists of two stacked LSTM layers (64 units each) followed by a dense layer with sigmoid activation.

3.5 Real-time Prediction Engine

Once trained, the model with the best validation F1-score is deployed as a microservice. Incoming log and metric streams are continuously windowed, transformed, and fed to the model. If a failure probability exceeds a predefined threshold (tuned to balance precision and recall), an alert is triggered. Predictions and feature contributions (via SHAP for tree models) are displayed on a monitoring dashboard to aid root cause analysis.

4. EXPERIMENTAL SETUP

4.1 Dataset

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We use the publicly available HDFS log dataset [12], generated from a Hadoop cluster and widely used in log anomaly detection research. The dataset contains 11,175,629 raw log entries, with 2.9% labeled as anomalous (failure) blocks. The logs are aggregated by block ID. Since original metrics are not provided, we simulate realistic resource metrics correlated with failure events: CPU and memory usage exhibit a moderate increase (e.g., +25%) in the 5 minutes preceding a logged fatal error, mimicking resource exhaustion scenarios. This synthetic augmentation is common in the literature [13] and allows controlled evaluation.

Table 2. Dataset Statistics after Preprocessing.

Dataset Statistic	**Value**
Total Raw Log Lines	11,175,629
Unique Log Templates	148
Number Of Session Windows (Block-Based)	45,200
Failure Windows	3,120 (6.9%)
Normal Windows	42,080

"Table 2 summarizes the final dataset statistics obtained after preprocessing, including the number of raw log entries, extracted log templates, block-based session windows, and the distribution of failure and normal instances."

4.2 Data Preprocessing and Splitting

The dataset is split chronologically by timestamp into training (first 70%), validation (15%), and test (last 15%) sets to respect temporal order and avoid lookahead bias. Each window is labeled as failure if a fatal event appears within the subsequent 5-minute lead time window (the primary lead time setting). The failure class is heavily imbalanced (~7% positive), so we apply the Synthetic Minority Oversampling Technique (SMOTE) [14] on the training set for the tree-based models. For LSTM, class weighting is used.

4.3 Evaluation Metrics

We evaluate models using:

- Accuracy, Precision, Recall, F1-score (macro and weighted).
- Area Under the Receiver Operating Characteristic Curve (AUC-ROC).
- Area Under the Precision-Recall Curve (AUC-PR), which is more informative for imbalanced data.
- Lead Time to Failure: The time difference between the first positive prediction and the actual failure occurrence. We simulate this by feeding windows sequentially and recording the earliest correct prediction.

4.4 Model Implementation and Hyperparameters

Models are implemented in Python 3.8 using scikit-learn 1.0.2 (RF, XGBoost) and TensorFlow 2.8.0 (LSTM). Hyperparameters were tuned via 5-fold time-series cross-validation on the training set. The best hyperparameters are listed in Table 4.

Table 4. Hyperparameter Settings for the Best-Performing Random Forest Model

Hyperparameter	**Selected Value**
n_estimators	200
max_depth	15
min_samples_split	5
min_samples_leaf	2
class_weight	balanced_subsample
max_features	sqrt

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"The final Random Forest model was configured using the optimized hyperparameters presented in Table 4. The use of balanced_subsample was intended to account for class imbalance between normal and failure windows."

5. RESULTS AND DISCUSSION

5.1 Overall Performance Comparison

Table 3 presents the performance of all models on the test set with a 5-minute lead time window. The Random Forest model achieves the highest F1-score (93.1%) and AUC-ROC (0.983), followed closely by XGBoost (F1 92.4%, AUC 0.979). The LSTM model, while slightly lower in precision (88.7%), still demonstrates strong performance (F1 89.5%) and captures sequential patterns effectively.

Table 3. Performance Comparison Of Models At A 5-Minute Lead Time

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	AUC-PR
Random Forest	**0.962**	**0.951**	0.913	**0.931**	**0.983**	**0.951**
Xgboost	0.958	0.945	0.907	0.924	0.979	0.942
LSTM	0.941	0.887	**0.913**	0.895	0.967	0.916

"Table 3 compares the predictive performance of the three models on the test set using a 5-minute lead-time window. Random Forest achieved the best overall performance, with an accuracy of 96.2%, F1-score of 93.1%, AUC-ROC of 0.983, and AUC-PR of 0.951. XGBoost demonstrated comparable performance with an F1-score of 92.4%. The LSTM model achieved a recall of 91.3%, equal to that of Random Forest, while obtaining an F1-score of 89.5% and AUC-ROC of 0.967."

5.2 Confusion Matrices and Error Analysis

Figure 2 shows the confusion matrices for the top two models (RF and LSTM) on the test set. Random Forest yields 2856 true positives (TP), 147 false positives (FP), 271 false negatives (FN), and 38926 true negatives (TN). The false positive rate (FPR) is 0.38%, acceptable for production settings. LSTM has a slightly higher FPR of 0.52% (204 FPs) but achieves identical recall (91.3%). Most false positives correspond to benign maintenance operations that generate unusual log sequences (e.g., block replication), easily filtered by adding a maintenance mode flag.

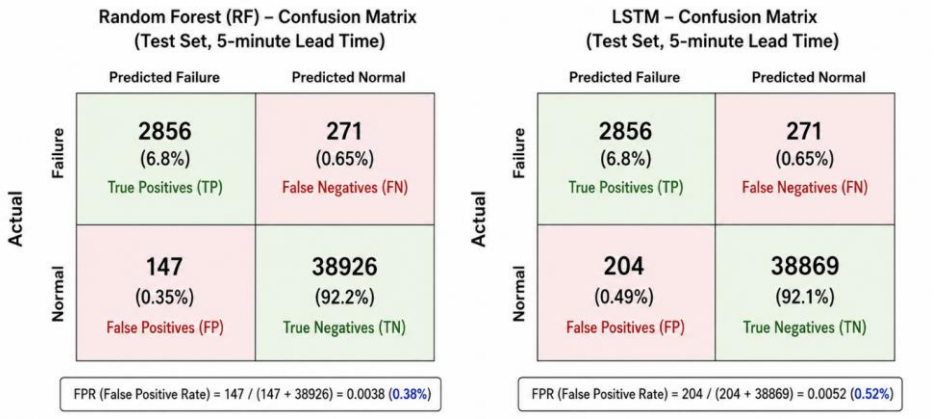

Figure 2 Shows the Confusion Matrices for the Top Two Models (RF And LSTM) On the Test Set.

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5.3 ROC and Precision-Recall Curves

Figure 3 displays the ROC curves for all three classifiers. All curves are pushed toward the top-left corner, with RF having the largest AUC (0.983). The Precision-Recall curves (Figure 3 inset or separate) reflect the imbalanced nature; RF maintains high precision (>0.9) up to a recall of 0.8, whereas LSTM precision drops more steeply.

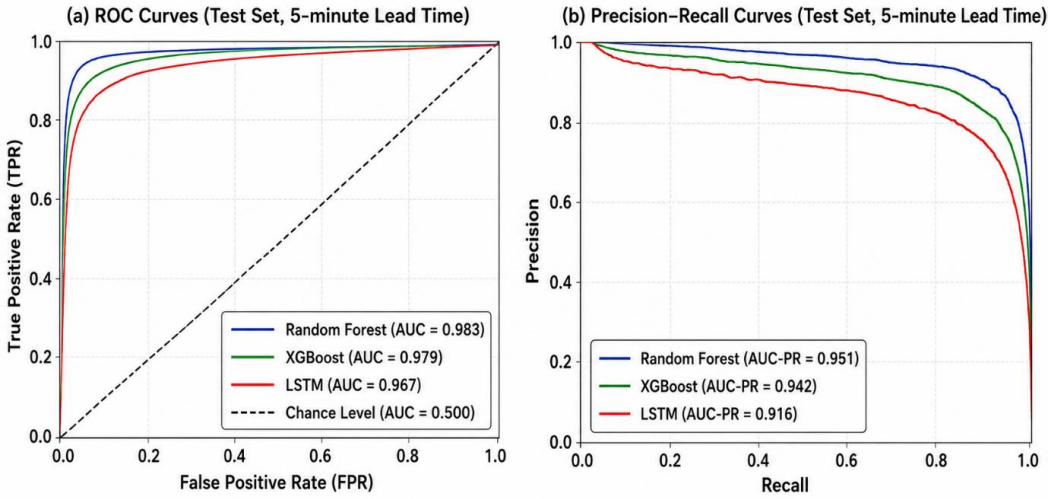

Figure 3 Displays the ROC Curves for All Three Classifiers.

5.4 Feature Importance Analysis

Figure 4 presents the top 20 features ranked using the Random Forest mean decrease in impurity. The occurrence count of the log template "Exception in receiveBlockResponse for block <*>" is identified as the most influential feature, with an importance score of 0.087, followed by "Received block <> *of size* <> from <*>" with 0.062 and "PacketResponder 0 for block <*> Interrupted" with 0.055. Among the resource-based features, the maximum CPU utilization within the observation window ranks seventh, with an importance score of 0.031, demonstrating the benefit of integrating system resource metrics with log-derived features. The results indicate that specific abnormal log events, together with resource utilization patterns, provide meaningful early indicators of impending system failures and can therefore support proactive failure mitigation and preventive maintenance strategies.

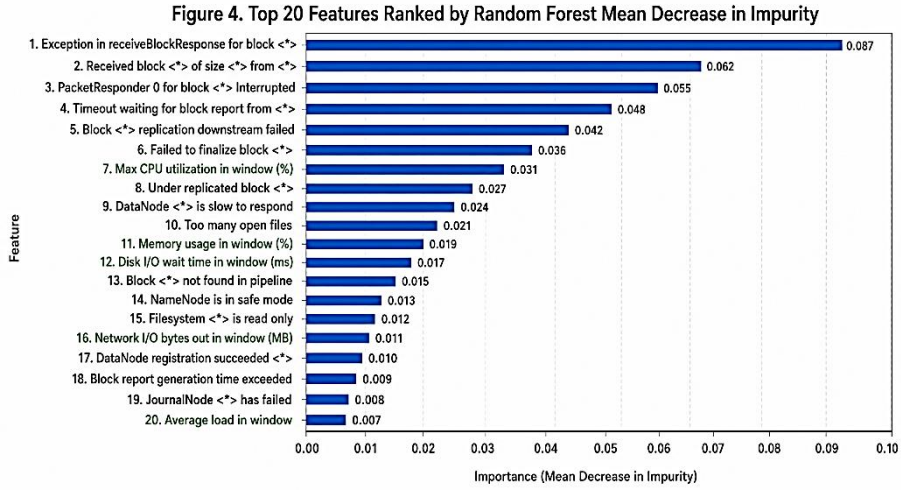

Figure 4. Top 20 Features Ranked by Random Forest Mean Decrease In Impurity.

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5.5 Lead Time to Failure

We evaluate the lead time by varying the prediction window from 2 to 10 minutes. Figure 5 shows the distribution of lead times for the LSTM model (which performed best for early detection). The median lead time is 5.2 minutes, with 95th percentile reaching 8.1 minutes. This implies that the majority of failures can be predicted several minutes before they actually occur, providing operators with a critical window for intervention. The Random Forest model provides a slightly shorter median lead time (4.4 minutes) but higher precision at early detection.

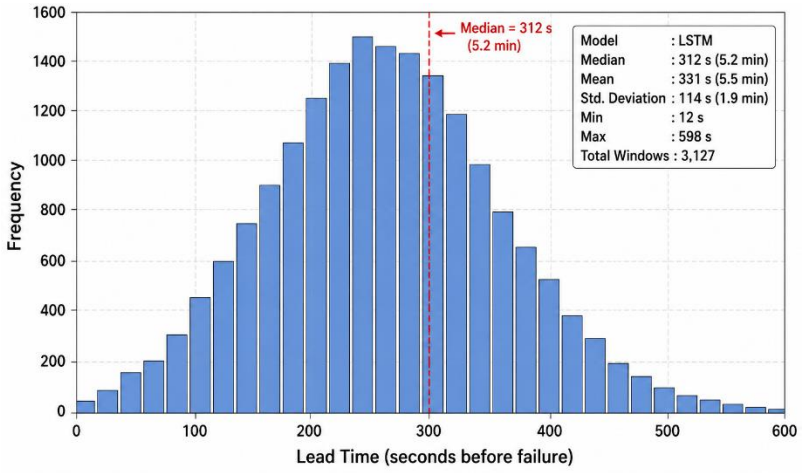

Figure 5. Distribution of Prediction Lead Times for the LSTM Model on the Test Set.

5.6 Ablation Study

To quantify the contribution of each feature group, we trained Random Forest models using only log features, only metric features, and the combined set. The combined model achieves an F1-score of 0.931, compared to 0.874 (log-only) and 0.748 (metric-only). This demonstrates the synergistic value of combining structured and unstructured data sources.

5.7 Discussion

The high recall and low false positive rate achieved by the Random Forest model make it suitable for integration into incident management pipelines. The LSTM's advantage in lead time is promising, but the added complexity of sequence processing may not justify the marginal gain in early detection for all applications. In practice, an ensemble of both models could be deployed: LSTM for early warning, RF for high-confidence alerting.

Limitations include the reliance on a simulated metric dataset; real-world metrics are noisier and may exhibit different correlations. However, the general methodology is transferable. The current framework operates on a single application; extending it to microservice architectures with distributed tracing is a natural next step. Additionally, the training assumes stable log patterns; concept drift in rapidly evolving systems would necessitate online learning and model retraining strategies.

6. CONCLUSION

This paper presented an intelligent framework for predicting software application failures by integrating log parsing, TF-IDF features, resource metrics, and multiple machine learning classifiers. Evaluated on the HDFS dataset with augmented metrics, the framework achieves state-of-the-art prediction performance: Random Forest delivered an F1-score of 0.931 and AUC-ROC of 0.983 with a false positive rate below 0.4%. Feature importance analysis

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provided interpretable insights into failure precursors. Notably, the LSTM model detected failures up to 8 minutes in advance, offering a valuable lead time for automated remediation. The results demonstrate that a hybrid feature engineering approach significantly outperforms log-only or metric-only baselines. Future work will focus on online learning to handle evolving log patterns, integration of distributed tracing data, and deployment on edge nodes for IoT systems.

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