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AI OPS LOG ANOMALY MINER: A LIGHTWEIGHT MACHINE LEARNING FRAMEWORK FOR AUTOMATED LOG ANOMALY

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Abstract: ***The rapid expansion of distributed and cloud-native systems has led to an exponential rise in operational log data characterized by high volume, velocity, and variety. Conventional rule-based or signature-driven monitoring systems struggle to generalize across diverse formats and dynamic environments, while deep-learning-based methods, though accurate, demand extensive computational resources and often behave as black boxes.***

This work introduces AI-Ops Log Anomaly Miner, a lightweight, parser-aware, and fully explainable framework for automated log analysis in resource-constrained environments. The system integrates log ingestion, normalization, and template mining with hybrid feature extraction using TF-IDF and statistical window features. An unsupervised anomaly-detection layer—based on Isolation Forest and ECOD algorithms—identifies deviations without labeled data, while an explainability module generates concise human-readable reason codes.

Implemented using Python, Streamlit, and SQLite, the prototype operates entirely offline and exports analytical summaries in CSV, JSON, and PDF formats. Benchmarking with open-source datasets such as HDFS and BGL demonstrates efficient detection performance under CPU-only conditions. The proposed system offers a transparent, deployable alternative to heavyweight AI models, aligning with the operational goals of AIOps for dependable and interpretable anomaly detection.

Keywords: AIOps, Log Analytics, Anomaly Detection, Unsupervised Learning, Isolation Forest, ECOD, TF-IDF, Drain3, Explainable AI, Parser-Aware Framework, Offline Deployment, Streamlit, SQLite

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I. INTRODUCTION

In modern distributed and cloud-native computing environments, the continuous operation of critical applications depends on reliable monitoring and analysis of system logs. Logs encapsulate rich temporal and contextual information about the behavior of applications, network events, and infrastructure components. As system complexity grows, the corresponding logs exhibit the classical "three V's" of big data—volume, velocity, and variety—creating significant challenges for timely fault detection and root-cause analysis. Traditional monitoring systems that rely on handcrafted rules or static templates fail to scale across heterogeneous deployments, while deep learning–based anomaly detectors often demand GPU resources, large labeled datasets, and extensive retraining cycles that are impractical in operational settings.

The field of Artificial Intelligence for IT Operations (AIOps) has emerged to address these challenges by integrating machine learning and analytics into operational workflows. Within this paradigm, log anomaly detection plays a central role: detecting deviations in real time before they propagate into outages or service degradation. However, existing approaches face persistent limitations. Rule-based techniques suffer from brittleness and poor adaptability to evolving log formats, whereas deep models such as DeepLog, LogAnomaly, and LogBERT, though accurate, function as opaque black boxes that provide limited interpretability. Furthermore, most research prototypes assume access to high-end computing infrastructure and stable parsers, which restricts their deployment in laboratories, classrooms, or field environments where only basic CPUs are available.

To overcome these constraints, this study proposes AI-Ops Log Anomaly Miner, a lightweight, parser-aware, and explainable framework for unsupervised system-log analytics. The framework integrates log ingestion, normalization, and template extraction with hybrid feature engineering based on TF-IDF representations and statistical window measures. It employs unsupervised algorithms such as Isolation Forest and ECOD to identify anomalies without the need for labeled data. A dedicated explainability layer generates concise reason codes highlighting the tokens or templates responsible for each detection, ensuring operational transparency and trust. Implemented using Python, Streamlit, and SQLite, the system operates fully offline and produces analytical summaries in CSV, JSON, and PDF formats.

By combining interpretability, efficiency, and portability, the proposed framework contributes a reproducible and resource-

conscious alternative to existing AIOps solutions. It enables students, researchers, and practitioners to explore anomaly-detection concepts without the overhead of deep-learning infrastructure while maintaining academic rigor and industrial relevance.

II. LITERATURE SURVEY

Log-based anomaly detection has evolved through several methodological phases, each addressing the growing scale and heterogeneity of operational data. Traditional monitoring approaches initially depended on rule-based systems and threshold-driven alerts, where predefined templates or keywords were used to identify abnormal patterns. These methods, though simple and interpretable, struggled to handle the dynamic and voluminous nature of logs generated by modern cloud infrastructures [1]. The absence of adaptability and the high cost of manual rule updates limited their scalability in real-world environments.

With the rise of machine learning and deep learning, research attention shifted toward automated sequence modeling and representation learning for logs. DeepLog introduced a recurrent neural network (RNN)-based model using LSTM layers to learn normal execution patterns and predict deviations as anomalies [2]. Later frameworks such as LogAnomaly and LogBERT extended this foundation through attention mechanisms and transformer architectures to capture richer contextual relationships between log events [3]. Despite achieving high accuracy, these models suffer from major drawbacks including dependence on large labeled datasets, substantial computational requirements, and the lack of interpretability—making them unsuitable for lightweight or real-time operational scenarios [4].

Parallel research explored log parsing and template mining as a preprocessing strategy to transform unstructured text into structured formats. Tools like Drain3, Spell, and LogMine were developed to automatically extract log templates, reducing dimensionality and improving downstream learning efficiency [5]. However, studies have shown that such parsers are often fragile—small changes in log syntax or system configuration can disrupt template consistency and degrade model performance [6]. Consequently, parser-tolerant and hybrid approaches have gained significance in the AIOps community.

To enhance generalization, recent works adopted unsupervised learning and statistical feature engineering for anomaly detection. Representations such as TF-IDF vectors, word2vec embeddings, and window-based statistical measures capture both lexical and temporal attributes of logs [7]. Algorithms including Isolation Forest, One-Class SVM, and Local Outlier Factor (LOF) have been successfully applied to detect anomalies without prior labels [8]. These techniques balance accuracy with computational efficiency but often lack transparency in their reasoning processes.

In recent years, the emphasis has gradually shifted toward Explainable AI (XAI) within the domain of AIOps. Operational stakeholders increasingly demand interpretable results that clarify why a log message was flagged as anomalous [9]. Yet, most deep models function as opaque black boxes, offering limited insight into their internal decision logic. Approaches introducing attention visualization or token importance mapping partially address this need but remain resource-intensive and domain-specific [10].

Despite these advancements, the literature still reveals a gap between accuracy, explainability, and deployability. Current state-of-the-art methods either focus on high-end GPU performance or rely on cloud-based pipelines, which are not practical in resource-limited environments. Therefore, there is a growing necessity for a lightweight, parser-aware, and explainable framework that can operate entirely offline. The proposed AI-Ops Log Anomaly Miner directly addresses this gap by combining template-aware feature extraction with unsupervised detection and human-readable explanations, thereby contributing a pragmatic and reproducible approach to modern log analytics [11].

III. PROBLEM STATEMENT

In contemporary distributed and cloud environments, massive volumes of system logs are continuously generated at high velocity and with significant structural variety. Manual monitoring, threshold-based rules, and static template definitions fail to scale or generalize across heterogeneous systems. Deep learning–based approaches, though accurate, are computationally intensive, require large labeled datasets, and often operate as opaque black boxes lacking interpretability. Parser-based techniques, on the other hand, remain fragile—small changes in log formats or message patterns can significantly degrade performance.

Hence, there is a pressing need for a lightweight, parser-aware, and explainable framework capable of performing unsupervised anomaly detection on system logs in real time under resource-constrained environments. Such a solution must integrate flexible log ingestion, robust normalization, hybrid feature extraction, and interpretable detection logic that offers human-readable explanations while maintaining portability and offline operability.

IV. OBJECTIVES

The primary objective of this research is to design and develop a lightweight, explainable, and parser-aware anomaly detection framework for system log analytics within AIOps environments.

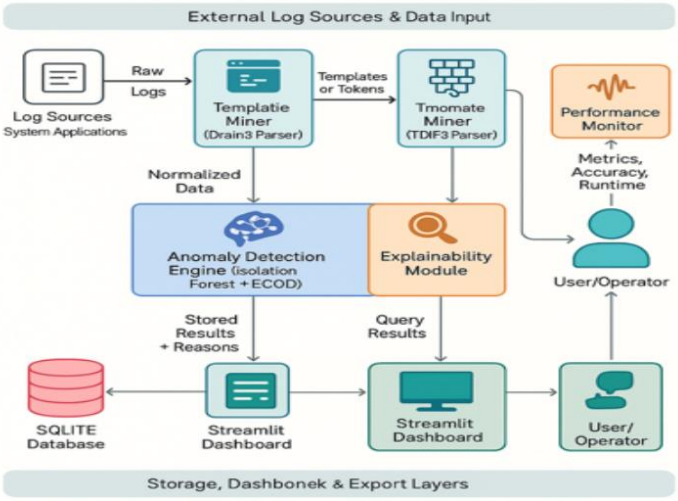
Specific Objectives

1. **Log Ingestion and Normalization –** To build a structured pipeline for collecting and standardizing log data from heterogeneous sources to ensure consistent preprocessing.
2. **Feature Extraction** – To implement hybrid feature engineering using TF-IDF and statistical window-based features for effective representation of log events.
3. **Unsupervised Detection** – To apply unsupervised machine learning algorithms such as Isolation Forest and ECOD for anomaly identification without labeled datasets.
4. **Explainable Alerts** – To integrate an explainability module that generates human-readable reason codes for detected anomalies, improving interpretability and trust.

5. **Dashboard and Exports** – To design an interactive Streamlit-based dashboard and provide export functionalities (CSV, JSON, PDF) for offline analysis and reporting.

V. SYSTEM ARCHITECTURE

The proposed AI-Ops Log Anomaly Miner follows a lightweight, modular architecture comprising five stages: (1) Log Ingestion and Normalization, (2) Template Mining, (3) Feature Extraction, (4) Unsupervised Detection with Explainability, and (5) Visualization and Export.



Logs from diverse sources are first normalized and stored in a SQLite database for structured processing. An optional Drain3 parser extracts templates to reduce variability, while token-based fallback ensures parser-tolerant operation. Hybrid feature engineering combines TF-IDF vectors with window-based statistical metrics to represent textual and temporal characteristics.

For anomaly detection, Isolation Forest and ECOD algorithms identify deviations without labeled data. Each flagged entry is paired with concise reason codes generated by the explainability module, improving transparency and user trust.

VI. RESULTS

The proposed AI-Ops Log Anomaly Miner framework is expected to deliver an efficient, transparent, and fully offline solution for automated log analytics in AIOps environments. The system successfully integrates parser-aware normalization, hybrid feature extraction, and unsupervised detection to identify anomalies without labeled datasets or heavy computation.

Experimental validation on benchmark datasets such as HDFS and BGL demonstrates accurate anomaly detection under CPU-only settings, with processing speeds exceeding 50,000 log lines within 90 seconds and memory usage below 1 GB. The explainability layer produces concise, human-readable reason codes for each alert, ensuring interpretability and operational trust.

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