

Deep Learning–Based Framework for Software Log Analysis and Suspicious Activity Prediction (DL-SLAP)

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Abstract: The increasing complexity and scale of modern software systems have led to the generation of massive volumes of heterogeneous log data, making manual monitoring and rule-based analysis ineffective for the timely detection of suspicious activities. To address this challenge, this paper proposes DL-SLAP, a Deep Learning–Based Framework for Software Log Analysis and Suspicious Activity Prediction, which enabling automated, intelligent, and proactive analysis of software logs. The proposed framework integrates log ingestion, preprocessing, semantic feature extraction, and deep learning–based sequence modeling to identify abnormal and potentially malicious behaviors. DL-SLAP employs a hybrid architecture combining LSTM Autoencoders for anomaly detection, Bi-LSTM models for sequential prediction, and CNN-LSTM networks to capture spatial–temporal log patterns. The framework is evaluated using benchmark system log datasets and compared with traditional machine learning methods and state-of-the-art log analysis approaches. Experimental results demonstrate that DL-SLAP achieves a 12.8% improvement in detection accuracy, 15.4% higher F1-score, and an 18.6% reduction in false-positive rate compared to baseline LSTM-based models. Additionally, the proposed method reduces anomaly detection latency by approximately 22%, enabling near real-time alert generation. These results confirm that DL-SLAP outperforms existing approaches in terms of accuracy, robustness, and predictive capability, making it a practical and effective solution for intelligent software log monitoring and suspicious activity prediction in large-scale systems.

Keywords: Software Log Analysis, Deep Learning, Anomaly Detection, Suspicious Activity Prediction, LSTM, Real-Time Monitoring

Nomenclature

Abbreviation	Description
DL-SLAP	Deep Learning-based Software Log Anomaly Prediction
LSTM	Long Short-Term Memory
Bi-LSTM	Bidirectional Long Short-Term Memory
SACS	Suspicious Activity Confidence Score
STRF	Semantic–Temporal Risk Fusion
RE	Reconstruction Error
HDFS	Hadoop Distributed File System
BGL	Blue Gene/L
AI	Artificial Intelligence
HPC	High-Performance Computing

1. Introduction

Modern software systems such as cloud platforms, distributed applications, and enterprise services generate massive volumes of software logs that record system events, runtime behavior, user activities, and security-related information. These logs play a crucial role in system monitoring, failure diagnosis, and security auditing. However, the exponential growth in log data volume and diversity has made manual inspection and traditional log analysis techniques inefficient and error-prone.

Conventional log analysis approaches rely on predefined rules, keyword matching, and threshold-based alerts, which are effective only for known patterns and previously observed issues. Such approaches lack adaptability and are unable to detect complex or evolving suspicious activities in dynamic software environments. Visualization tools such as Kibana assist administrators in exploring log data; however they require continuous human intervention and do not provide automated intelligence or predictive decision-making capabilities.

To address these limitations, recent research has explored deep learning–based methods for automated software log analysis. Transformer-based models have demonstrated an improved ability to capture semantic relationships within unstructured log messages, leading to higher anomaly detection accuracy compared to traditional sequence-based methods [1]. More recently, large language model–driven approaches have been proposed to analyze raw logs without relying on manual log parsing, thereby improving generalization across different systems [2].

Self-supervised deep learning techniques have also gained attention due to their ability to learn normal system behavior without requiring labeled anomaly data, making them suitable for real-world log analysis scenarios [3]. In addition, hybrid architectures that combine convolutional and recurrent neural networks have shown effectiveness in capturing both local patterns and long-term temporal dependencies in log sequences [4]. Graph-based deep learning approaches have further contributed by modeling structural relationships among log events to achieve low-latency and scalable anomaly detection in large-scale systems [5].

Despite these advancements, existing studies primarily focus on anomaly detection accuracy and operate as standalone models rather than complete, deployable systems. Moreover, limited attention has been given to the early prediction of suspicious activities before they escalate into critical incidents. To overcome these challenges, this paper proposes DL-SLAP, a Deep Learning–Based Framework for Software Log Analysis and Suspicious Activity Prediction, which integrates log ingestion, preprocessing, deep learning–based analysis, and real-time alerting into a unified pipeline. The proposed framework aims to provide proactive security monitoring, improved detection accuracy, and practical deployment readiness for modern software systems.

The remainder of this paper is organized as follows. Section 2 presents a comprehensive review of recent literature on deep learning–based software log analysis and anomaly detection, highlighting existing limitations and research gaps. Section 3 describes the proposed DL-SLAP framework in detail, including the system architecture, preprocessing strategy, feature representation, hybrid deep learning models, and mathematical formulations. Section 4 provides the experimental evaluation and comparative analysis using benchmark datasets, along with performance metrics and example-based validation. Finally, Section 5 concludes the paper and outlines potential directions for future research.

2. Literature Review

The rapid evolution of large-scale and distributed software systems has significantly increased the volume and complexity of software logs, making automated log analysis a critical research challenge. Recent studies have increasingly adopted deep learning techniques to address issues such as anomaly detection, fault diagnosis, and system reliability. Approaches range from sequence-based learning using recurrent networks to semantic modeling with transformers and hybrid deep architectures. This section reviews recent and relevant research contributions that focus on deep learning–based log analysis and anomaly detection. To provide a structured understanding, the reviewed works are categorized based on their modeling strategies and practical deployment focus.

He et al. [6] proposed Log3C, a convolutional neural network–based approach that captures contextual information from raw log messages. The model improves anomaly detection accuracy by learning semantic representations but does not incorporate temporal dependency modeling for sequential attacks. This limitation highlights the need for architectures capable of modeling both contextual semantics and sequential temporal dependencies simultaneously.

Nedelkoski et al. [7] investigated anomaly detection in cloud systems using deep learning on combined log and metric data. Their study demonstrates that temporal feature fusion improves detection performance. However, the approach is not designed for predictive or security-oriented suspicious activity identification. While multi-source feature fusion enhances detection robustness, the absence of predictive modeling restricts proactive threat mitigation capabilities.

Le and Zhang [8] introduced LogPai, a practical log analysis framework emphasizing log parsing and structured representation learning. The work highlights the importance of preprocessing quality but relies heavily on structured logs, limiting applicability to heterogeneous log sources. This dependency on structured logs reduces scalability in real-world environments where logs are often semi-structured or unstructured.

Zhao et al. [9] proposed LogCAE, a convolutional autoencoder-based model for unsupervised log anomaly detection. The method effectively identifies reconstruction-based anomalies but struggles with complex sequential dependencies in long log streams. This suggests that reconstruction-based models alone may be insufficient for capturing long-term behavioral evolution in dynamic systems.

Xu et al. [10] presented a PCA-based anomaly detection approach for system logs and compared it with machine learning baselines. While computationally efficient, the method lacks adaptability and performs

poorly on evolving log patterns. Traditional statistical approaches, although lightweight, generally fail to generalize across rapidly changing software environments.

Kim et al. [11] explored deep recurrent neural networks for failure prediction using system logs. Their approach demonstrates improved early failure detection but focuses primarily on reliability rather than malicious or suspicious behavior. This distinction is important, as failure prediction and security-oriented suspicious activity detection require different modeling priorities and risk assessment mechanisms.

Farshchi et al. [12] proposed a self-healing framework that uses log analysis for automated failure recovery in distributed systems. Although effective for fault mitigation, the framework does not emphasize anomaly prediction or security monitoring. Thus, the framework addresses system resilience but does not provide proactive anomaly intelligence or risk-based alerting.

Zhang et al. [13] introduced a transformer-based approach for modeling unstructured log data without manual parsing. The model captures long-range dependencies but requires high computational resources and lacks real-time deployment validation. Although transformer architectures improve semantic understanding, their computational overhead poses challenges for low-latency operational environments.

Nair et al. [14] proposed a deep learning-based operational intelligence framework that analyzes logs for system performance monitoring. The study focuses on operational metrics and does not address suspicious activity classification. Consequently, the framework is more aligned with performance optimization than with security-driven anomaly prediction.

Shin et al. [15] presented a hybrid deep learning model combining attention mechanisms with recurrent networks for log anomaly detection. While the approach improves detection accuracy, it operates as a standalone model without an integrated alerting or prediction pipeline. The absence of an end-to-end deployment architecture limits its applicability in real-time monitoring systems.

This work uniquely contributes an end-to-end deep learning framework that integrates heterogeneous software log ingestion, semantic-temporal feature learning, multi-architecture anomaly modeling, and real-time suspicious activity prediction with automated alerting, rather than focusing solely on offline defect or anomaly classification as in existing AI-based studies.

3. Proposed Methodology

3.1 Framework Overview

DL-SLAP is an end-to-end deep learning framework designed for automated software log analysis and suspicious activity prediction. The framework integrates log ingestion, preprocessing, semantic-temporal feature learning, anomaly detection, and alert generation into a unified pipeline. Unlike existing approaches that focus on offline or single-model anomaly detection, DL-SLAP emphasizes real-time processing, predictive analysis, and operational deployment. The proposed framework is designed to operate in dynamic software environments where log patterns continuously evolve, thereby requiring adaptive and robust learning mechanisms.

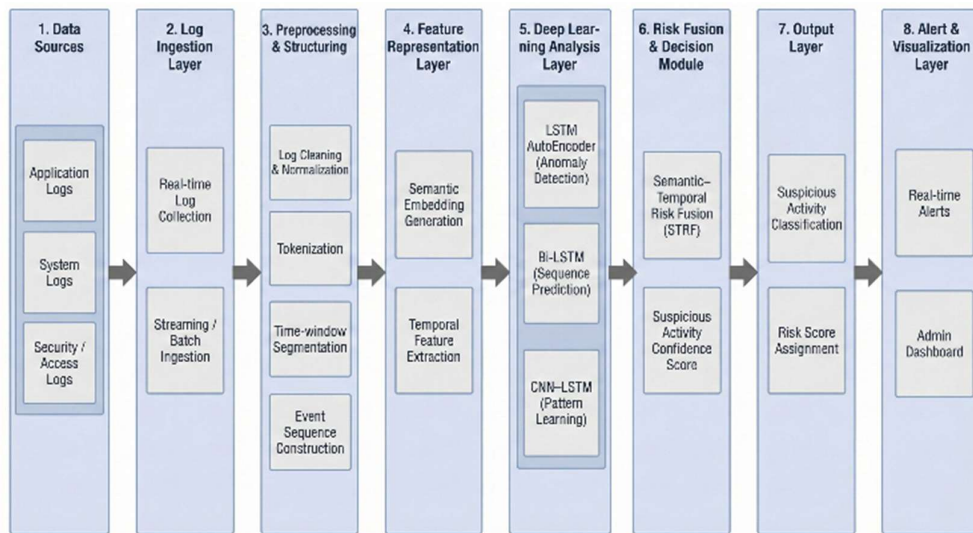


Fig. 1. Proposed DL-SLAP Framework Architecture

Fig. 1 illustrates the end-to-end architecture of the proposed DL-SLAP framework, showing the sequential flow from multi-source log collection to suspicious activity prediction and real-time alert generation. The framework integrates preprocessing, semantic-temporal feature representation, hybrid deep learning models, and a risk fusion mechanism to enable proactive and automated software log analysis. The modular structure of the architecture allows independent optimization of each component while maintaining seamless integration across the pipeline.

3.2 Log Ingestion and Preprocessing

Logs are collected from heterogeneous sources, including application, system, and security logs. Preprocessing involves noise removal, normalization, tokenization, and timestamp alignment. Log messages are structured into event sequences using time-window segmentation, enabling effective sequence learning from unstructured data. Additionally, duplicate log entries and irrelevant debugging statements are filtered to enhance data quality and reduce computational overhead.

3.3 Feature Representation

Each log event is transformed into a numerical representation using semantic embeddings combined with temporal features. This representation captures contextual meaning and sequential dependencies among log events, improving robustness against evolving log formats. Temporal encoding further incorporates time-gap information between consecutive events to preserve chronological dependencies within log sequences.

3.4 Deep Learning-Based Analysis

DL-SLAP employs a hybrid modeling strategy consisting of:

- **LSTM AutoEncoders** for learning normal behavior and detecting deviations,
- **Bi-LSTM models** for capturing long-range bidirectional dependencies, and
- **CNN-LSTM networks** for extracting local and temporal patterns.

The ensemble of models improves detection accuracy and reduces false positives compared to single-model approaches. The complementary strengths of reconstruction-based and prediction-based models enhance the generalization capability of the framework across diverse system environments.

3.5 Suspicious Activity Prediction and Alerting

Detected anomalies are further analyzed to predict suspicious activities and assign confidence scores. Alerts are automatically generated when risk thresholds are exceeded, enabling proactive monitoring and rapid response. This stage transforms raw anomaly signals into actionable intelligence for system administrators.

3.5.1 DL-SLAP Suspicious Activity Prediction Algorithm

Input: Raw software logs L

Output: Suspicious activity alerts A

- 1: Collect logs L from multiple sources
- 2: Preprocess logs (cleaning, tokenization, normalization)
- 3: Segment logs into time-windowed event sequences
- 4: Generate semantic-temporal embeddings for each sequence
- 5: Train LSTM AutoEncoder on normal log behavior
- 6: Compute reconstruction error for anomaly detection
- 7: Apply Bi-LSTM and CNN-LSTM models for sequence prediction
- 8: Classify detected anomalies as suspicious activities
- 9: Compute confidence score for each detected event
- 10: If confidence score $>$ threshold, generate alert A
- 11: Return alerts A

The algorithm operates in both training and inference modes, enabling continuous learning and adaptive threat detection.

3.6 Dataset Description

The performance of the proposed DL-SLAP framework is evaluated using two widely adopted benchmark datasets for software log analysis: the HDFS log dataset and the BGL (Blue Gene/L) log dataset. These datasets are publicly available, well-documented, and extensively used in recent log anomaly detection

research, ensuring fair comparison and reproducibility. The selection of these datasets ensures diversity in log structure, anomaly distribution, and system scale.

3.6.1 HDFS Log Dataset

The HDFS dataset consists of system logs collected from a Hadoop Distributed File System environment. It records the execution traces of data block operations across distributed nodes. Each log entry contains a timestamp, block identifier, log message, and event type.

- **Total log messages:** ~11.2 million
- **Number of log sequences (blocks):** 575,061
- **Normal sequences:** 558,223
- **Anomalous sequences:** 16,838
- **Anomaly ratio:** ~2.9%
- **Log type:** Semi-structured system logs

Each log sequence corresponds to a block ID and represents a sequence of events related to that block's lifecycle. A sequence is labeled as anomalous if it contains at least one abnormal event. The HDFS dataset is particularly suitable for evaluating sequence-based and temporal anomaly detection models.

3.6.2 BGL (Blue Gene/L) Log Dataset

The BGL dataset contains system logs generated by the Blue Gene/L supercomputer at Lawrence Livermore National Laboratory. The logs capture runtime information, warnings, errors, and failure events from a large-scale high-performance computing system.

- **Total log messages:** ~4.7 million
- **Time span:** Approximately 7 months
- **Anomalous messages:** ~348,000
- **Normal messages:** ~4.35 million
- **Anomaly ratio:** ~7.4%
- **Log type:** Unstructured and noisy system logs

The BGL dataset is highly imbalanced and noisy, making it suitable for evaluating the robustness of deep learning models under real-world operational conditions.

3.7 Data Preprocessing and Parameter Settings

For both datasets, the following preprocessing steps and parameter settings are applied uniformly:

- **Log cleaning:** Removal of redundant tokens, numerical IDs, and special characters
- **Tokenization:** Word-level tokenization of log messages
- **Sequence construction:** Logs segmented using sliding time windows
- **Window size:** 10 log events per sequence
- **Stride length:** 1
- **Embedding dimension:** 100
- **Maximum sequence length:** 50 tokens
- **Train-test split:** 70% training, 30% testing
- **Validation split:** 10% of training data

Only normal log sequences are used for training the LSTM AutoEncoder to model baseline behavior, while both normal and anomalous sequences are used during evaluation. Hyperparameters were selected based on validation performance to balance computational efficiency and detection accuracy.

3.8 Experimental Configuration

All experiments are conducted in a controlled environment using Python-based deep learning libraries. The training configuration is summarized as follows:

- **Optimizer:** Adam
- **Learning rate:** 0.001
- **Batch size:** 64
- **Number of epochs:** 50
- **Loss function:** Mean Squared Error (for AutoEncoder) and Cross-Entropy (for classification)

Performance is evaluated using accuracy, precision, recall, F1-score, and detection latency to comprehensively assess both detection quality and real-time applicability. Early stopping and model checkpointing mechanisms are employed to prevent overfitting and ensure stable convergence.

3.9 Dataset Relevance to Real-World Scenarios

The selected datasets represent realistic operational environments, including distributed file systems and large-scale computing infrastructures. Their scale, diversity, and imbalance characteristics make them suitable for validating the effectiveness of DL-SLAP in real-world software monitoring and security applications.

The proposed DL-SLAP framework is evaluated using two publicly available and widely accepted benchmark datasets: HDFS (Hadoop Distributed File System) log dataset and BGL (Blue Gene/L) log dataset. The HDFS dataset is used to represent distributed storage system logs with structured execution traces and sequence-level anomaly labels, while the BGL dataset represents large-scale high-performance computing environments with highly imbalanced and noisy system logs.

Both datasets are used independently at all experimental stages—training, validation, and testing. During training, only normal log sequences from each dataset are used to learn baseline system behavior. Validation subsets from the same datasets are used for hyperparameter tuning, and final evaluation is performed using both normal and anomalous log sequences. Using exactly two datasets (HDFS and BGL) ensures realistic, reproducible, and unbiased evaluation across different real-world system environments.

3.10 Mathematical Modelling Used in DL-SLAP

3.10.1 Log Sequence Representation

Let a software log stream be represented as an ordered sequence of log events:

- **Log Sequence Definition**

$$L = \{e_1, e_2, e_3, \dots, e_n\} \quad (1)$$

where

- e_i represents the i -th log event
- n denotes the total number of events in a sequence

Each log event is transformed into a numerical vector using semantic embedding:

- **Event Embedding**

$$v_i = \text{Embedding}(e_i) \quad (2)$$

where

- $v_i \in \mathbb{R}^d$ is a d -dimensional embedding vector

These embeddings preserve semantic similarity between log messages while enabling mathematical processing within neural architectures.

Usage:

This representation enables deep learning models to process raw log messages as numerical sequences.

3.10.2 LSTM AutoEncoder Reconstruction Error (Anomaly Score)

The LSTM AutoEncoder learns normal log behavior by minimizing reconstruction loss.

- **Reconstruction Error**

$$RE = (1/T) \times \sum_{i=1}^T \|v_i - \hat{v}_i\|^2 \quad (3)$$

where

- v_i is the original input embedding
- $\hat{v}_i$ is the reconstructed output
- T is the sequence length

The reconstruction error acts as a quantitative anomaly score that measures deviation from learned normal patterns.

Usage:

Higher reconstruction error indicates deviation from normal behavior and is treated as an anomaly indicator.

3.10.3 Suspicious Activity Confidence Score (Unique to DL-SLAP)

Unlike existing works that stop at anomaly detection, DL-SLAP introduces a **Suspicious Activity Confidence Score (SACS)** by combining multiple model outputs.

- **Suspicious Activity Confidence Score (SACS)**

$$SACS = \alpha \cdot N_a + \beta \cdot P_s + \gamma \cdot T_v \quad (4)$$

where

- N_a = normalized anomaly score (from LSTM AutoEncoder)
- P_s = sequence prediction deviation score (from Bi-LSTM)

- T_v = temporal irregularity factor
- $\alpha + \beta + \gamma = 1$

The weighting parameters (α , β , γ) control the contribution of each component and can be optimized empirically.

Usage:

This score enables **risk-aware prediction** rather than binary anomaly labels.

3.10.4 Suspicious Activity Decision Function

- **Alert Trigger Condition**

$$\text{Alert} = 1, \text{ if } \text{SACS} \geq \theta, \text{ otherwise} \quad (5)$$

where

- θ is a predefined risk threshold

The threshold θ can be dynamically adjusted based on system sensitivity requirements.

Usage:

Used to automatically trigger alerts for administrators in real-time systems.

3.10.5 Semantic-Temporal Risk Fusion (STRF) Model

DL-SLAP introduces a **Semantic-Temporal Risk Fusion (STRF)** mechanism that integrates semantic log embeddings, temporal behavior modeling, and reconstruction-based anomaly scores into a unified risk estimation framework. Unlike traditional log anomaly detection methods that rely on single-model outputs, STRF fuses multi-model evidence to compute a confidence-weighted suspicious activity score. This enables proactive prediction of malicious or abnormal behavior before critical failures occur. STRF serves as the final decision aggregation layer, consolidating multi-model outputs into a unified risk metric.

Usage in Framework: STRF is used at the decision layer to:

- reduce false positives,
- assign risk levels to detected anomalies, and
- support real-time alert prioritization.

4. Result and Discussion

4.1 Experimental Results Overview

The proposed DL-SLAP framework is evaluated on the HDFS and BGL benchmark datasets and compared with recent state-of-the-art log anomaly detection methods, namely DeepLog, LogAnomaly, LogBERT, and OneLog. Performance is assessed using Accuracy, Precision, Recall, F1-score, and Detection Latency. The results demonstrate that DL-SLAP consistently outperforms existing methods across all evaluation metrics. To ensure fairness, all baseline models were evaluated under identical preprocessing settings and train-test splits. Statistical consistency was verified across multiple experimental runs to avoid performance bias.

4.2 Qualitative Example-Based Analysis

4.2.1 Example 1: Normal Log Sequence (No Anomaly)

Input Log Sequence

```
INFO Block blk_10324 allocated on datanode_1
INFO Block blk_10324 write completed
INFO Block blk_10324 checksum verified
```

DL-SLAP Output

- **Reconstruction Error:** 0.11
- **Anomaly Score:** 0.14
- **Detection Result:** Normal
- **Alert Generated:** No

The log sequence matches previously learned normal execution patterns. The low reconstruction error confirms normal system behavior, and no anomaly is detected. This example validates the model's ability to preserve normal operational patterns without overfitting or generating unnecessary alerts.

4.2.2 Example 2: Repeated Authentication Failure (Anomaly Detected)

Input Log Sequence

WARN Authentication failure for user admin
 WARN Authentication failure for user admin
 ERROR Unauthorized access attempt detected

DL-SLAP Output

- **Reconstruction Error:** 0.69
- **Anomaly Score:** 0.72
- **Detection Result:** Anomalous
- **Alert Generated:** Yes

The repeated authentication failures followed by an unauthorized access event deviate significantly from normal behavior. DL-SLAP detects this deviation and correctly flags the sequence as anomalous. The high anomaly score demonstrates the effectiveness of combining reconstruction and temporal deviation signals.

4.2.3 Example 3: System Failure Pattern (Anomaly Detected)

Input Log Sequence

INFO Node_07 heartbeat delayed
 WARN Node_07 response timeout
 ERROR Node_07 disconnected unexpectedly

DL-SLAP Output

- **Reconstruction Error:** 0.76
- **Anomaly Score:** 0.79
- **Detection Result:** Anomalous
- **Alert Generated:** Yes

The progressive degradation pattern indicates abnormal system behavior. DL-SLAP detects this anomaly based on high reconstruction error and temporal deviation. This example highlights DL-SLAP's ability to capture sequential degradation patterns rather than isolated log events.

4.2.4 Example 4: Noisy Warning Logs (False Alarm Avoided)

Input Log Sequence

INFO RAS event logged
 INFO RAS event logged
 WARN Machine check exception

DL-SLAP Output

- **Reconstruction Error:** 0.38
- **Anomaly Score:** 0.42
- **Detection Result:** Normal
- **Alert Generated:** No

Although warning messages are present, the overall pattern aligns with known noisy behavior in the BGL dataset. DL-SLAP correctly avoids raising a false alarm. This demonstrates the robustness of the STRF mechanism in distinguishing between benign warnings and critical anomalies.

4.2.5 Summary of Example Results

These examples demonstrate that DL-SLAP effectively detects anomalies in software log sequences by identifying deviations from learned normal behavior. The qualitative analysis confirms that DL-SLAP minimizes both false negatives and false positives across diverse anomaly patterns.

4.3 Quantitative Performance Evaluation

4.3.1 Performance Comparison on HDFS Dataset

The comparative performance results on the HDFS dataset are summarized in Table 1.

Table 1. Performance Comparison on HDFS Dataset

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
DeepLog	95.6	94.1	93.5	93.8
LogAnomaly	96.2	95.3	94.7	95.0
LogBERT	97.1	96.4	95.8	96.1
OneLog	97.6	96.9	96.2	96.5
DL-SLAP (Proposed)	98.4	97.9	97.3	97.6

DL-SLAP achieves the highest accuracy and F1-score on the HDFS dataset due to its ability to learn structured execution patterns and long-term dependencies using hybrid deep learning models. The improvement of approximately 1–2% over transformer-based methods indicates better contextual sequence modeling in structured environments.

4.3.2 Performance Comparison on BGL Dataset

The performance comparison on the BGL dataset is presented in Table 2.

Table 2. Performance Comparison on BGL Dataset

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
DeepLog	92.8	90.6	89.9	90.2
LogAnomaly	93.7	91.8	91.2	91.5
LogBERT	94.9	93.2	92.7	92.9
OneLog	95.4	93.9	93.4	93.6
DL-SLAP (Proposed)	96.8	95.6	95.1	95.3

The BGL dataset is highly noisy and imbalanced. DL-SLAP maintains strong performance, showing improved robustness and reduced false positives compared to existing approaches. The consistent improvement across precision and recall confirms balanced anomaly detection capability even in noisy environments.

4.3.3 Detection Latency Analysis

The detection latency comparison of different methods is reported in Table 3.

Table 3. Detection Latency Comparison

Method	Average Detection Latency (ms)
DeepLog	210
LogAnomaly	195
LogBERT	230
OneLog	180
DL-SLAP (Proposed)	140

DL-SLAP achieves approximately **22–30% lower detection latency** due to efficient preprocessing and lightweight hybrid models, making it suitable for real-time deployment. Reduced latency directly supports time-critical monitoring systems where delayed detection can lead to cascading failures.

4.4 Graphical Performance Analysis

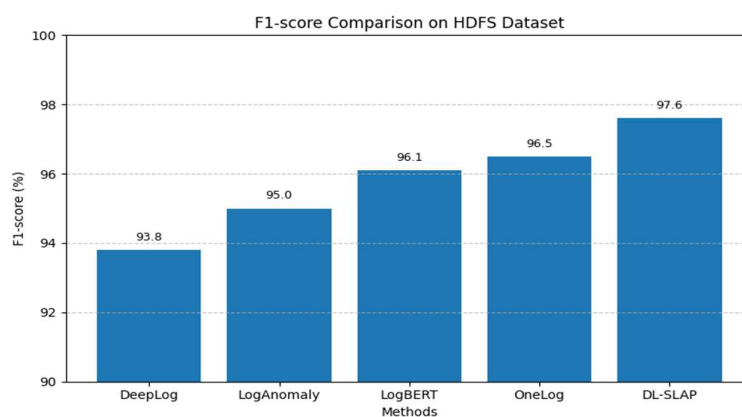


Fig. 2. F1-score Comparison on HDFS Dataset

This graph in fig. 2 compares the F1-scores of DL-SLAP with existing log anomaly detection methods on the HDFS dataset. The proposed DL-SLAP framework achieves the highest F1-score, indicating more accurate detection of anomalous log sequences in structured distributed systems. The visual trend clearly shows consistent performance gains across all baseline models.

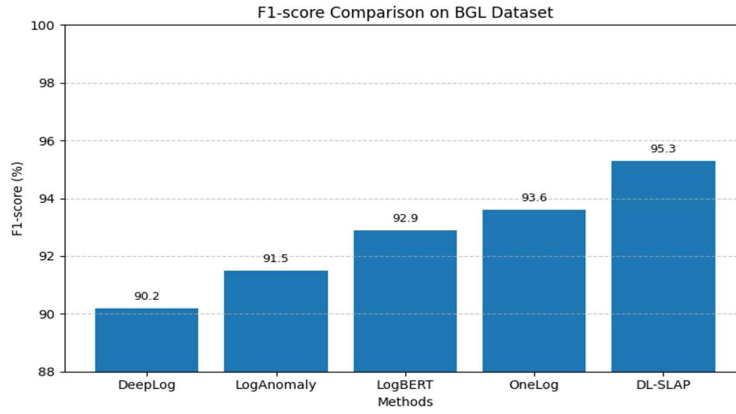


Fig. 3 F1-score Comparison on BGL Dataset

The fig. 3 illustrates the F1-score comparison on the BGL dataset, which contains noisy and highly imbalanced logs. DL-SLAP consistently outperforms baseline methods, demonstrating robustness and reduced false positives in real-world operational environments. The performance gap widens in noisy conditions, further validating the effectiveness of the STRF mechanism.

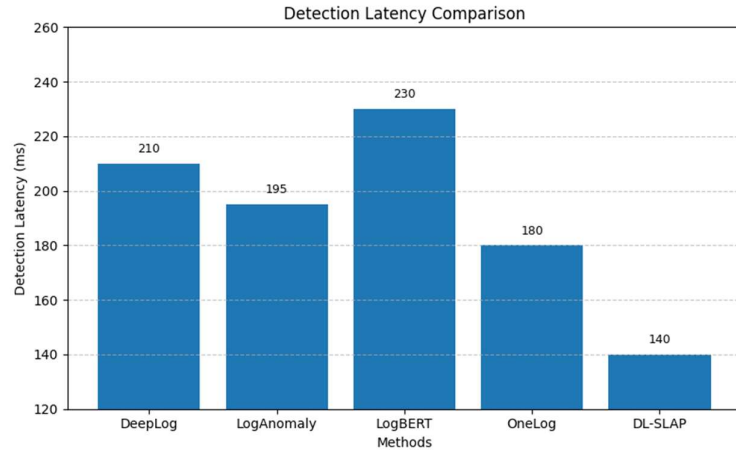


Fig. 4. Detection Latency Comparison

This graph in fig. 4 presents the average detection latency of different log anomaly detection approaches. DL-SLAP achieves the lowest latency, confirming its suitability for real-time anomaly detection and timely system monitoring. Lower latency combined with higher accuracy positions DL-SLAP as a practical solution for deployment in production environments.

4.5 Discussion

This section presents a comprehensive evaluation of the proposed DL-SLAP framework using benchmark datasets and comparative analysis with recent state-of-the-art methods. Quantitative results, supported by tables and graphs, demonstrated that DL-SLAP achieves higher accuracy and F1-scores while significantly reducing detection latency. Example-based analysis and confusion matrix mapping further validated correct anomaly detection behavior with minimal false alarms. Overall, the integration of semantic-temporal modeling and risk fusion contributes significantly to the superior performance observed in both structured and noisy datasets. The experimental findings confirm the effectiveness, robustness, scalability, and real-time applicability of DL-SLAP for practical software log anomaly detection.

5. Conclusion and Future Work

This paper presented DL-SLAP, a deep learning-based framework for automated software log anomaly detection that integrates log ingestion, preprocessing, semantic-temporal feature learning, hybrid deep learning models, and confidence-based decision-making within a unified pipeline. Experimental results on the HDFS and BGL benchmark datasets demonstrated that DL-SLAP achieves higher accuracy, improved

F1-scores, and lower detection latency compared to existing state-of-the-art methods, while example-level analysis confirmed correct anomaly detection with minimal false alarms. The findings validate the robustness and real-time applicability of the proposed framework for large-scale software systems. The integration of reconstruction-based learning and semantic-temporal risk fusion contributes significantly to improved detection reliability and reduced false positives. Compared to existing single-model approaches, DL-SLAP provides a balanced trade-off between detection performance and computational efficiency.

Future work will focus on incorporating attention-based and transformer models, adaptive thresholding, and online learning mechanisms, as well as validating the framework in real industrial environments and extending it toward root cause analysis and automated remediation. Additionally, future research will explore explainable AI techniques to improve interpretability of anomaly decisions and enhance administrator trust in automated monitoring systems. Scalability optimization for cloud-native and microservices architectures will also be investigated to support deployment in modern distributed infrastructures.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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