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Research Article

Unique Log Parsing Framework for Enhanced Anomaly Detection in Network Security: Lauki Log Parser

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ABSTRACT
The increasing complexity of information security demands effective strategies to protect data across various domains. Traditional system log analysis, relying on unstructured logs, employs data mining and machine learning techniques to detect network threats. However, existing methods often struggle with logs of diverse formats and structures, resulting in missed anomalies and vulnerabilities. This paper introduces LaukiLogParser, a novel real-time log parsing framework designed to address these challenges by processing both structured and unstructured logs from multiple formats, including JSON, Syslog, and CEF. By incorporating unique parsing equations, the proposed parser enhances the identification of network threats, insider threats, and system vulnerabilities. Through comprehensive testing on publicly available datasets, LaukiLogParser demonstrated a significant 15% increase in anomaly detection accuracy compared to traditional parsers, along with improved F1-scores, precision, and recall. The parser's ability to handle a variety of log formats provides unmatched flexibility in real-time environments, making it highly effective for modern network security systems. The paper compares LaukiLogParser with existing parsers, such as LogParser-LLM, OpenLog, and LogPPT, showcasing its superiority in accuracy, scalability, and adaptability. The results highlight the limitations of current parsers, while LaukiLogParser's novel approach offers a robust solution for enhancing anomaly detection and improving real-time security monitoring.
Keywords—Cyber Security, Real-time Log Parsing, Multi-format Log Analysis, Machine Learning, Cybersecurity Threat Identification

I. INTRODUCTION

Log parsing plays a critical role in network security by extracting valuable information from logs generated by various systems, applications, and network devices. Logs are essential records of system activities and events, and they serve as a primary data source for identifying potential security breaches, anomalies, or performance issues. However, the raw logs themselves are often unstructured or follow a wide variety of formats, making them challenging to analyze directly.

Log parsing is the process of transforming these raw, often messy logs into structured data that can be more easily analyzed. By categorizing and extracting meaningful fields such as timestamps, IP addresses, user IDs, error codes, and event descriptions, log parsers make it possible to apply machine learning algorithms, detect anomalies, and generate actionable insights in real-time.

In traditional network security infrastructures, the ability to process logs in real-time is crucial. Real-time log analysis allows for the detection of suspicious patterns or behaviors as they happen, enabling immediate responses to potential threats. However, existing log parsers often fall short in several areas such as:

Handling Diverse Log Formats: Logs can vary dramatically depending on their source. While some logs are highly structured (e.g., JSON or XML), others are semi-structured or entirely unstructured (e.g., plain-text logs from legacy systems). Many existing parsers struggle to handle these varying formats, limiting their ability to extract useful data comprehensively.

Scalability and Performance: With the growth of network infrastructures and an increasing number of connected devices, the volume of log data has grown exponentially. Traditional parsers, designed for smaller or more structured datasets, often face difficulties in processing large volumes of logs in real-time, resulting in bottlenecks and delays in threat detection.

Accuracy and Precision: Traditional log parsers may rely heavily on predefined rules or regular expressions (regex) to identify patterns within logs. While these methods work well for certain types of logs, they can result in lower accuracy when logs deviate from the expected structure. This leads to either missed anomalies (false negatives) or incorrect classifications (false positives).

Error Handling and Robustness: Logs are not always complete or free from errors. In real-world environments, logs can contain missing data, inconsistent formats, or even corrupted entries. A robust log parser must handle these cases gracefully without discarding valuable information or causing the parsing process to fail.

In response to these challenges, researchers and developers have explored various techniques to improve log parsing efficiency. Modern approaches often combine traditional parsing techniques with advanced methods such as machine learning to enhance log parsing accuracy. Despite these advances, many existing parsers still lack the adaptability and real-time capabilities needed for today's fast-paced network environments.

This paper proposes a novel log parsing framework that addresses these issues by offering:

Multi-format Log Parsing: The ability to handle both structured and unstructured logs, ensuring comprehensive parsing across different data sources.

Advanced Regex and Machine Learning Hybrid Approach: A combination of regex for known log formats and machine learning techniques to dynamically adapt to previously unseen log patterns, thereby improving parsing accuracy and minimizing false negatives.

Real-Time Processing and Scalability: Optimized for processing large volumes of log data in real-time, the proposed parser ensures that security threats can be identified and addressed as they arise without delay.

By focusing on enhancing the core functionalities of log parsing—namely format adaptability, real-time processing, accuracy, and robustness—the proposed parser aims to fill the gaps left by traditional log parsers, offering a more efficient and effective solution for log-based anomaly detection in network security.

In this paper, we present the conducted tests on the existing log parsers and proposed parser. Provided a comparison with state of the art literature for log-based parsing for network security.

The paper is structured as follows: Section I introduces the imperative for novel methodologies in safeguarding data. Section II delves into an extensive review of the existing literature. In Section III, a meticulously crafted flowchart is presented, complete with detailed step-by-step explanations. Section IV encompasses the examination of log processing and the execution of real-time tests. Finally, It also offers a comprehensive array of diverse observations and outcomes. Section V shows applications of the model. Section VI shows the conclusion of the entire paper followed by the list of references.

II. Literature Survey

Log Parsing in Network Security: Various authors have explored log parsing for anomaly detection in network security, addressing different aspects through diverse parsers. Existing Log-Based Parsers are provided below.

I. Advanced LLM-based and ML Parsers

LogParser-LLM, OpenLogParser, Log3T, AdaptParse, LogPTR: These are cutting-edge, often employing large language models or advanced machine learning techniques. They are particularly useful in research involves exploring the application of AI in log parsing, handling complex or less structured log formats [1-3].

II. Traditional Log Parsers:

Drain, Spell, UniParser, LogPPT: These parsers use more traditional parsing techniques using structured log data only and are well-established in the field. This paper is focused on benchmarking against standard methods and dealing with more structured log types. [4,5]

III. Conventional Log Management Tools:

Syslog, ELK Stack, Graylog, NXLog, Splunk, LogRhythm: These tools are broadly used in industry for log management and analysis. They are not just parsers but provide comprehensive solutions including storage, analysis, visualization, and alerting. This paper does not involves the operational aspects of log management, scalability, real-time processing, or integration with security information and event management (SIEM) systems.

IV. Our Approach:

This paper focuses is on pushing the boundaries of what can be done with log parsing using the latest AI technologies. If opting for the first group involving LLM-based and machine learning parsers would be beneficial. Also the goal is to compare or enhance traditional parsing methods or apply them in practical, real-world settings, the second and third groups would be more appropriate.

Syslog: Often used for transmitting log messages, its limitations in handling unstructured logs result in lower anomaly detection accuracy[8]. ELK Stack: Noted for its scalability and flexibility, ELK Stack faces performance issues in real-time environments, which are addressed by newer parsers offering optimized processing capabilities[9]. Graylog: While excellent for real-time logging, its performance in parsing unstructured logs is less efficient, an area where more advanced parsers excel. NXLog: Recognized for its versatility in handling various log formats, NXLog's real-time performance is outstripped by more specialized parsers. Splunk: Although advanced in parsing and machine learning capabilities, its high resource demands limit its use in smaller setups, a gap filled by more cost-effective parsers. LogRhythm: Integrates well with SIEM tools but has limited capabilities in parsing unstructured logs, a niche addressed by newer parsing technologies.

III. LOG-BASED PARSING

In this section, the paper explains how the proposed method provides effectiveness in network security by processing small to large volumes of log events and organizing them based on the organization's needs.

A. About Proposed Log Parser "LaukiLogParser"

LaukiLogParser (LLP) uses a hybrid approach combining rule-based parsing techniques with Machine Learning (ML) models that adapt dynamically to the log format variations they encounter. This parser would utilize a meta-learning framework where the parser learns optimal parsing strategies from a variety of log formats and continually adjusts its parsing algorithm based on new log data.

Features of LaukiLogParser (LLP)

- **Dynamic Template Detection**: Leveraging LLMs to understand and adapt to the structure of logs without predefined templates.
- **Contextual Anomaly Detection**: Using context-aware models to identify anomalies not just based on the log entries themselves but also considering their context within the sequence.
- **Incremental Learning**: Continuously learning from new logs to improve parsing accuracy and adapt to new log formats.
- **High Scalability and Performance**: Optimized for performance in both small-scale and large-scale environments.

B. Steps in LaukiLogParser (LLP)

1. Input Log Data: Gather diverse datasets of logs from various sources to train the initial model.These logs can be structured, semi-structured, or unstructured.

Example log entries:

```
{"timestamp": "2024-09-01T12:34:56Z", "event": "login", "user": "user1", "ip": "192.168.0.1"}
192.168.0.1 - - [01/Sep/2024:12:34:56 +0000] "GET /index.html HTTP/1.1" 200 1024
```

2. Parsing Process - Preprocessing

a. Log Format Detection:

The parser begins by detecting the format (like JSON, Syslog, Syslog CEF, LEEF, Mixed logs, Regex based logs) of each log entry. For example, if the log follows JSON format, it applies JSON parsing rules. For unstructured logs, such as the second log entry, the parser uses regex and/or machine learning-driven techniques to identify key fields.

The first log is detected as JSON format, and the second is detected as unstructured.

Regex Parsing for Unstructured Logs:

For unstructured logs, the parser applies advanced regex matching. In the case of the second log entry (an Apache access log), the regex pattern will extract fields such as the IP address, timestamp, HTTP method, and status code.

Example regex applied to the second log entry:

```
(\d{1,3}\.\d{1,3}\.\d{1,3}\.\d{1,3}) - - \[(.*?)\] "(.*?) (.*?) (.*?)" (\d{3}) (\d+)
```

This regex will extract:

```
IP: 192.168.0.1
Timestamp: 01/Sep/2024:12:34:56 +0000
Method: GET
Resource: /index.html
Status Code: 200
Response Size: 1024
```

b. **DataTokenization:** Convert logs into tokens for ML processing based on syntax and semantics. The tokenization process is a critical step in preparing log data for machine learning (ML) models. It involves breaking down the log entries into smaller, manageable pieces called tokens, which can be analyzed for patterns, structures, and anomalies.

Consider input from a database access log:

```
2024-09-12 14:45:03 INFO User 'admin' executed query 'SELECT * FROM users WHERE user_id = 101'
```

Tokenization Process

Step 1: Identifying Elements The log entry contains several elements like IP address, timestamp, HTTP method, resource accessed, HTTP status code, and response size. Each of these elements has syntactic and semantic significance.

Step 2: Applying Tokenization

```
Timestamp: 2024-09-12 14:45:03
Log Level: INFO
User: admin
Query: SELECT * FROM users WHERE user_id = 101
```

Step 3: Token Extraction The raw log line is parsed to extract and isolate these components into discrete tokens.

```
[
  "2024-09-12 14:45:03",
  "INFO",
  "User",
  "admin",
  "executed",
  "query",
  "SELECT * FROM users WHERE user_id = 101"
]
```

Tokenization Supporting ML Processing

- **Syntax and Semantics**: Each token represents a syntactic element (like an IP address or timestamp) and carries semantic meaning (like identifying a user session or indicating a response status).
- **ML Model Feeding**: These tokens can be used as input for various ML models. For example, sequence models might look at the order and frequency of HTTP methods to predict potential security threats or operational issues, while clustering models might analyze IP addresses and response codes to identify patterns of normal or anomalous network behavior.

c. Data Normalization:

This section standardizes the logs to reduce the variability in data. After parsing, the parser normalizes the data fields. For example, timestamps are converted to a standard format (YYYY-MM-DD HH:MM:SS) and IP addresses are stored in a consistent structure.

Example normalized output:

```
{"timestamp": "2024-09-01 12:34:56", "event": "login", "user": "user1", "ip": "192.168.0.1"}
{"timestamp": "2024-09-01 12:34:56", "ip": "192.168.0.1", "method": "GET", "resource": "/index.html", "status": "200", "size": "1024"}
```

d. Error Handling and Correction:

The parser checks for missing or corrupted fields. If it detects incomplete data (e.g., missing user info), the parser attempts to fill in the gaps using context-aware heuristics.
Example: If a log entry has a missing timestamp, the parser can infer the correct time by referencing the previous log entry or using a placeholder value.

e. Real-Time Processing:

The logs are processed in real-time, with each log entry being parsed, normalized, and passed to the anomaly detection system (if applicable) without significant delays. The parser's multi-threaded architecture ensures that high volumes of logs can be processed concurrently.
Output: The parser outputs the normalized, structured logs, ready for further analysis (e.g., for anomaly detection or storage in a database).
Example output for the two logs:


```
[
  {"timestamp": "2024-09-01 12:34:56", "event": "login", "user": "user1", "ip": "192.168.0.1"},
  {"timestamp": "2024-09-01 12:34:56", "ip": "192.168.0.1", "method": "GET", "resource": "/index.html", "status": "200", "size": "1024"}
]
```


3.Model Training

- Train separate models on different aspects of logs, such as syntax, semantics, and temporal features.
- Use transfer learning to adapt pre-trained NLP models to the specific domain of log parsing.

4. Continuous Learning

- Implement a learning algorithm that updates the model in real-time as new logs are parsed.
- Use reinforcement learning to optimize parsing strategies based on feedback loops from parsed log accuracy and anomaly detection rates.

C. Proposed LaukiLogParser (LLP): How It Learns and Modifies Automatically

This paper has created custom equations specifically tailored for LaukiLogParser (LLP) proposed log parser and its unique model training process. This paper defines how the parser dynamically learns and adapts to new log formats and structures. Below are the customized set of equations designed specifically for LaukiLogParser (LLP) while still leveraging known ML techniques but contextualizing them to this system's unique characteristics.

Log Feature Representation in LaukiLogParser

This section represents the log tokens in a feature space where each token can hold structural and semantic information.
For each log entry □ shown in equation 1, we define:

- $□ = \{□_1, □_2, .., □_□\}$ where $□_□$ is a token from the log (like IP, timestamp, status code).
- Each token $□_□$ is represented by a feature vector $□_{□_□}$ containing both syntactic and semantic information:

$$□_{□_□} = [□□□□□□(□_□), □□□□□□□□(□_□)] \quad (1)$$

Where:

- Syntax ($□_□$) extracts structural features like position and type (e.g., "IP address" or "timestamp").
- symantec ($□_□$) captures the meaning of the token (e.g., "user action").

This is a custom equation to represent each log's feature as a combination of syntax and semantics, making it more powerful for both structured and unstructured logs.

Template Matching for Log Parsing

In LaukiLogParser (LLP), templates are dynamically learned and updated based on the structure of incoming logs. For a given set of logs $□_1, □_2, . . . , □_□$ the parser clusters them into groups where similar logs share a common template.
For each log □ in equation 2, the distance from an existing template $□_□$ is computed as:

$$□□□□□□□□(□, □_□) = \sum_{□=1}^{□} □_□ \cdot □(□_□, □_{□□}) \quad (2)$$

Where:

- $□_□$ is the weight of the feature (based on its importance in parsing, such as IP address having more importance than a timestamp).
- $□(□_□, □_{□□})$ is the distance between the token $□_□$ and the corresponding token in the template $□_□$.
- Templates $□_□$ are continuously updated as new logs are parsed, allowing dynamic adjustment.

This equation is customized to handle how logs deviate from expected templates, enabling LaukiLogParser to parse diverse log formats automatically.

Dynamic Learning Update in LaukiLogParser

LaukiLogParser (LLP) continually learns and adjusts its parsing strategies. A unique learning update mechanism is applied when a new log deviates significantly from existing templates. The update rule for template refinement is given in equation 3:

$\square_{\square}^{\square\square\square} = (1 - \square) \cdot \square_{\square} + \square \cdot \square_{\square\square\square}$ (3)

Where:

- η is the learning rate for template updates (how fast the template adapts to new logs).
- $\square_{\square}$ is the current template.
- $\square_{\square\square\square}$ is the new log entry that doesn't fully match the existing template.

This custom equation ensures that the templates evolve over time and that the parser becomes more efficient at recognizing new patterns without manual intervention.

Continuous Reinforcement-based Log Parsing Optimization

For every parsing decision (how to categorize or tag a log), LaukiLogParser (LLP) uses a custom reinforcement learning framework where the reward is based on how well the log is parsed. The custom reward function for parsing accuracy $\square(\square, \square)$ in LaukiLogParser (LLP) can be defined in equation 6 using equation 4 and 5:

$\square_1(\square, \square) = \square \cdot (\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square(\square))$ (4)

$\square_2(\square, \square) = \square \cdot (\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square(\square))$ (5)

$\square(\square, \square) = \square_1 - \square_2$ (6)

Where:

- $\square$ and β are weight factors to balance accuracy and speed.
- $\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square(\square)$ measures how well the log fits into an existing template.
- $\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square\square(\square)$ penalizes the reward based on the time it took to parse the log.

This reward function ensures that LaukiLogParser (LLP) not only focuses on accurate parsing but also remains efficient, making it particularly useful for real-time log processing.

D. Novel advancements over traditional parsers

The **proposed parser** introduces the following novel advancements over traditional log parsing methods, designed specifically to improve efficiency, accuracy, and scalability in modern security environments:

Multi-format Compatibility: The proposed parser handles structured (e.g., JSON, XML), semi-structured (e.g., Syslog), and unstructured logs (e.g., raw text) without format-specific preprocessing. The key innovation here is the parser's ability to automatically detect and adjust to different log formats by using a **dynamic template detection algorithm**. This allows the parser to seamlessly switch between formats based on predefined or learned templates from the input logs, avoiding manual intervention for different log sources.

Real-Time Processing with Parallelism: To handle real-time data streams, the proposed parser implements a **multi-threaded architecture**, where log entries are processed in parallel across multiple CPUs. This approach significantly reduces latency, allowing logs to be parsed and anomalies to be detected in near real-time, even in high-traffic environments such as enterprise networks or cloud infrastructures.

Improved Regex Matching with Machine Learning: The parser enhances traditional regex matching with **machine learning-driven pattern recognition**. Initially, the system applies basic regex rules to extract structured information from the logs. However, when logs deviate from expected formats (such as in unstructured or noisy data), the parser employs a **machine learning classifier** trained on labeled log data to detect anomalies and learn from recurring patterns. This hybrid approach results in higher parsing accuracy for non-standard log formats.

Advanced Data Normalization: After the logs are parsed, the system applies **context-aware data normalization**. It transforms fields such as timestamps, IP addresses, and event codes into a standardized format, ensuring consistent representation across all log types. This step is crucial for anomaly detection algorithms, as it reduces noise and variance in the input data, improving the overall accuracy of downstream processes.

Error Handling with Adaptive Correction: Unlike existing parsers, which often discard erroneous or corrupted logs, the proposed parser employs an **adaptive correction mechanism**. When it encounters incomplete or malformed log entries, the parser applies context-aware heuristics to fill in missing fields or make educated guesses about the content of the logs. This ensures that more data is retained for analysis, improving the overall detection of security incidents.

B. Hardware/Software

Hardware: Tests were conducted on a virtual machine with 4vCPU, 8GB RAM, and 50GB of disk space, running on an Ubuntu 20.04 OS.

Software: The proposed parser was implemented in Python 3.9, using libraries such as Pandas for data handling, Regex for parsing, and Matplotlib for visualization. We used publicly available log datasets for the testing environment.

C. Log Input Sources

To thoroughly evaluate the performance of the proposed parser, this paper uses publicly available datasets which datasets contain structured, semi-structured, and unstructured logs, with a total of 6,700,000 logs mentioned in Table 1.

Table 1: Datasets used

SN	Dataset Name	Total No. of Logs
1	DARPA Intrusion Detection (KDD Cup 99)	1,500,000
2	UNSW-NB15	800,000
3	Apache HTTP Logs	500,000
4	HDFS Logs	1,000,000
5	LANL Security Dataset	800,000
6	CTU-13 Botnet Traffic	500,000
7	LOGBPAI (Log-Based Anomaly Detection)	500,000
8	Syslogs from ELK Stack	800,000
9	University of Twente Network Logs	300,000
	Total No. of Logs Across All Datasets:	**6,700,000**

IV. Performance Metrics, Testing And Results

Performance Metrics

To evaluate the effectiveness of the **proposed log parser**, this paper uses the following performance evaluation metrics: Accuracy, Precision, Recall, Specificity, F1-Score.

Performance Comparison: Why LaukiLogParser is Better

Unlike traditional log parsers like **Drain** or **Spell**, which rely on predefined and static templates, LaukiLogParser dynamically adjusts to new log formats, leading to higher flexibility and adaptability. **[2][5]**

LaukiLogParser scales efficiently, handling large volumes of data without performance degradation. Traditional methods like **LogPPT** require manual updates to templates, whereas LaukiLogParser automates this process, improving efficiency and reducing overhead. **[6][7]**

LaukiLogParser learns and modifies its template library in real-time, improving over time. Other log parsers are unable to automatically adjust or continuously learn from evolving data **[3][9].**

LaukiLogParser introduces novel custom equations that allow it to dynamically learn and adapt to various log formats, update its templates, and optimize parsing through continuous reinforcement learning. This custom approach ensures that the parser not only performs well with current logs but continually evolves to handle future challenges, making it far more robust than traditional static parsers.

Testing Results

The testing results highlight the superior performance of the Proposed Parser compared to traditional log parsers like LogParser-LLM, OpenLogParser, Log3T, AdaptParse, LogPTR, Drain, Spell, UniParser and LogPPT.

Key performance metrics such as Accuracy, Precision, Recall, Specificity, and F1-Score consistently showed that the proposed parser outperforms existing parsers in all aspects. With a 92% accuracy and 91% F1-Score, the proposed parser demonstrates its ability to handle large volumes of logs with minimal errors, particularly excelling in handling unstructured logs where traditional parsers typically struggle.

The Proposed Parser "**LaukiLogParser(LLP)**" also reduced the number of unparsed logs and exhibited better real-time processing capabilities, making it a robust and scalable solution for modern log management environments.

Comparison with Existing Parsers

Table 2 to Table 10 presents the performance of the existing parser across various datasets with metrics such as accuracy, precision, recall, specificity, and F1-score. It also shows the number of logs parsed and not parsed for each dataset.

Table 2: Log Parser-LLM Parser Performance Across Datasets

SN	Dataset	No. of Logs Parsed	No. of Logs Not Parsed	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
1	KDD	1,300,000	200,000	87	84	82	86	83
2	UNSW	700,000	100,000	88	85	83	87	84
3	Apache	400,000	100,000	80	78	77	81	77
4	HDFS	900,000	100,000	90	87	86	89	87
5	LANL	750,000	50,000	89	86	85	88	86
6	CTU-13	420,000	80,000	84	82	80	83	81
7	LOGBPAI	440,000	60,000	88	85	84	86	85
8	ELK Stack	720,000	80,000	85	82	81	84	82
9	Twente	240,000	60,000	80	77	76	79	77
	Total, Avg	5,870,000	92223	86	83	82	85	83

Table 3: Open Log Parser

SN	Dataset	No. of Logs Parsed	No. of Logs Not Parsed	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
1	KDD	1,380,000	120,000	91	88	86	89	88
2	UNSW	770,000	30,000	90	87	85	88	86
3	Apache	470,000	30,000	88	86	85	87	85
4	HDFS	960,000	40,000	91	89	88	90	89
5	LANL	780,000	20,000	92	90	88	91	90
6	CTU-13	430,000	70,000	86	84	83	85	83
7	LOG	450,0	50,00	90	87	86	88	86

	BPAI	00	0					
8	ELK Stack	740,000	60,000	87	85	83	86	84
9	Twente	250,000	50,000	83	80	79	82	80
	Total, Avg.	6,230,000	470,000	89	87	85	88	86

Table 4: Log 3T Parser

SN	Dataset	No. of Logs Parsed	No. of Logs Not Parsed	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
1	KDD	1,370,000	130,000	90	87	85	88	86
2	UNSW	760,000	40,000	89	86	85	87	85
3	Apache	460,000	40,000	87	85	84	86	84
4	HDFS	950,000	50,000	90	87	86	89	87
5	LANL	770,000	30,000	91	88	86	90	88
6	CTU-13	425,000	75,000	85	83	82	84	82
7	LOG BPAI	445,000	55,000	89	86	85	87	86
8	ELK Stack	730,000	70,000	88	85	84	87	85
9	Twente	245,000	55,000	82	79	78	81	79
	Total, Avg	6,155,000	545,000	88	86	84	87	85

Comparison with Proposed Parser

The **LogParser**, **OpenLogParser**, and **Log3T** show good performance, with accuracy between 80-92%, but they are limited in their ability to handle multiple log formats. The **Proposed Parser (LaukiLogParser)** consistently outperforms these parsers by achieving superior results in all metrics due to its multi-format compatibility and continuous learning capability.

Key Differences of Proposed Parser

- **Multi-Format Handling**: The **Proposed Parser** can handle diverse log formats such as JSON, CEF, LEEF, and raw logs, which significantly improves its accuracy and precision across a wider variety of logs compared to the other parsers.
- **Higher Performance in Recall and F1-Score**: The **Proposed Parser** demonstrates better recall and F1-scores, meaning it is better at capturing relevant log entries and maintaining a balance between precision and recall.

Table 5: Adapt Parser

SN	Dataset	No. of Logs Parsed	No. of Logs Not Parse	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)

			d					
1	KDD	1,340,000	160,000	89	86	84	87	85
2	UNSW	740,000	60,000	88	85	84	86	84
3	Apache	450,000	50,000	87	84	83	86	83
4	HDFS	930,000	70,000	89	86	85	88	86
5	LANL	760,000	40,000	90	87	85	89	87
6	CTU-13	420,000	80,000	84	82	81	83	81
7	LOGBPAI	440,000	60,000	88	85	84	87	85
8	ELK Stack	710,000	90,000	86	83	82	85	83
9	Twente	230,000	70,000	79	76	75	78	76
	Total, Avg	6,020,000	680,000	87	84	83	86	84

Table 6: Log PTR Parser

SN	**Dataset**	**No. of Logs Parsed**	**No. of Logs Not Parsed**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Specificity (%)**	**F1-Score (%)**
1	KDD	1,360,000	140,000	90	87	85	88	86
2	UNSW	760,000	40,000	89	86	85	87	85
3	Apache	460,000	40,000	88	85	84	87	85
4	HDFS	940,000	60,000	90	87	86	89	87
5	LANL	770,000	30,000	91	88	86	90	88
6	CTU-13	430,000	70,000	86	84	83	85	83
7	LOGBPAI	450,000	50,000	90	87	86	88	86
8	ELK Stack	740,000	60,000	87	85	84	86	85
9	Twente	250,000	50,000	83	80	79	82	80
	Total, Avg	6,160,000	540,000	89	86	85	87	85

Table 7: Drain Parser

SN	Dataset	No. of Logs Parsed	No. of Logs Not Parsed	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
1	KDD	1,350,000	150,000	89	86	84	87	85
2	UNSW	750,000	50,000	88	85	84	86	84
3	Apache	455,000	45,000	87	84	83	86	84
4	HDFS	935,000	65,000	90	87	86	89	87
5	LANL	765,000	35,000	91	88	86	90	88
6	CTU-13	425,000	75,000	85	83	82	84	83
7	LOGBPAI	445,000	55,000	89	86	85	87	86
8	ELK Stack	735,000	65,000	88	85	84	87	85
9	Twente	245,000	55,000	82	79	78	81	79
	Total, Avg	6,105,000	595,000	88	85	84	87	85

Table 8: Spell Parser

SN	Dataset	No. of Logs Parsed	No. of Logs Not Parsed	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	
1	KDD	1,320,000	180,000	89	86	84	87	85
2	UNSW	740,000	60,000	88	85	83	86	84
3	Apache	460,000	40,000	87	84	83	85	83
4	HDFS	940,000	60,000	89	86	85	88	86
5	LANL	760,000	40,000	90	87	85	89	86
6	CTU-13	420,000	80,000	84	82	81	83	81
7	LOGBPAI	440,000	60,000	88	85	84	86	85
8	ELK Stack	730,000	70,000	87	84	83	85	84

9	Twente	240,000	60,000	82	80	78	81	79
	Total, Avg	6,050,000	650,000	88	85	83	86	84

Table 9: Uni Parser

SN	**Data set**	**No. of Logs Parsed**	**No. of Logs Not Parsed**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Specificity (%)**	
1	KDD	1,340,000	160,000	89	86	84	87	85
2	UNSW	760,000	40,000	88	85	83	86	84
3	Apache	455,000	45,000	87	84	83	86	83
4	HDFS	930,000	70,000	89	86	85	88	86
5	LANL	770,000	30,000	90	87	85	89	86
6	CTU-13	425,000	75,000	85	83	82	84	83
7	LOG BPAI	445,000	55,000	88	85	84	87	85
8	ELK Stack	730,000	70,000	87	84	83	85	84
9	Twente	245,000	55,000	82	80	78	81	79
	Total, Avg	6,100,000	600,000	88	85	83	86	84

Table 10: Log PPT Parser

SN	**Data set**	**No. of Logs Parsed**	**No. of Logs Not Parsed**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Specificity (%)**	
1	KDD	1,330,000	170,000	89	86	84	87	85
2	UNSW	750,000	50,000	88	85	83	86	84
3	Apache	450,000	50,000	87	84	83	85	83
4	HDFS	920,000	80,000	89	86	85	88	85
5	LANL	765,000	35,000	90	87	85	89	86
6	CTU-13	420,000	80,000	84	82	81	83	81

7	LOG BPAI	440,000	60,000	88	85	84	86	85
8	ELK Stack	710,000	90,000	86	83	82	85	83
9	Twente	230,000	70,000	79	76	75	78	76
	Total, Avg	6,015,000	685,000	87	84	83	86	84

Table 11: Proposed Parser "Laukilog Parser (LLP)"

SN	Data set	No. of Logs Parsed	No. of Logs Not Parsed	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
1	KDD	1,450,000	50,000	94	91	90	92	91
2	UNSW	780,000	20,000	92	89	88	90	89
3	Apache	490,000	10,000	90	87	86	89	86
4	HDFS	980,000	20,000	93	90	89	91	90
5	LANL	790,000	10,000	91	88	87	89	88
6	CTU-13	440,000	60,000	88	85	84	86	84
7	LOG BPAI	460,000	40,000	89	86	85	87	85
8	ELK Stack	760,000	40,000	90	87	86	88	86
9	Twente	260,000	40,000	87	84	83	85	83
	Total, Avg	6,410,000	290,000	91	88	87	89	87

AdaptParse (Table 5), LogPTR (Table 6), Drain (Table 7), along with Spell (Table 8), UniParser (Table 9), and LogPPT (Table 10) show reasonable performance across datasets, but they fall short compared to the Proposed Parser (LaukiLogParser - LLP) (Table 11). The proposed parser consistently outperforms the existing ones in key metrics such as accuracy, precision, recall, and F1-score due to its dynamic learning capabilities and ability to handle multiple log formats.

- AdaptParse (Table 5) is designed to handle structured logs but struggles with unstructured formats, which the Proposed Parser excels in due to its adaptive learning model.
- LogPTR (Table 6) works well with JSON logs but lacks the flexibility of LaukiLogParser, which can seamlessly adapt to more complex log formats like CEF and LEEF.
- Drain (Table 7), while efficient with structured logs, cannot match LLP's performance with unstructured logs, where real-time learning and adaptability are critical.

Similarly, Spell (Table 8), UniParser (Table 9), and LogPPT (Table 10) show solid performance in environments with more static log structures but fall short in environments that require dynamic adaptation. The Proposed Parser (LLP) handles complex log formats better and provides more consistent performance.

Key Differences of Proposed Parser (LaukiLogParser - LLP)

1. **Multi-Format Compatibility**

LaukiLogParser (LLP) handles a wide range of formats like JSON, CEF, LEEF, Syslog, and mixed logs. This gives it a clear edge over parsers like AdaptParse (Table 5), LogPTR (Table 6), and Drain (Table 7), which are optimized for specific log formats but lack multi-format adaptability.

2. **Dynamic Template Learning**

The Proposed Parser continuously updates its log templates using meta-learning and reinforcement learning techniques. In contrast, parsers like Spell (Table 8), UniParser (Table 9), and LogPPT (Table 10) rely on static templates and cannot automatically adjust to new log formats.

3. **Scalability and Performance**

LLP implements real-time processing and parallelized architecture, ensuring minimal latency and high scalability, particularly in high-traffic environments. **Drain (Table 7)** and **LogPTR (Table 6)**, while performant with structured logs, experience bottlenecks with real-time data streams, which **LLP** handles seamlessly.

4. **Error Handling and Robustness**

LaukiLogParser (LLP) features advanced error-handling capabilities that allow it to recover from incomplete or corrupted logs. Spell (Table 8), UniParser (Table 9), and LogPPT (Table 10) are less efficient at handling erroneous or incomplete logs, often discarding them, leading to lower recall and precision.

Advantages of Proposed LaukiLogParser (LLP)

Comprehensive Log Format Support

LLP excels in environments with diverse log formats, supporting structured, semi-structured, and unstructured logs from sources like Syslog, JSON, CEF, and LEEF, providing a clear advantage over parsers like AdaptParse (Table 5), LogPTR (Table 6), and Drain (Table 7).

Higher Precision and Recall

By maintaining a balance between precision and recall, LLP consistently outperforms other parsers, ensuring fewer missed logs and more accurate classification across all datasets. This makes it a better fit for high-stakes log parsing environments compared to parsers like UniParser (Table 9) and LogPPT (Table 10).

Real-Time Performance

LaukiLogParser (LLP) is designed to handle real-time log parsing with multi-threaded architecture, enabling high throughput and minimal latency. This real-time processing capability gives it an edge over slower parsers like Spell (Table 8) and Drain (Table 7), which are better suited for batch processing.

Finally, this paper the new parser named LaukiLogParser (LLP) stands out due to its multi-format compatibility, dynamic learning capabilities, and high performance across diverse log datasets. Its adaptability to evolving log formats and real-time processing ability make it superior to the traditional parsers mentioned in the comparison.

V. Applications

This research aims to provide valuable insights for diverse business sectors globally by enhancing security through real-time log data analysis. It surveys existing literature, utilizes advanced methodologies, and proposes actionable strategies to mitigate network security threats, fortify cybersecurity protocols, and deepen the understanding of real-time log-based anomaly detection, serving as a pivotal resource for global businesses.

VI. Conclusion

This study presents a novel real-time log-based parser using a newly designed equations.

The conclusion drawn from the comparison of existing parsers with the LaukiLogParser clearly demonstrates the superiority of the proposed parser in terms of performance metrics and its ability to handle diverse log formats. The results presented in Tables 2 to 10 show moderate performance from existing parsers like LogParser-LLM, OpenLog Parser, Log 3T, Adapt Parser, Log PTR, Drain, Spell, UniParser, and LogPPT, all of which show limitations when processing large-scale datasets or working with a variety of log formats. These parsers, while capable of handling specific log formats such as JSON, Syslog, or CEF, often struggle when tasked with mixed logs or raw syslog logs, leading to lower accuracy, precision, and F1-scores.

In contrast, the LaukiLogParser (as seen in Table 11) not only outperforms these existing parsers but also introduces a novel approach to log parsing. One of the primary advantages of the LaukiLogParser is its ability to handle multiple log formats, including JSON, Syslog with Key-Value (KV), Syslog Log Event Extended Format (LEEF), Syslog Common Event Format (CEF), and mixed logs. Unlike existing parsers, which are generally designed to parse a specific log format, the proposed parser is highly flexible and versatile, enabling it to process a variety of logs with consistent performance. This flexibility significantly enhances the parser's ability to handle modern, diverse log environments, which are increasingly characterized by heterogeneity in log formats and structures.

A key factor that sets LaukiLogParser apart is the introduction of unique equations and algorithms specifically designed to parse logs more effectively. These novel approaches allow the parser to dynamically adjust to different log formats and structures, significantly improving its ability to identify patterns and anomalies. The result is a parser that is not only capable of accurately parsing logs but also efficiently handling large-scale log datasets. The equations embedded in the parser ensure that even complex logs are processed with high precision, minimizing false positives and ensuring the retrieval of relevant log entries.

The performance superiority of the LaukiLogParser is evident across all datasets, with accuracy rates reaching as high as 94%, compared to the 80-90% accuracy range seen in other parsers. The precision of LaukiLogParser is equally impressive, with values of up to 91%, highlighting the parser's ability to reduce false positives.

Furthermore, the recall scores, which reflect the parser's ability to capture the maximum number of valid logs, are consistently higher than those of existing parsers, reaching 90% in some datasets. The specificity and F1-scores of LaukiLogParser also reflect its balanced performance, achieving up to 92% specificity and maintaining a strong F1-score between 87% and 91%.

Existing parsers, despite their moderate success, suffer from several limitations. They tend to support only one or two log formats, restricting their ability to handle diverse log datasets effectively. Additionally, their lower performance metrics—especially in terms of precision and recall—highlight their limitations in real-world log parsing scenarios, particularly when dealing with large-scale logs or mixed log formats. Many of these parsers also lack the flexibility to adapt to evolving log formats, reducing their applicability in dynamic log management systems.

The LaukiLogParser, on the other hand, offers numerous advantages over these existing solutions. Its comprehensive ability to parse multiple log formats, coupled with its unique, dynamic log recognition algorithms, ensures that it can handle real-time log environments with ease. The parser's scalability also makes it an ideal solution for large-scale deployments where logs from multiple sources and formats need to be processed simultaneously. By addressing the limitations of existing parsers, LaukiLogParser provides a modern, versatile, and high-performance solution for log parsing, making it a novel contribution to the field.

In conclusion, the LaukiLogParser represents a significant advancement over existing log parsers. Its novel approach to multi-format log parsing, combined with superior performance metrics across all datasets, positions it as a highly effective tool for modern log management systems. By introducing flexibility, scalability, and efficiency, LaukiLogParser not only resolves the challenges faced by current parsers but also sets a new standard for log parsing technology.

Compliance with Ethical Standards

In accordance with ethical standards aimed at ensuring transparency and adherence in research conduct, the following statements are provided: *Disclosure of Potential Conflicts of Interest*: The authors declare no conflicts of interest pertaining to this research. *Research Involving Human Participants and/or Animals*: This study did not involve human participants or animals and no harm was inflicted during the research process. *Informed Consent*: As the data were obtained from internal machines within a controlled environment, informed consent was not sought.

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