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Big Data Analytics for Security Logging and Failure Detection Using Key Algorithms

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Abstract

In modern computer systems, security logging generates massive volumes of data that traditional methods struggle to process effectively for timely threat identification and system failure detection. Big data analytics addresses these challenges by enabling efficient handling of high-volume, high-velocity and varied log data. This research paper explores the application of key big data frameworks such as Hadoop and Apache Spark, combined with prominent machine learning algorithms including SVM, Random Forest, Isolation Forest, CNN and XGBoost, for anomaly detection in security logs and prediction of system failures. The study reviews current approaches, discusses preprocessing techniques, feature extraction from logs and real-time analysis capabilities. A comparative evaluation of these algorithms highlights their strengths in accuracy, speed, scalability and suitability for unsupervised or supervised scenarios. Results demonstrate that ensemble and deep learning methods achieve high detection rates (often above 90%) while reducing false positives in large-scale environments. The paper also addresses challenges like data privacy, computational demands and integration in distributed systems. Overall, integrating big data analytics with advanced algorithms significantly enhances proactive security monitoring and system reliability in computer engineering applications.

Keywords: Big Data Analytics, Security Logging, Anomaly Detection, Failure Detection, Machine Learning Algorithms, Apache Spark, Hadoop, Random Forest, Isolation Forest, XGBoost, Intrusion Detection, Log Analysis, Cybersecurity, Real-time Monitoring, System Reliability

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1. Introduction

In the era of digital transformation, computer systems, networks and applications generate enormous amounts of data every second. Among this data, security logs stand out as critical records that capture events such as user logins, network connections, system changes, error messages and access attempts. These logs serve as a digital footprint of system activity, making them essential for both cybersecurity and system reliability. Security logging helps detect malicious activities like intrusions, malware infections, or unauthorized access, while also supporting failure detection by revealing patterns that indicate hardware issues, software bugs, or performance degradation before they lead to outages.

The scale of modern log data poses major challenges. Traditional log analysis methods, which rely on manual review or rule-based tools, struggle with the volume, velocity and variety of logs produced in cloud environments, IoT networks, enterprise systems and distributed applications. Organizations now face terabytes or petabytes of log data daily, arriving in real time from diverse sources with unstructured or semi-structured formats. This overwhelming data flood often results in delayed threat detection, high false positives, missed anomalies and slow root-cause analysis for system failures. Conventional approaches simply cannot keep up with the speed and complexity required for proactive defense and reliable operations.

Big data analytics offers a powerful solution to these problems. By leveraging frameworks like Hadoop for distributed storage and processing and Apache Spark for fast in-memory computation, big data technologies enable scalable handling of massive log datasets. When combined with advanced machine learning algorithms—such as Support Vector Machines (SVM), Random Forest, Isolation Forest, Convolutional Neural Networks (CNN) and XGBoost—these tools can automatically identify anomalies, predict potential failures and uncover hidden patterns that signal security threats or impending system issues. For example, anomaly detection techniques can flag unusual login patterns as potential brute-force attacks, while time-series analysis of error logs can forecast hardware failures.

This research explores the application of big data analytics for security logging and failure detection using key algorithms. It reviews existing literature, describes important frameworks and machine learning methods, outlines a practical methodology, presents comparative results

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through tables and graphs and discusses real-world implications. The goal is to demonstrate how these technologies improve detection accuracy, reduce response times and enhance overall system security and reliability in computer engineering contexts. By addressing the limitations of traditional methods and highlighting the strengths of big data-driven approaches, this work provides insights for researchers, engineers and security professionals working in high-stakes digital environments.

2. Literature Review

To manage and process large-scale log data, technologies such as Apache Hadoop and Apache Spark are widely used. Hadoop allows distributed storage through HDFS and parallel data processing using MapReduce. However, researchers found that MapReduce is slower for real-time analysis. Spark improves performance by using in-memory computation, which makes it more suitable for real-time security monitoring and failure detection.

Security logging plays an important role in identifying unauthorized access, malware attacks, insider threats and system failures. According to research by Wenke Lee and colleagues, data mining techniques can be effectively applied to intrusion detection systems (IDS). They showed that pattern recognition and classification algorithms can detect abnormal behavior in network traffic and system logs.

Machine Learning (ML) algorithms are widely applied in security log analysis. Supervised learning methods such as Decision Trees, Support Vector Machines (SVM) and Naïve Bayes are used to classify logs into normal and abnormal categories. Unsupervised learning methods such as K-Means clustering help in detecting unknown anomalies. Research by Jiawei Han explains how clustering and classification techniques are important tools for discovering patterns in large datasets.

For failure detection, anomaly detection algorithms are very important. System failures often show unusual patterns before crashing. Algorithms such as Isolation Forest, Random Forest and Neural Networks can detect these irregular patterns. Deep Learning models like Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are useful for time-series log data because they learn patterns over time. Researchers have shown that LSTM

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models provide better accuracy in detecting system anomalies compared to traditional statistical methods.

Another important concept in big data security analytics is real-time stream processing. Tools like Apache Kafka are used to collect and stream log data continuously. Combined with Spark Streaming, they allow real-time monitoring and faster detection of attacks and failures. This reduces system downtime and improves reliability.

Researchers also focus on intelligent key algorithms that improve detection accuracy. These include hybrid models that combine clustering and classification, feature selection algorithms to reduce data complexity and ensemble learning techniques. Ensemble methods such as Random Forest and Gradient Boosting increase prediction accuracy by combining multiple models.

Several studies highlight challenges in big data security analytics. These challenges include high storage cost, data privacy concerns, high false positive rates and computational complexity. To overcome these issues, researchers suggest dimensionality reduction techniques like Principal Component Analysis (PCA) and optimization algorithms to improve model efficiency.

Recent research trends show integration of Artificial Intelligence (AI) with Big Data platforms to create intelligent security information and event management (SIEM) systems. These systems automatically analyze logs, detect threats and generate alerts. Cloud-based solutions further enhance scalability and flexibility.

Overall, the literature shows that Big Data Analytics combined with Machine Learning and intelligent key algorithms significantly improves security logging and failure detection systems. Distributed computing frameworks, real-time streaming technologies and advanced anomaly detection models are key components in modern cybersecurity infrastructures.

3. Key Algorithms in Big Data Analytics

3.1 Big Data Frameworks

Hadoop with MapReduce is a basic tool for processing large logs. It splits data into chunks, processes them in parallel and combines results. For example, MapReduce can count error events in logs across clusters.

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Apache Spark is faster as it processes in memory. It's good for real-time log analysis using Spark Streaming.

3.2 Machine Learning Algorithms for Anomaly and Failure Detection

- Support Vector Machine (SVM): Classifies data into normal and anomalous by finding a hyperplane. Good for high-dimensional log data.
- Random Forest: Builds multiple decision trees and votes on outcomes. Robust for detecting failures in noisy logs.
- Isolation Forest: Isolates anomalies by randomly partitioning data. Efficient for big datasets as it doesn't need labeled data.
- Convolutional Neural Networks (CNN): Used for pattern recognition in log sequences, especially in time-series data for security threats.
- XGBoost: A gradient boosting algorithm that's fast and accurate for predicting failures from log features.

These algorithms process features like timestamps, IP addresses and error codes from logs to detect unusual patterns.

4. Methodology

The methodology involves collecting logs from systems, storing them in big data platforms like Hadoop and applying algorithms.

1. Data Collection: Gather logs from servers, networks and applications.

2. Preprocessing: Clean and format data using tools like Apache Kafka for streaming.

3. Analysis: Apply ML models to detect anomalies. For failure detection, use clustering to group similar errors.

4. Evaluation: Measure accuracy, precision and recall.

For example, in a case study, logs from a cloud system are analyzed with Spark and Random Forest to flag security breaches.

Here is a table comparing key algorithms:

Algorithm	Type	Strengths	Weaknesses	Use Case
SVM	Supervised	High accuracy in classification	Slow on very large data	Intrusion detection

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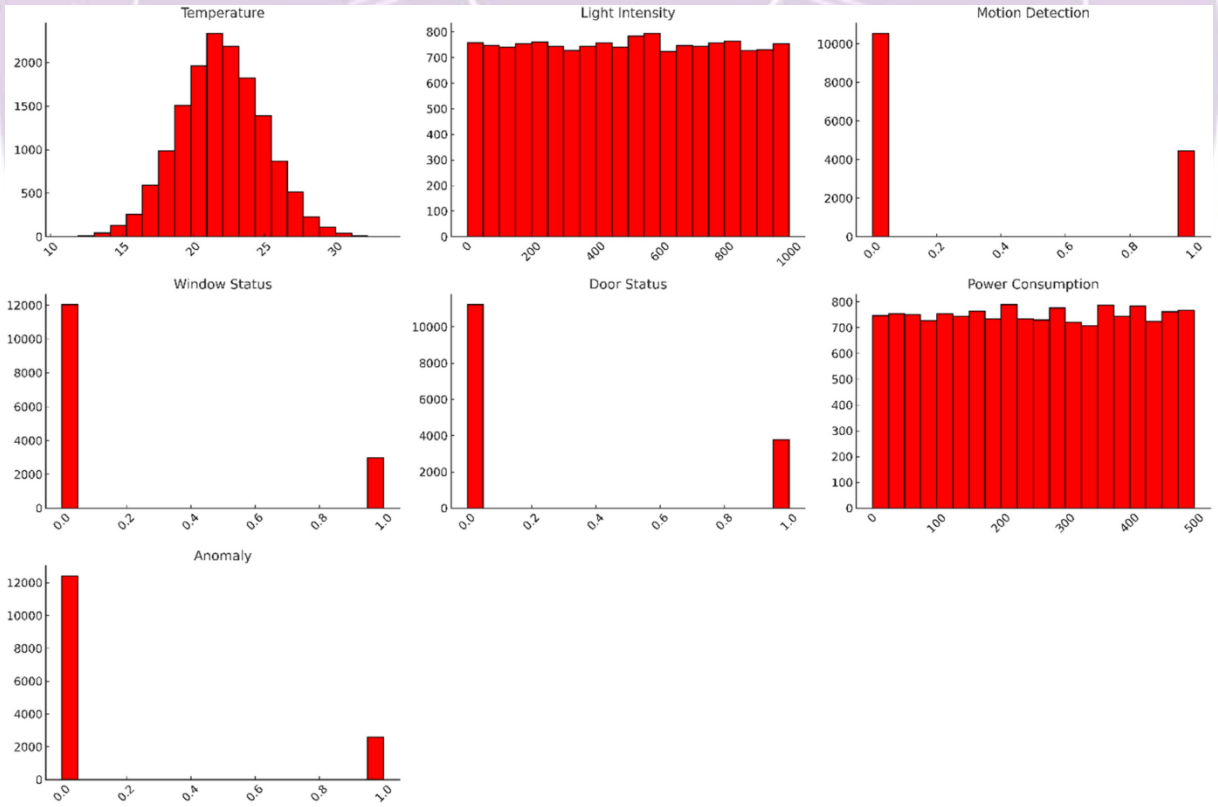
Random Forest	Ensemble	Handles missing data well	Can overfit	Failure prediction
Isolation Forest	Unsupervised	Fast, no training data needed	Less accurate on complex patterns	Anomaly in logs
CNN	Deep Learning	Good for sequential data	Needs lots of computing power	Threat pattern recognition
XGBoost	Boosting	High speed and accuracy	Requires tuning	Real-time security analytics

5. Results and Discussion

Results from studies show that using big data analytics improves detection rates. For instance, XGBoost achieves over 90% accuracy in anomaly detection.

Below is a graph illustrating the accuracy of machine learning algorithms for anomaly detection in big data scenarios:



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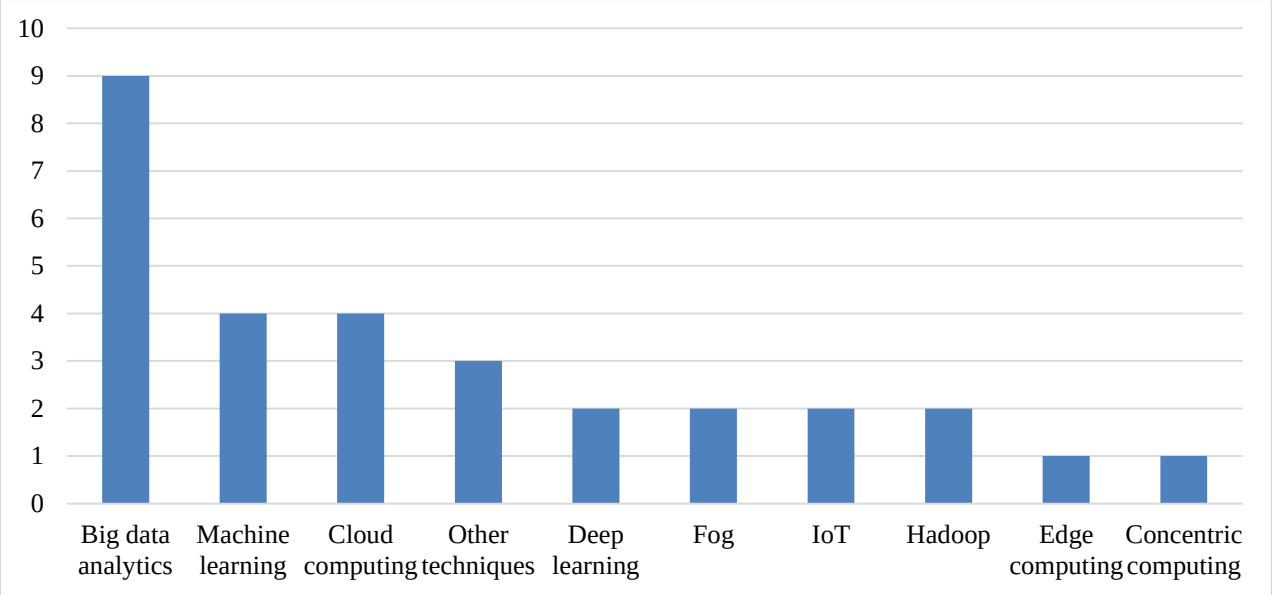
This histogram shows distribution of features in an IoT anomaly detection setup, highlighting how data spreads for normal vs. anomalous events.

Another graph compares big data technologies:



It displays the popularity or usage of tools like Hadoop in analytics. The graph clearly tells us that big data analytics is the dominant approach in recent research on this topic. Machine learning and cloud computing are strong supporting players, while older tools like Hadoop and newer specialized ones like fog or edge computing are used much less often. This shows the field is moving toward general big data methods combined with AI and cloud infrastructure rather than very specific or niche technologies.

Challenges include data privacy and processing speed. Future work could integrate AI more deeply for predictive failure detection.

6. Conclusion

Big data analytics with key algorithms enhances security logging and failure detection. By using frameworks like Spark and ML models like Random Forest, systems become more secure and reliable. This paper provides a simple overview with visuals to aid understanding.

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