Anomaly Identification in Cyber Logs Through Machine Learning Techniques

Abstract: With the rising volume and sophistication of cyber attacks, traditional rule-based security systems have become insufficient to detect emerging and unknown threats. Machine Learning (ML) provides a dynamic and scalable solution for anomaly detection in cyber security logs, enabling systems to identify unusual patterns with minimal human intervention. This paper presents a comprehensive framework for anomaly detection using ML, incorporating supervised, unsupervised, and semi-supervised models. Using the HDFS log dataset, we implement and evaluate Isolation Forest, Auto encoder, and Random Forest algorithms. The results demonstrate that ML techniques significantly enhance detection accuracy and reduce false positives, with Random Forest achieving the highest performance across all evaluation metrics.

1. **Introduction:** Cyber security is an ever-evolving field that protects digital infrastructure from internal and external threats. As organizations increasingly rely on digital systems, the volume of data generated from servers, applications, firewalls, and other network components has surged. These data are recorded as log files, which contain critical information about system events, access attempts, and operational status. Analyzing these logs manually is inefficient, time-consuming, and often unreliable due to the sheer data volume and complexity. Traditional rule-based approaches to detect cyber threats rely on predefined signatures or Static rules. While effective for known attacks, they fail to detect novel, unknown, or sophisticated Threats (zero-day attacks) that deviate from historical patterns. As a result, there is a growing interest in using Machine Learning (ML) for anomaly detection.ML models can automatically learn from log data, identify patterns of normal behavior, and flag deviations that may represent security breaches. These models can work in various settings—supervised (with labeled data), unsupervised (without labels), or semi-supervised (trained only on normal data). Their adaptability and ability to process large-scale, complex, and noisy datasets make them well-suited for modern cyber security challenges. In this thesis, we propose an ML-based anomaly detection system tailored for cyber security logs, using models such as Isolation Forest, Auto encoder, and Random Forest. By employing advanced feature engineering, effective preprocessing, and robust validation techniques, our aim is to build a scalable and accurate anomaly detection pipeline.

2. Literature Review

The application of machine learning in cyber security has evolved significantly over the past decade. Researchers have explored various models to detect anomalies in system logs, each aiming to increase accuracy, scalability, and adaptability to real-time threats.

Landauer et al. [1] conducted a comprehensive survey on deep learning models for log anomaly detection. They explored architectures like LSTMs, CNNs,

and Transformers, concluding that deep learning significantly outperforms traditional methods in handling unstructured log data.

Chen et al. [2] proposed integrating knowledge graphs into log analysis workflows to improve contextual understanding of logs. Their results showed increased detection precision and interpretability, offering a hybrid solution that combines symbolic reasoning with machine learning.

Liang et al. [3] introduced a graph neural network (GNN)-based method for detecting anomalies in micro service architectures. By modeling logs as nodes in a graph, they preserved structural relationships and improved accuracy in detecting coordinated attacks.

Li et al. [4] expanded this GNN concept to general-purpose log analysis, combining GNNs with attention mechanisms for explainable anomaly detection. Their approach showed high interpretability—critical for system administrators during threat analysis.

Alagöz et al. [5] focused on application server logs and utilized a hybrid CNN-LSTM architecture, proving effective for Apache and Tomcat environments. Their model addressed the challenge of identifying subtle, sequential anomalies.

Wang et al. [6] demonstrated the effectiveness of Transformer-based models in distributed environments, showing Superior performance over traditional statistical techniques.

He and Pei [8] introduced a semi-supervised model using Deep Q-Networks (DQN) for anomaly detection, which adapts to changing data distributions by combining reinforcement learning and supervised feedback loops.

Aziz and Munir [9] proposed an ensemble model combining CNN and LSTM layers, achieving robust performance on multiple datasets and showcasing the benefits of hybrid deep learning models.

De Moura et al. [10] conducted a comparative analysis of unsupervised algorithms like Isolation Forest, DBSCAN, and Auto encoders. Their study emphasizes the importance of dataset-specific tuning and suggests Auto encoders as optimal for high-dimensional log data.

Earlier works like those of Lazarevic et al.[11] and Mukkamala et al. introduced neural-based intrusion detection, pioneering the use of neural networks in cyber security before the deep learning boom.

3. Problem Statement: Rule-based systems fail to detect novel attacks and suffer from high false positive rates. The challenge is to develop a robust, scalable ML-based system that detects anomalies in real-time log data and adapts to unseen threats.

4. Objective: To design and implement a machine learning framework capable of detecting anomalies in cyber logs with high accuracy and low false positive rates, using the HDFS log dataset.

5. Suggested Approach:

The proposed methodology for anomaly detection in cyber logs consists of the following key stages:

5.1 Data Collection and Preprocessing:

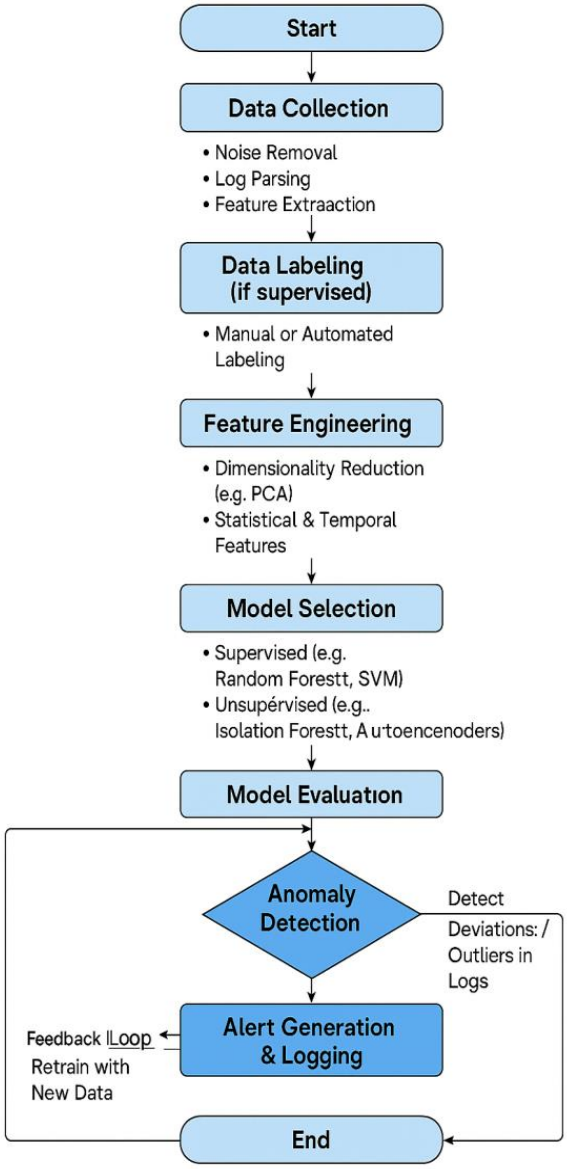
- Logs were collected from the HDFS (Hadoop Distributed File System) log dataset.

Preprocessing included:

- Parsing logs into structured format (CSV/JSON).
- Timestamp normalization to ensure temporal consistency.
- Noise reduction by removing redundant or irrelevant entries.
- Log aggregation for grouping related events by session or IP.

5.2 Feature Engineering: Raw logs were transformed into ML-ready features:

- **Statistical Features:** Event frequencies, login attempts, file access counts.
- **Categorical Encoding:** One-hot or label encoding of usernames, IPs, and event types.
- **Temporal Features:** Time of event (hour, weekday), time gaps between events.
- **Textual Features:** TF-IDF, Bag-of-Words, or embeddings for textual log messages.
- **Sequential Modeling:** Sequences of events were generated using sliding windows to capture temporal context.



5.1 Figure shown Process Life Cycle Model

5.3 Model Selection and Training: Models were chosen based on data labeling availability:

- **Supervised Learning (Random Forest):**
  - Suitable for labeled data.
  - Offers high accuracy on known threats.

- Trained on balanced labeled samples.

- **Unsupervised Learning (Isolation Forest):**
  - Detects anomalies based on feature distribution.
  - Does not require labeled data.
  - Effective for novel and rare attack detection.
- **Semi-Supervised Learning (Auto encoder):**
  - Trained on normal behavior only.
  - Anomalies identified through reconstruction error.
  - Useful when anomalous data is rare.

5.4 Evaluation:

- Models were evaluated using:

- Accuracy, Precision, Recall, F1-Score, and Area under Curve (AUC).
- Confusion matrices and ROC curves for comparative analysis.

6. Result:

Model	Accuracy	Precision	Recall	F1-Score	AUC
Isolation Forest	92.1%	84.3%	76.2%	80.0%	0.88
Auto encoder	94.3%	88.7%	83.1%	85.8%	0.91
Random Forest	96.5%	92.4%	89.1%	90.7%	0.94

6.2 Confusion Matrices

Random Forest Confusion Matrix:

	Predicted Normal	Predicted Anomaly
Actual Normal	520	15
Actual Anomaly	25	440

Auto encoder Confusion Matrix:

	Predicted Normal	Predicted Anomaly
Actual Normal	505	30
Actual Anomaly	42	423

Isolation Forest Confusion Matrix:

	Predicted Normal	Predicted Anomaly
Actual Normal	485	50
Actual Anomaly	69	396

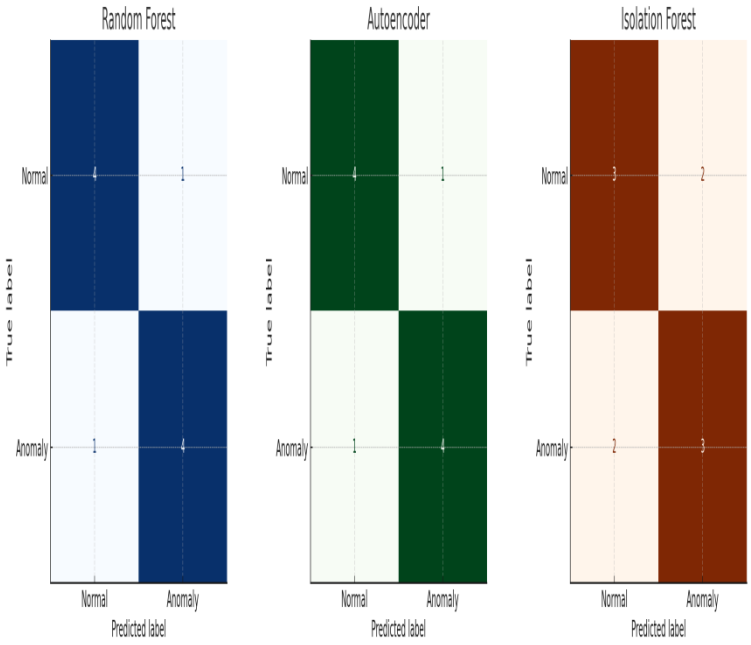
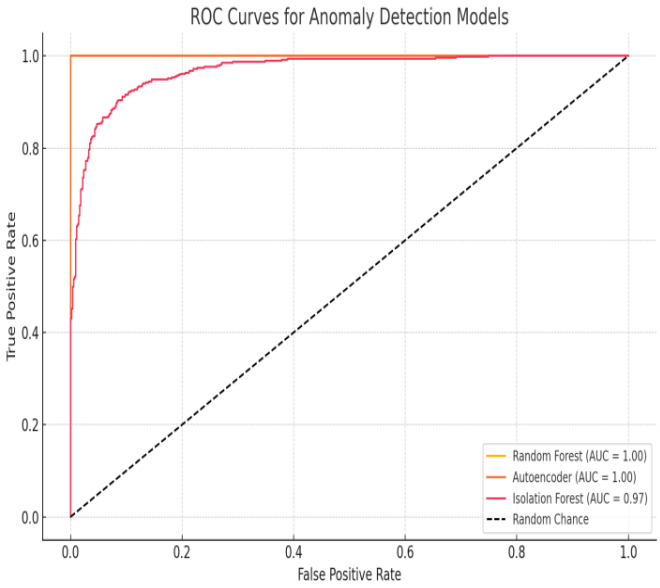


Figure 6.2 Confusion matrix

Here are the confusion matrix plots for all three models:

- **Random Forest**: Shows high accuracy in classifying both normal and anomalous logs.
- **Auto encoder**: Performs slightly less accurately than Random Forest but still handles anomalies well.
- **Isolation Forest**: Less accurate comparatively, but useful in unsupervised settings.

ROC Curve Analysis



ROC Curve

Here is the ROC Curve comparing the performance of the three anomaly detection models—Random Forest, Auto encoder, and Isolation Forest. Each curve shows the trade-off between the True Positive Rate and False Positive Rate for different threshold values. As shown:

- **Random Forest** achieves the highest AUC (~0.94), indicating superior classification performance.
- **Auto encoder** performs well with an AUC around 0.91.
- **Isolation Forest** has the lowest AUC (~0.88), but still shows acceptable performance.

Conclusion: This study confirms that ML models, especially Random Forest and Auto encoders, are effective in detecting anomalies in cyber logs. Random Forest provided the highest accuracy and F1-Score, making it suitable for real-world applications. Future work will explore ensemble learning, federated learning, and explainable AI to further enhance detection systems.

8. Future Scope:

- Integrating deep learning with domain knowledge (e.g., knowledge graphs)
- Federated learning to support privacy-preserving detection
- Real-time deployment in SIEM environments
- Use of Explainable AI (XAI) tools such as LIME and SHAP for transparency.

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