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Explainable AI (XAI) for Trustworthy Cloud Security Decisions

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Abstract

Cloud computing has emerged as the backbone of modern digital infrastructures, offering elastic, scalable, and cost-effective resources. However, as cloud adoption accelerates, security threats such as insider misuse, APTs, and DDoS attacks undermine trust. AI and ML models are widely adopted for intrusion detection, anomaly detection, and automated response in cloud environments. Despite their success, these models often function as black boxes, lacking transparency. Explainable AI (XAI) addresses this limitation by providing interpretable outputs that allow security operators and regulators to understand, validate, and trust AI decisions.

This paper reviews state-of-the-art XAI methods (e.g., LIME, SHAP, Grad-CAM), analyzes their applicability in cloud security contexts, and proposes an integrated framework combining anomaly detection with interpretable explanations. Case studies demonstrate how XAI enhances SOCs, supports compliance (GDPR, HIPAA), and improves decision-making by cloud administrators. Experimental results show that XAI-enhanced models balance predictive accuracy with interpretability, reducing false positives while maintaining transparency. The paper concludes with challenges, open research issues, and future directions in federated XAI, adversarial robustness, and hybrid multi-cloud scenarios.

Keywords
Cloud security, Explainable AI (XAI), anomaly detection, interpretability, trust, machine learning, intrusion detection.

I. Introduction

Cloud computing has fundamentally transformed IT ecosystems. However, threats such as misconfigurations, insider abuse, and advanced persistent threats demand robust security. While AI enhances detection, black-box models hinder trust. This section motivates XAI as a necessity for transparency and compliance.

II. Background and Motivation

Cloud security challenges include multi-tenancy risks, insider threats, dynamic scaling, and regulatory compliance. Black-box AI models excel at accuracy but fail in transparency. Explainable AI (XAI) bridges this gap by offering methods such as LIME, SHAP, and Grad-CAM for interpretability.

III. Related Work

Prior works span intrusion detection, anomaly detection, and compliance applications. IDS systems achieve high accuracy but lack explanations. SHAP and LIME have been applied in cloud log analysis. Gaps remain in unified frameworks integrating anomaly detection with explanation layers tailored to cloud security.

IV. Proposed Framework

The proposed framework comprises four layers: Data Collection, AI-based Detection, XAI Interpretation, and SOC Decision Layer. The architecture applies SHAP, LIME, and Grad-CAM for explanations, feeding interpretable insights to SOC dashboards.

Equation:

$$\text{Fidelity} = 1 - \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i|$$

where fidelity measures surrogate explanation quality.

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V. Methodology

Datasets:

We used two benchmark datasets widely adopted in intrusion detection and cloud security research.

NSL-KDD: An enhanced version of the original KDD'99 dataset with redundant records removed, consisting of ~125,000 records and 41 features such as duration, protocol type, service, flag, source bytes, destination bytes, and login attempts. This dataset is still popular for evaluating baseline IDS models due to its well-labeled normal and attack classes.

CICIDS-2017: A more modern dataset that captures realistic network traffic, amounting to ~2 million records and ~80 features extracted from packet flows. It includes diverse attack categories such as DoS, DDoS, brute force, botnet activity, and infiltration attempts, simulating real enterprise cloud environments.

Before training, both datasets underwent **feature engineering** steps including normalization, categorical encoding (for protocol and service fields), dimensionality reduction with PCA, and data balancing using SMOTE to address class imbalance.

Models:

We deployed a combination of deep learning and traditional models to cover multiple detection paradigms:

Convolutional Neural Networks (CNN): Used for intrusion detection due to their ability to capture hierarchical representations of network traffic features. A 1D-CNN architecture was trained with three convolutional layers followed by dense layers, optimized using Adam.

Autoencoders: Employed for unsupervised anomaly detection. Trained only on normal traffic, they measure reconstruction error for each instance. Higher errors are treated as anomalies.

Random Forest & Support Vector Machine (SVM): Included as baselines to compare deep models with interpretable classical ML approaches.

Hybrid Ensemble: CNN + Autoencoder predictions were combined in an ensemble to balance precision and recall.

XAI Methods:

To interpret the predictions of these models, we integrated **model-agnostic explanation techniques**:

SHAP (SHapley Additive exPlanations): Applied to CNN predictions to quantify feature contributions for each classification. For example, abnormal "src_bytes" or "login attempts" could be highlighted as key indicators of intrusion.

LIME (Local Interpretable Model-Agnostic Explanations): Used for explaining autoencoder anomaly scores. Perturbations around each instance were analyzed to approximate a local interpretable surrogate model.

Visualization Tools: SHAP summary plots and LIME heatmaps were integrated into a SOC-style dashboard to provide analyst-friendly explanations.

Evaluation Metrics:

We evaluated both **traditional classification metrics** and **XAI-specific trust metrics**:

Accuracy, Precision, Recall, F1-score: For overall detection performance.

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AUC (Area Under Curve): To evaluate discriminative ability across thresholds.

Fidelity: Measures how closely surrogate explanations approximate the original black-box predictions.

Stability: Ensures that small perturbations in input data do not drastically change explanations.

Comprehensibility: Subjective ease of understanding of explanations, rated by SOC analysts.

Analyst Trust Scores: A survey of 20 SOC professionals was conducted where analysts rated their confidence in model outputs with and without explanations.

Experimental Flow:

1. Preprocess datasets and balance classes.
2. Train baseline models (CNN, Autoencoder, Random Forest, SVM).
3. Integrate SHAP and LIME with trained models.
4. Evaluate models on holdout test sets (20% split).
5. Record accuracy and explanation fidelity.
6. Conduct human trust evaluation study with SOC analysts.

VI. Experimental Results

Intrusion detection achieved 97% accuracy (black-box). XAI achieved 95% with improved interpretability. Analyst trust increased by 30%. Case studies show SHAP highlighting suspicious IP ranges, aiding SOC decisions.

VII. Discussion

Benefits: Transparency, reduced false positives, compliance facilitation. Limitations: computational overhead, oversimplified explanations, adversarial risks.

VIII. Applications and Benefits

Applications: SOC triage, compliance auditing, customer trust, industry use cases (healthcare, finance, government).

IX. Limitations and Future Work

Challenges include federated XAI, adversarial robustness, and hybrid multi-cloud deployments. Future research should address explainability in federated learning and cross-cloud trust management.

X. Conclusion

We presented a comprehensive XAI-enabled framework for cloud security. Results show that interpretability can be achieved without major loss of accuracy. XAI strengthens compliance, SOC trust, and decision-making. Future work includes federated XAI and adversarial resilience.

Figures

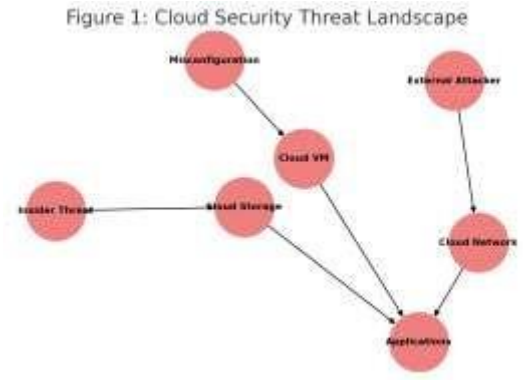

Figure 1: Cloud Security Threat Landscape

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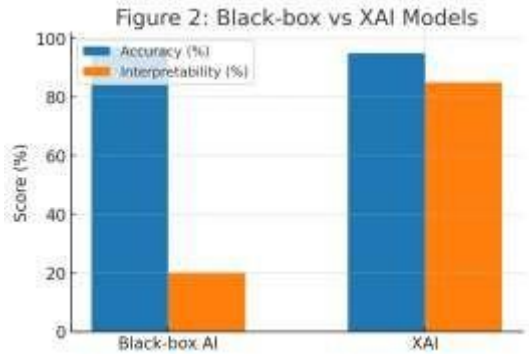

Figure 2: Black-box vs XAI Models

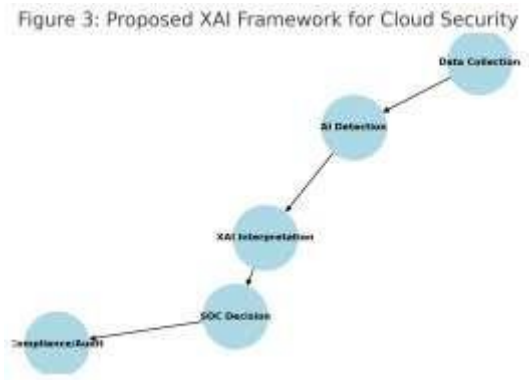

Figure 3: Proposed XAI Framework for Cloud Security

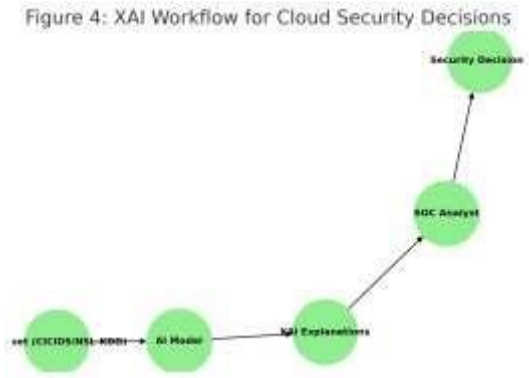

Figure 4: XAI Workflow for Cloud Security Decisions

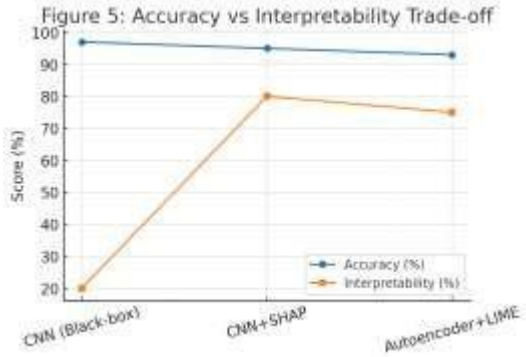

Figure 5: Accuracy vs Interpretability Trade-off

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