Explainable AI (XAI) for Transparent Cyber Defense

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Abstract

The increasing sophistication of cyberattacks calls for advanced cybersecurity techniques. Traditional AI models, though highly effective, often operate as black-box systems, making it difficult for security professionals to understand their decision-making process. This paper explores the concept of Explainable AI (XAI) and its application in enhancing transparency in cybersecurity defenses. By leveraging techniques like SHAP and LIME, XAI can make AI-driven systems more interpretable and trustworthy. This paper reviews the role of XAI in cyber defense systems, particularly in Intrusion Detection Systems (IDS) and malware detection, and discusses its impact on trust, accountability, and regulatory compliance. We propose methodologies to implement XAI in real-world cybersecurity applications, evaluating its ethical impact and market relevance, and explore potential future directions in the domain.

Problem Statement & Objective

Cybersecurity systems rely heavily on machine learning models to detect and mitigate threats. However, many of these models are not transparent, creating trust issues among security professionals and raising concerns regarding their decision-making processes. Objective: To explore the implementation of Explainable AI (XAI) techniques in cybersecurity, specifically focusing on Intrusion Detection Systems (IDS) and malware detection, with the aim of improving model transparency and trust.

Literature Review

- Overview of Cybersecurity Threats
- Traditional AI in Cybersecurity
- Explainable AI (XAI) Techniques
- XAI in Cyber Defense
- Challenges in XAI Implementation

Research Methodology

- Data Collection: Using datasets like NSL-KDD or malware datasets.
- Modeling Techniques: Implementing ML models such as Random Forest.
- XAI Techniques: Using SHAP and LIME.
- Evaluation Metrics: Accuracy, precision, recall, and explanation fidelity.

Tool Implementation

Tools Used: Python, scikit-learn, SHAP, LIME.
Steps:
1. Data Preprocessing
2. Model Training
3. Applying XAI
4. Evaluation with Visualizations

Results & Observations

- Model Performance Metrics (Accuracy, Precision, Recall)
- Feature Importance through SHAP and LIME
- Visual Insights from XAI Techniques

Ethical Impact & Market Relevance

- Ethical Aspects: Transparency, accountability, privacy.
- Market Relevance: Industry adoption, compliance (GDPR, HIPAA), enterprise trust.

Future Scope

- Advancements in Deep XAI
- Real-time Cyber Defense Integration
- Federated Learning with XAI

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