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In the name of God

Lateral Movement Attack Detection using Variational Autoencoders

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Introduction

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Introduction: The Stealthy Threat of Lateral Movement

Definition:
Lateral movement is a critical post-breach phase where an adversary pervasively compromises a network after an initial foothold.

Adversary's Goal:
To access high-value assets, culminating in large-scale data exfiltration or systemic service disruption.

The Core Challenge:
These attacks are designed to blend in with legitimate network traffic, thereby evading traditional signature-based security systems.

Limitations of Existing Methods:

- **Supervised Models:** Brittle when facing novel (zero-day) attack vectors due to their reliance on pre-labeled training data.
- **Unsupervised Models:** Prone to high false-positive rates and often fail to categorize specific attack typologies.

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Problem Statement

How can we design an efficient and accurate detection system for lateral movement that provides:

High Accuracy: To reliably identify known attack patterns and minimize false alarms.
Computational Efficiency: To be fast enough for real-time monitoring and rapid threat response.
Generalization Potential: To be capable of flagging novel and unseen anomalies.

Our Proposed Solution: A Hybrid Deep Learning Framework based on a Variational Autoencoder

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Key Concepts

Key Concepts: Variational Autoencoder (VAE)

Generative Model:
The VAE is a neural network architecture that learns to model the underlying probability distribution of input data.

Core Components:
Encoder: Maps high-dimensional input data to a lower-dimensional, probabilistic latent space.
Decoder: Attempts to reconstruct the original input by sampling from this latent distribution.

Anomaly Detection Mechanism:
The VAE is trained exclusively on a robust baseline of normal system and network behavior.
Data points that the model fails to reconstruct accurately (i.e., those with a high reconstruction error) are identified as anomalies, signaling a deviation from the learned norm.

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Proposed Architecture

Key Concepts: Variational Autoencoder (VAE)

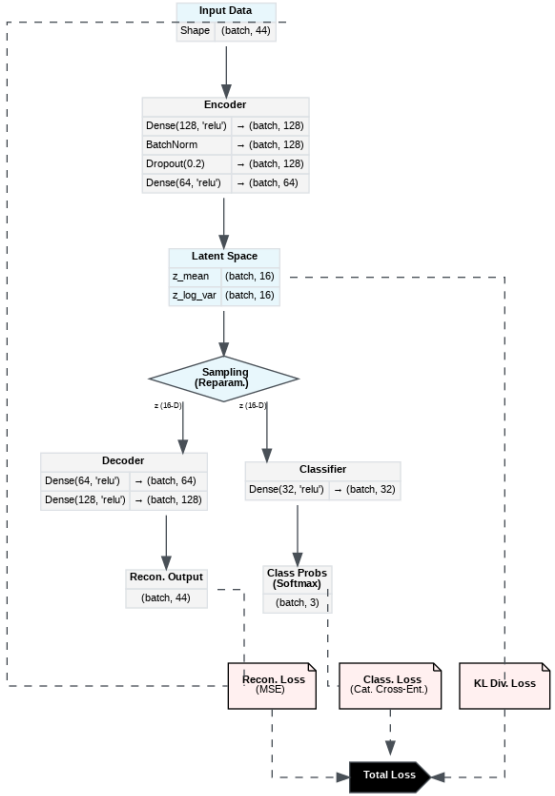
Dual-Purpose Design: A single, end-to-end model featuring a shared encoder with two distinct output heads.

1. **Reconstruction Head (Decoder):** For unsupervised, robust feature representation learning.
2. **Classification Head (Classifier):** For supervised, fine-grained threat classification.

Key Advantage: The reconstruction task acts as a powerful regularizer, compelling the encoder to learn a rich and generalizable latent representation that significantly benefits the classification task.

Data Flow:

1. A 44-dimensional feature vector enters the Encoder.
2. A 16-dimensional latent vector (z) is sampled.
3. This vector is simultaneously fed to the Decoder (for reconstruction) and the Classifier (for prediction).



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Dataset and Feature Engineering

Dataset:

LMD-2023: The only benchmark corpus comprising Sysmon logs specifically for evaluating lateral movement detection methods.

1. Contains approximately 1.75 million log samples.
2. Highly imbalanced, with normal traffic constituting about 92% of the samples.
3. Three classes: 'Normal', 'EoRS' (Exploitation of Remote Services), and 'EoHT' (Exploitation of Hashing Techniques).

Feature Engineering Process:

Initial Extraction: Started with 93 features from raw Sysmon logs.

Feature Selection: Used PCA and model coefficient analysis to select 15 key conceptual features.

Encoding: Converted categorical features (e.g., hostnames) to numerical format using one-hot encoding.

Normalization: Scaled all numerical features to a standard [0, 1] range using Min-Max normalization.

Final Result: A 44-dimensional input feature vector for the model.

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Experimental Setup

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Experimental Setup

Environment: Google Colaboratory (Colab) with an NVIDIA Tesla T4 GPU and 16GB of VRAM.

Frameworks & Libraries: Python 3.10.12, TensorFlow 2.15.0 (with Keras), Scikit-learn 1.2.2.

Model Training Parameters:

- **Optimizer:** Adam with a learning rate of 0.001.
- **Batch Size:** 128.
- **Loss Function:** A composite function combining Reconstruction (MSE), KL Divergence, and Classification (Categorical Cross-Entropy) losses.

Overfitting Prevention: Employed EarlyStopping and ReduceLROnPlateau callbacks.

Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, and AUC (Area Under the Curve).

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Experimental Setup

Model	Features	Cis	AUC	Prec	Recall	F1	Acc	Epochs	k-fold	T.E. Time
Lateral movement previous works										
MV (RF, LB, LoR)	4	2	-	-	-	0.66	99.62	N/A	✓	-
GRU DNN	8	2	-	93.23	-	-	96.68	60	✓	-
Ensemble ML	8	2	-	88.70	-	-	-	N/A	✓	-
SS DL	8	2	-	91.3	-	-	99.9	N/A	×	-
UML with JD	15	2	-	6	-	-	-	N/A	×	-
K-Means UML	27	2	81	-	-	-	-	N/A	×	-
RF	29	2	-	83.73	81.23	0.82	-	N/A	✓	00:00:02:06
LaBi	32	2	-	99.87	99.47	0.97	99.9	N/A	✓	00:00:11:28
RF	35	2	-	80.31	80.29	0.8	-	N/A	✓	00:00:03:11
ET	15	3	99.84	99.05	99.79	99.41	99.89	N/A	×	00:07:30:12
LSTM	15	3	95.82	95.11	94.36	95.55	98.93	30	×	00:15:44:18
This work. In each case, the best performers based on F1 score for LMD dataset										
VAE	44	3	99.6983	88.4756	88.5484	88.5029	98.3570	58	✓	00:00:02:54

Key Findings:

Our model achieved an excellent AUC of 99.70%, demonstrating outstanding class separation capability. While the Extra Trees (ET) model shows a slightly higher F1-score, our VAE model is dramatically faster. A total execution time of 2.54 seconds versus 7.5 minutes for ET validates our model's viability for real-time, operational deployment.

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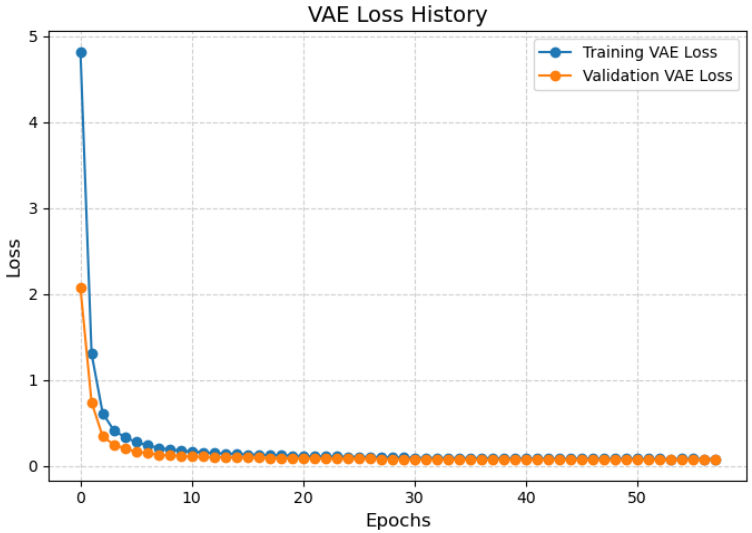
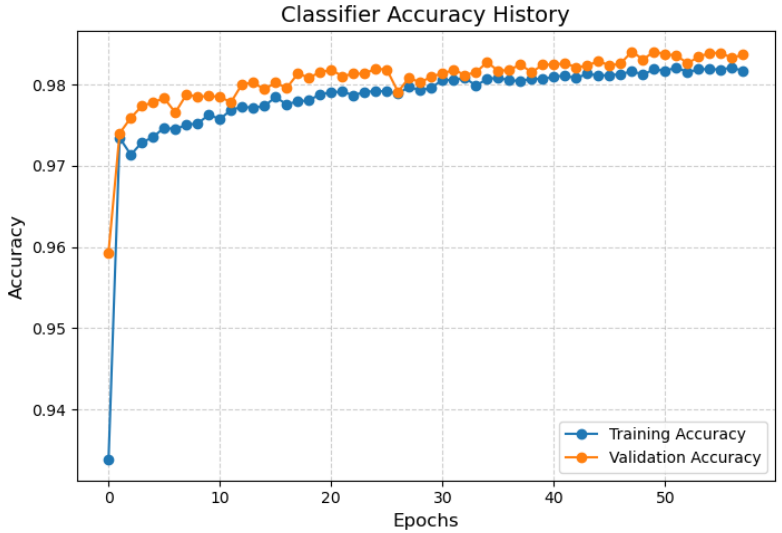
Model evaluation





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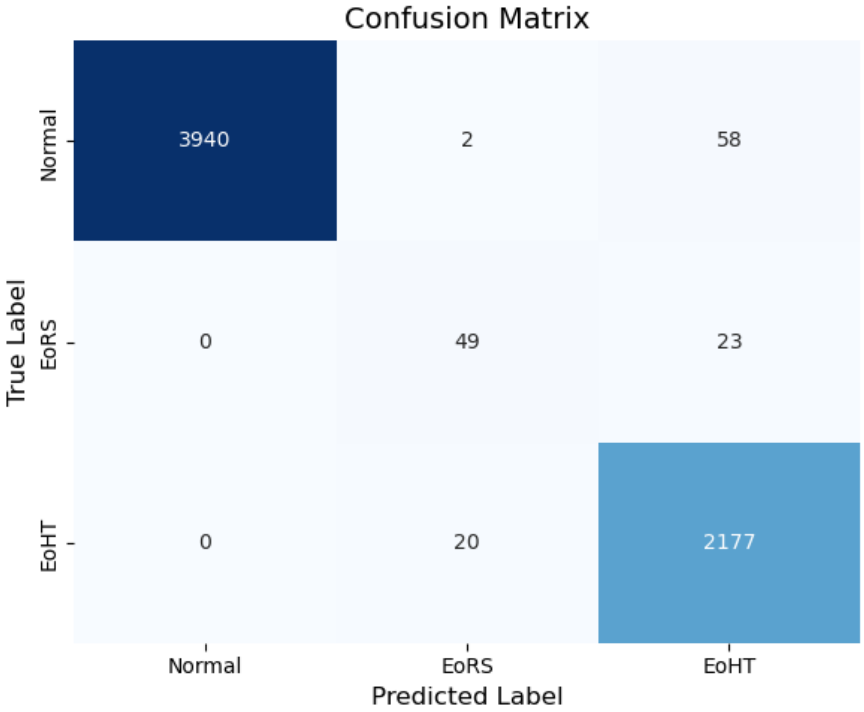
Confusion Matrix



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Discussion and Analysis

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Conclusion & Future Work

Key Contributions of This Work:

1. A Novel Hybrid Framework: We proposed and successfully implemented a VAE-centric hybrid framework, proving the viability of generative models for this complex cybersecurity challenge.

2. A Compelling Balance of Accuracy and Efficiency: Our empirical results demonstrate a strong balance between high discriminative power (AUC of 99.70%) and operational speed, establishing the VAE as a powerful and viable tool against Advanced Persistent Threats (APTs).

Future Work:

1. Enhancing Interpretability: Analyzing the learned latent space to better understand the model's decision-making process.
2. Exploring Unsupervised Capabilities: Formally leveraging reconstruction error as a standalone mechanism for zero-day threat detection.
3. Hybridization with Other Methods: Combining VAEs with Graph Neural Networks (GNNs) or Bayesian approaches to enhance detection capabilities.
4. Evaluating on more diverse and noisy real-world datasets to further test model robustness.

Thank you for your attention.

Do you have any questions?