AI & Machine Learning in Network Security

CYB 260: Network Defenses and Countermeasures

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Why This Matters

- Cyberattacks are increasingly leveraging AI and automation
- 5G networks introduce higher speeds and larger data volumes
- Increased connectivity expands the overall attack surface
- Traditional security systems struggle with real-time analysis
- Organizations need scalable and adaptive security solutions
- AI-based intrusion detection systems are emerging as a solution for modern threats

Problem Statement

- Signature-based detection relies on known attack patterns
- New or modified attacks can bypass traditional systems
- Large-scale network traffic creates detection challenges
- High false negatives in dynamic environments
- Limited ability to detect zero-day attacks
- Traditional systems fail to detect anomaly-based attacks in real-time environments

Why AI/ML?

- Identifies patterns in large-scale network data
- Detects anomalies using learned patterns in network behavior
- Adapts to new and evolving threats over time
- Enables faster and more automated threat detection
- Scales more effectively than manual or rule-based systems

Project Objectives

1. Developed an AI-based intrusion detection system (IDS)
2. Simulated network traffic in a controlled environment
3. Analyzed differences between normal and malicious behavior
4. Applied machine learning to classify network activity
5. Evaluated performance using detection metrics

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Research Questions

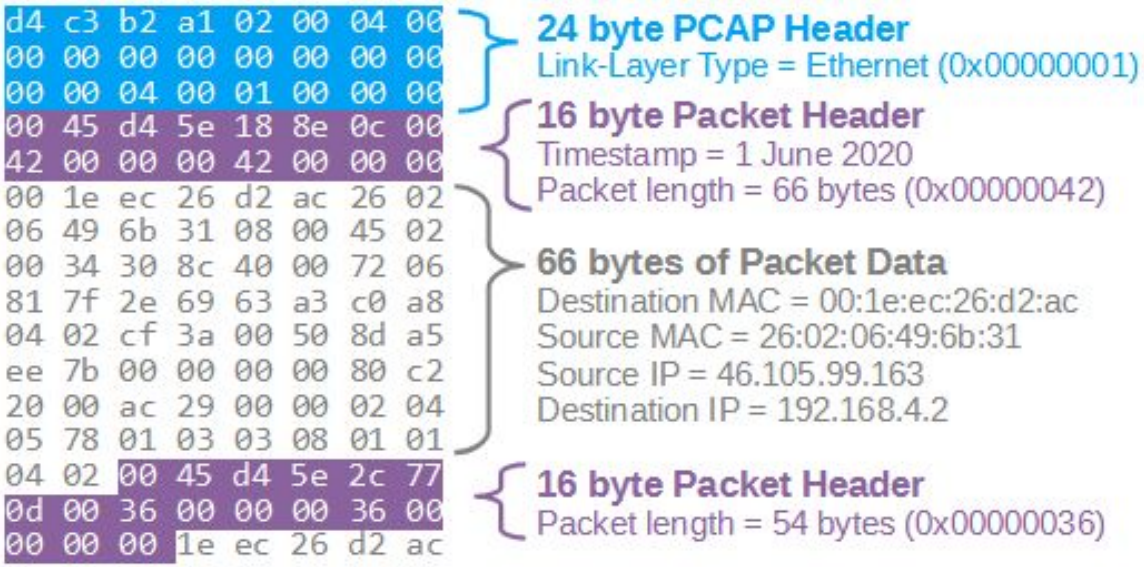
1. How effectively can an AI-based IDS detect anomalies in network traffic?
2. Can machine learning maintain accuracy when analyzing high-volume data?
3. How does anomaly detection improve network security (CIA triad)?

Lab Environment Architecture

- Isolated virtual environment
- Scapy (custom packet generation)
- Wireshark (packet capture)
- Python (model + preprocessing)

Data Collection Process

- Network traffic captured using packet analysis tools (Wireshark)
- ~1100 packets generated using Scapy (benign + malicious traffic)
- Includes simulated attacks (SYN flood, UDP flood, scans)
- Data stored in PCAP format for analysis
- Data prepared and converted for machine learning model input



Feature Extraction

- Source and destination IP addresses
- Network protocol types (TCP, UDP, etc.)
- Packet size and transmission patterns
- TCP flags and session behavior
- Port numbers and timestamps
- Data normalized and converted to CSV
- Extracted features used to train detection models

Real-Life Example

CrowdStrike Falcon — AI/ML in Modern Network Security

- Uses cloud-native AI/ML for real-time threat detection
- Analyzes trillions of events per day across global endpoints
- Detects behavioral anomalies, lateral movement, and zero-day attacks

Machine Learning Approach

- Autoencoder neural network used for anomaly detection
- Model trained on normal network traffic only
- Detects attacks using reconstruction error
- Learns patterns of normal vs abnormal behavior

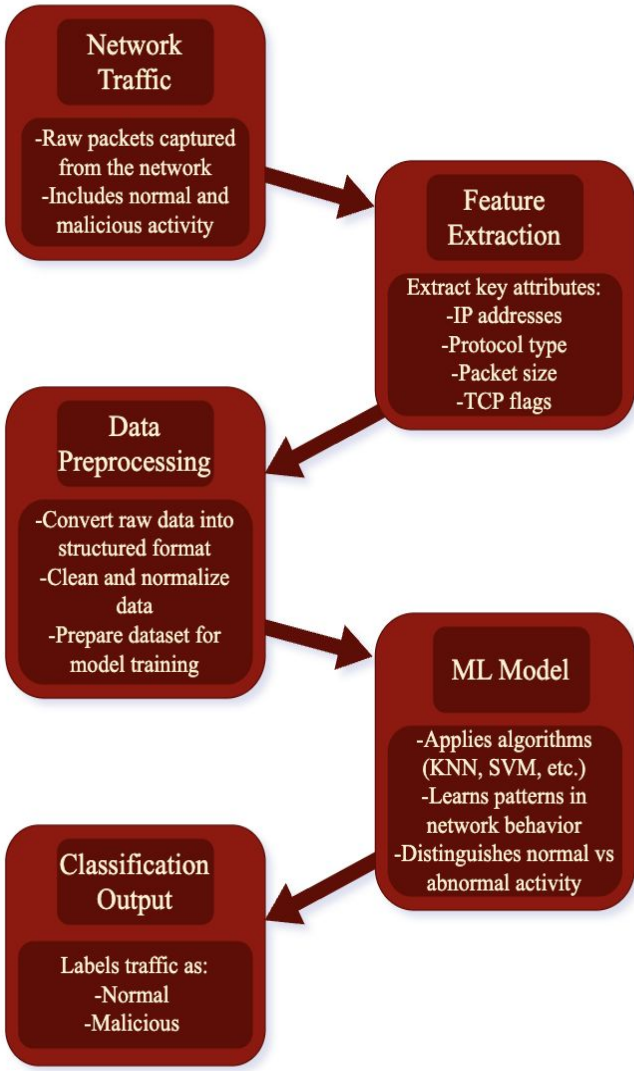
```python
def create_model(input_size, hyper_param):

    act_func = 'elu'
    model = Sequential()

    # ENCODER
    model.add(Dropout(hyper_param.drop_out[0], input_shape=(input_size,)))

    model.add(Dense(
        hyper_param.layers[0],
        activation=act_func,
        kernel_initializer=initializers.glorot_uniform(seed=hyper_param.random_seed),
        activity_regularizer=regularizers.l1(hyper_param.kernel_reg[0])
    ))

    model.add(Dropout(hyper_param.drop_out[1]))

    for i in range(1, len(hyper_param.layers) - 1):
        model.add(Dense(
            hyper_param.layers[i],
            activation=act_func,
            kernel_initializer=initializers.glorot_uniform(seed=hyper_param.random_seed),
            activity_regularizer=regularizers.l1(hyper_param.kernel_reg[i])
        ))
        model.add(Dropout(hyper_param.drop_out[i+1]))

    # BOTTLENECK
    model.add(Dense(
        hyper_param.layers[-1],
        activation=act_func,
        kernel_initializer=initializers.glorot_uniform(seed=hyper_param.random_seed)
    ))

    # DECODER
    for i in range(len(hyper_param.layers) - 2, -1, -1):
        model.add(Dense(
            hyper_param.layers[i],
            activation=act_func,
            kernel_initializer=initializers.glorot_uniform(seed=hyper_param.random_seed),
            activity_regularizer=regularizers.l1(hyper_param.kernel_reg[i])
        ))

    model.add(Dense(
        input_size,
        kernel_initializer=initializers.glorot_uniform(seed=hyper_param.random_seed)
    ))

    model.compile(loss='mse', optimizer='adam')

    print("\nModel Summary...")
    print(model.summary())

    return model
```

Learning Approaches

- Unsupervised learning used for anomaly detection (autoencoder)
- Reinforcement learning adapts based on system feedback
- Combination of approaches improves detection flexibility
- Allows identification of both known and unknown threats

Model Workflow

- Network traffic is collected and preprocessed
- Data is converted into structured feature sets
- Machine learning model is trained on labeled data
- Model analyzes incoming traffic patterns
- Output classifies activity as normal or malicious
  - Classification based on reconstruction error



Training & Validation

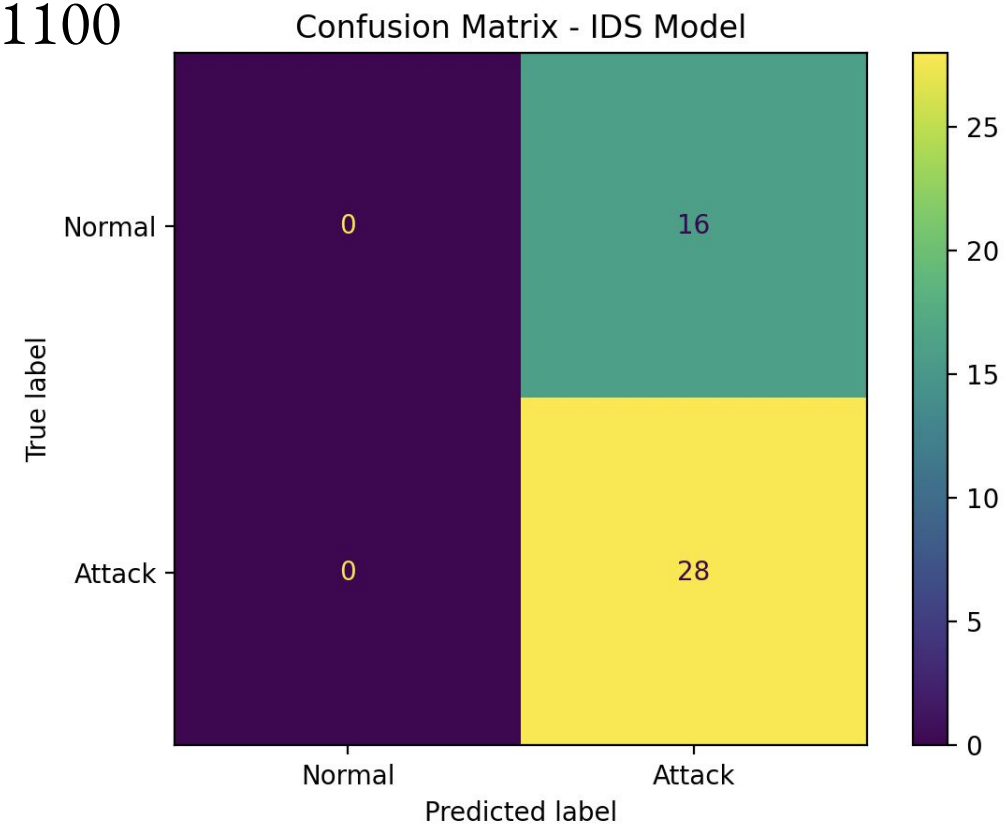
- Dataset split into 95% training and 5% validation
- Model trained only on normal traffic
- Early stopping used to prevent overfitting
- Performance monitored using reconstruction error

Example Detection

- Normal traffic:
  - Stable packet patterns
  - Consistent protocol behavior
  - Successful data reconstruction
- Malicious traffic:
  - SYN flood / abnormal packet spikes
  - Unusual flag patterns
  - Errors in data reconstruction

Results and Findings

- Total packets analyzed: ~1100
- Anomalies detected: 800
- Benign packets: 279
- Detected attacks: 44
- True Positives: 28
- False Positives: 16
- False Negatives: 0
- True Negatives: 0
- High detection rate with increased false positives



AI vs Traditional IDS Comparison

Feature	Traditional IDS	AI-Based IDS
Detection	Signature-based	Behavior-based
Unknown Threats	Incapable	Capable
Scalability	Limited	High

AI-based IDS uses anomaly detection via autoencoder.

Strengths of AI Detection

- Successfully detected all attack samples (FN = 0)
  - Very sensitive to threats
- Processes large volumes of data efficiently
- Reduces reliance on manual analysis
- Detects previously unknown attack patterns
- Enables real-time monitoring and response
- Improves scalability in complex network environments

Limitations and Risks

- High false positive rate observed in results
- Limited dataset size (~1100 packets)
  - Requires large, high-quality datasets for training
- High computational and resource requirements
- Potential for false positives and misclassification
- Model performance depends on training data quality

Real-World Implications

- Enhances enterprise network security systems
- Supports protection of critical infrastructure
- Applicable to cloud and large-scale environments
- Improves defense against modern cyber threats
- Plays a role in national cybersecurity strategies

Future Improvements

- Incorporate more diverse and complex datasets
- Combine AI with traditional detection systems
- Integrate with SIEM and monitoring platforms
- Improve real-time deployment capabilities
- Reduce false positives through model tuning

Conclusion

- Model achieved high detection but with false positives
- Demonstrated effectiveness of anomaly-based detection
- AI enhances intrusion detection capabilities
- Provides scalable and adaptive security solutions
- Effectiveness depends on data quality and implementation
- Represents a key direction for future cybersecurity defense
- Not a replacement, but a complement to traditional systems

References

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