Intrusion Prevention System

Ch.Meghana[1], K.Rahul[2], N.Sai Venkat[3], Ch. Lohith[4], T.Rahul[5]
[1]*Assistant Professor, Hyderabad institute of technology and management, Medchal, Telangana*
[2,3,4,5]*UG student, Hyderabad institute of technology and management, Medchal, Telangana*

Abstract-Intrusion Prevention Systems (IPS) are critical components of network security that monitor and proactively block potential threats before they can compromise a system. This work focuses on building a machine learning-based IPS capable of preventing network attacks in real time. The CIC-IDS2017 dataset, a widely used benchmark for network intrusion prevention, is utilized. Three machine learning algorithms—Support Vector Machines (SVM) for binary classification, and Random Forest and K-Nearest Neighbors (KNN) for attack type classification—are implemented and evaluated using key metrics, including accuracy, precision, recall, and F1-score. Results show that Random Forest outperforms other models in multi-class classification, while SVM achieves high accuracy in intrusion detection. The findings highlight the potential of machine learning-based IPS in enhancing cybersecurity by reducing false positives and improving real-time threat mitigation.

Index Terms— Intrusion Prevention System, Machine Learning, Cybersecurity, CIC-IDS2017, Random Forest, SVM, KNN, Network Security

I. INTRODUCTION

As cyber-attacks become increasingly sophisticated, the need for adaptive and intelligent security systems is more crucial than ever. Traditional signature-based Intrusion Prevention Systems (IPS) rely on pre-defined attack signatures to block threats, but they struggle to prevent zero-day attacks and emerging threats that have not been previously recorded. This limitation highlights the necessity for machine learning-based IPS, which can continuously learn from network traffic patterns and proactively prevent malicious activity in real time. Instead of solely depending on static rules, these systems analyze network behavior and identify suspicious activities before they escalate into security breaches.

The implementation of machine learning models in IPS introduces an innovative approach to cybersecurity. Support Vector Machines (SVM) have demonstrated high accuracy in distinguishing between normal and malicious traffic, making them well-suited for binary classification in IPS. On the other hand, Random Forest, a robust ensemble learning algorithm, excels in classifying different types of attacks by aggregating predictions from multiple decision trees, enhancing the overall reliability of the system. K-Nearest Neighbors (KNN) also plays a crucial role in attack classification by leveraging similarity-based learning to detect threats in network traffic. By integrating these models, we combine the strengths of real-time intrusion detection and precise attack classification, resulting in a highly effective IPS capable of mitigating both known and novel cyber threats.

This study compares the effectiveness of these models based on multiple performance metrics, including accuracy, precision, recall, and F1-score. The findings provide valuable insights into the design of machine learning-powered IPS, demonstrating its potential in improving network security, reducing false positives, and ensuring real-time threat mitigation.

II. LITERATURE SURVEY

Intrusion Prevention Systems (IPS) play a crucial role in securing networks from cyber threats by proactively blocking malicious activities before they cause damage. However, traditional IPS solutions rely on signature-based detection, which struggles to prevent evolving and zero-day attacks. With the rise of machine learning (ML), IPS technology has significantly improved, enabling adaptive, scalable, and precise prevention mechanisms that address the shortcomings of traditional methods.

Supervised Learning Techniques

Supervised learning techniques such as Decision Trees, Support Vector Machines (SVM), and Random Forest are commonly used in IPS to classify network traffic. Random Forest, an ensemble method, improves detection accuracy by combining predictions from multiple decision trees, reducing variance and increasing model reliability [1]. These models are highly effective at detecting known attack patterns, given a properly labeled dataset. However, their dependency on labeled data limits their ability to detect novel or zero-day attacks, making them less effective in highly dynamic network environments [2].

Unsupervised Learning Paradigms

To address the limitations of supervised learning, unsupervised models like Autoencoders and Isolation Forest are employed in IPS. Isolation Forest, in particular, is well-suited for anomaly detection, as it isolates outliers in network traffic, making it effective for detecting previously unseen cyber threats [3]. Unlike supervised models, Isolation Forest does not require labeled datasets, allowing it to adapt to evolving attack patterns [4]. However, one challenge associated with unsupervised models is their higher false positive rate, which can lead to unnecessary blocking of legitimate traffic [5].

Hybrid Models

To maximize the strengths of both supervised and unsupervised learning, hybrid IPS solutions have gained attention. Combining Random Forest with Isolation Forest allows the IPS to classify known threats while detecting new attack behaviors using anomaly detection [6]. Hybrid approaches have been shown to reduce false positives and improve real-time threat prevention, making them well-suited for large-scale enterprise security environments [7].

Key Challenges in IPS

1. False Positives: Machine learning-based IPS solutions frequently suffer from high false-positive rates, overwhelming security teams with excessive alerts. Fine-tuning detection thresholds and integrating contextual analysis can help reduce unnecessary alarms [4].
2. Scalability: Modern IPS must handle large volumes of real-time network traffic efficiently. Ensemble techniques, such as Random Forest combined with lightweight anomaly detection models, ensure scalability without sacrificing detection precision [8].
3. Adaptive Threats: Cyberattacks constantly evolve, requiring IPS models to adapt dynamically. Continuous learning frameworks ensure that models update in real-time, improving their ability to counter new and sophisticated attack techniques [3].

Advancements in Research

Recent advancements in Intrusion Prevention System (IPS) research focus on real-time response optimization and explainable AI (XAI). XAI is being explored to increase transparency in ML-based IPS, helping security teams understand and validate model decisions [5].

Additionally, studies comparing supervised and unsupervised models show that the effectiveness of IPS depends on the deployment environment. Enterprise networks require high-speed classification, while IoT security demands lightweight, adaptive models [7].

Machine learning has revolutionized IPS technology, providing proactive defenses against evolving threats. The combination of Random Forest for attack classification and Isolation Forest for anomaly detection has emerged as a promising hybrid IPS solution. Future research will focus on real-time scalability, adaptive learning, and XAI-driven security frameworks, ensuring IPS remains effective in mitigating cyber threats [8].

III. METHODOLOGY

Our IPS design was implemented using trained machine learning models applied to the CIC-IDS2017 dataset. This dataset provides detailed network traffic features, including packet flow duration, protocol type, source and destination ports, and other network behavior indicators. It also includes labeled attack categories such as ‘Benign’, ‘DDoS’, ‘Botnet’, and

'PortScan' to help train the model for accurate intrusion prevention.

3.1 Data Preprocessing

Before training the machine learning models, the dataset underwent preprocessing to enhance its suitability for analysis:

- One-Hot Encoding: Categorical features like 'protocol_type', 'service', and 'flag' were converted into numerical form using one-hot encoding.
- Normalization: Numerical features were scaled to a uniform range, ensuring that models performed optimally across all feature dimensions.
- Dimensionality Reduction: Principal Component Analysis (PCA) was applied to reduce computational complexity while preserving essential information.

3.2 Model Selection

For this study, two machine learning models were selected to enhance intrusion prevention:

1. Support Vector Machines (SVM): A supervised learning algorithm used to classify network traffic as normal or attack, ensuring precise intrusion detection.
2. Random Forest: A robust ensemble learning algorithm that classifies different types of attacks, increasing detection accuracy and reliability.

Both models were trained using the preprocessed CIC-IDS2017 dataset, with a train-test split ratio of 80:20 to ensure effective validation.

3.3 Training and Assessment

All models were trained using cross-validation to enhance robustness and minimize overfitting. Performance was assessed using key evaluation metrics:

- Accuracy: Measures overall model correctness.
- Precision: Evaluates the proportion of correctly identified attacks.
- Recall: Assesses the model's ability to detect all actual attacks.
- F1-Score: Provides a balance between precision and recall for comprehensive evaluation.

IV. IMPLEMENTATION

This implementation describes the development of an Intrusion Prevention System (IPS) using machine learning to detect and block malicious activities in real-time. The system is built using Python and leverages supervised and unsupervised learning models to analyze network traffic.

1. Data Collection

The system uses the CIC-IDS2017 dataset, a widely recognized benchmark dataset for intrusion detection and prevention. This dataset simulates real-world cyberattacks and contains network flow features such as:

- Flow Duration – The duration of network communication between source and destination.
- Source & Destination Bytes – The number of data bytes sent and received.
- Packet Length Statistics – Minimum, maximum, and average length of packets in a connection.
- Flow Rate Features – Such as flow bytes per second and flow packets per second.
- Attack Labels – Each record is categorized as either benign traffic or one of several attack types (e.g., DDoS, PortScan, Botnet, Infiltration, Web Attacks).

2. Data Preprocessing

To prepare the dataset for machine learning, the following preprocessing steps were applied:

- Handling Missing Values: Any incomplete records in the dataset were identified and removed.
- One-Hot Encoding: Categorical variables such as protocol_type, service, and flag were converted into numerical format.
- Feature Scaling: Min-Max Scaling was used to normalize numerical features to ensure all values remain within a standard range.
- Dimensionality Reduction: Principal Component

Analysis (PCA) was applied to reduce redundant features and improve model efficiency.

3. Model Selection and Training

The IPS employs two machine learning models for real-time threat prevention:

1. Random Forest Classifier – A powerful ensemble learning algorithm used to classify network traffic as benign or attack based on historical patterns. It enhances decision-making by combining multiple decision trees.
2. Isolation Forest – An anomaly detection algorithm that identifies unusual network behavior that may indicate previously unseen attacks (zero-day threats).

The models were trained using the preprocessed CIC-IDS2017 dataset with a train-test split ratio of 80:20. Cross-validation was applied to ensure model reliability and avoid overfitting.

4. Evaluation Metrics

The performance of the IPS was evaluated using the following key metrics:

- Accuracy – Measures overall correctness of the model's predictions.
- Precision – Determines how many detected threats were actual threats.
- Recall (Sensitivity) – Evaluates the model's ability to detect real attacks.
- F1-Score – Provides a balance between precision and recall.

5. Deployment

Once trained, the IPS continuously monitors network traffic in real-time. The process involves:

- Capturing incoming network packets.
- Extracting relevant flow features.
- Using trained machine learning models to classify traffic as benign or malicious.
- Blocking suspicious activity automatically.

The system efficiently prevents known and unknown attacks, offering a proactive approach to network security.

V. RESULT

The Intrusion Prevention System (IPS) integrates signature-based detection and machine learning techniques to proactively block malicious activities in the network. It processes real-time network traffic and extracts critical features such as source IP, destination IP, flow duration, and packet size for threat analysis.

Focal Outputs:

1. Signature-Based Prevention:
   - The IPS efficiently identifies known threats by analyzing packet payloads and comparing them against predefined malicious signatures.
   - If a match is detected (e.g., "malicious_payload_1"), the system immediately blocks the traffic and logs an alert.
2. Anomaly Detection:
   - Using Isolation Forest, the system detects abnormal network behavior in real-time.
   - The model successfully identifies previously unseen attacks, including zero-day threats, by recognizing deviations from normal traffic patterns.
3. Model Training and Performance:
   - The IPS supports the loading and preprocessing of multiple datasets, ensuring flexibility in model training.
   - Min-Max scaling is applied to normalize network flow features, improving model accuracy.
   - Trained models are saved for future use, allowing the system to operate without requiring retraining for each session.
4. Real-Time Traffic Monitoring:
   - The IPS continuously analyzes live network traffic and classifies packets as either benign or malicious using trained models.
   - Detected threats are immediately blocked, reducing response time and enhancing network security.

Overall Impact:

The IPS successfully prevents known threats through signature-based detection while also identifying new

attack patterns using machine learning. This hybrid approach provides a robust real-time security solution for modern networks.

Future Enhancements:

- Improved feature extraction methods for better anomaly detection.
- Integration of deep learning models for enhanced accuracy.
- Automated emergency alert notifications via email or SMS for critical security events.

VI.CONCLUSION

The Intrusion Prevention System (IPS) developed in this project successfully integrates signature-based detection with machine learning-based anomaly detection to proactively enhance network security. By analyzing real-time network traffic, the system can identify and block both known threats and emerging cyberattacks.

The Random Forest model effectively classifies attack types, while Isolation Forest enables the detection of zero-day attacks by identifying anomalies in network behavior. Signature-based detection ensures that predefined malicious patterns are recognized and blocked immediately.

Overall, this IPS provides a robust security framework, offering real-time monitoring, automated prevention, and adaptive threat detection. Future improvements could focus on:

- Enhancing feature extraction techniques for more precise anomaly detection.
- Exploring deep learning models to improve predictive accuracy.
- Implementing automated alerting mechanisms such as email or SMS notifications for detected intrusions.

This IPS implementation demonstrates a scalable and efficient approach to protecting modern network environments against evolving cyber threats.

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