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AN AI-DRIVEN HYBRID MODEL FOR CYBERSECURITY THREAT DETECTION USING AUTOENCODER AND LSTM

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ABSTRACT

Cybersecurity threats are evolving rapidly, requiring advanced detection mechanisms beyond traditional rule-based systems. This study proposes an AI-driven hybrid model integrating Autoencoder and Long Short-Term Memory (LSTM) networks to enhance real-time threat detection. The Autoencoder extracts hidden patterns and reduces dimensionality, while LSTM captures sequential attack behaviors for better classification. The proposed model effectively reduces false positives and negatives, addresses data imbalance issues, and classifies threats based on severity (Low, Medium, High). Performance evaluation using accuracy, precision, recall and F1-score demonstrates the model's reliability in detecting sophisticated cyber threats. The results confirm the potential of deep learning in improving cybersecurity resilience and real-time threat mitigation.

Keywords: Cybersecurity, LSTM, Threat Classification, AI.

1 INTRODUCTION

Cybersecurity threats are evolving rapidly with the increasing adoption of digital technologies Siddiqui, 2016 [1]. AI-based approaches have gained prominence in identifying, analyzing, and mitigating these threats. Traditional rule-based cybersecurity systems often fail to detect sophisticated cyberattacks due to their static nature Donepudi, 2015 [2]. In response, AI-driven models have been proposed to enhance real-time threat detection and response, leveraging machine learning techniques for pattern recognition and anomaly detection.

The growing complexity of cyberattacks is fueled by factors such as the rise of advanced persistent threats (APTs), ransomware, and phishing attacks Harel et al., 2017[3]. Attackers are utilizing AI-based tactics to evade detection, making traditional cybersecurity defenses insufficient Palomares Carrascosa et al., 2017[4]. Additionally, the expansion of IoT devices, cloud computing, and remote work environments has increased vulnerabilities, creating a demand for intelligent security mechanisms capable of handling large-scale data and detecting threats in real time.

Despite advancements in AI-driven cybersecurity, several challenges persist Adenusi Dauda et al., 2017 [5]. The primary issue is the high rate of false positives and negatives in threat detection systems Gill & Rodrigues, 2017[6]. AI models may misclassify threats, leading to unnecessary security alerts or failing to detect critical attacks. Furthermore, cybersecurity datasets often contain imbalanced data, making it difficult for models to generalize effectively. Privacy concerns and computational efficiency also pose significant barriers to implementing AI-based threat detection at scale.

To overcome these challenges, this study introduces a hybrid AI-based model utilizing autoencoders for feature extraction and LSTM for classification. Autoencoders help in identifying hidden patterns in cybersecurity data, reducing dimensionality and improving feature representation. LSTM, with its sequential learning capability, enhances threat detection accuracy by analyzing temporal attack patterns. The proposed approach aims to minimize false positives, improve real-time detection, and enhance cybersecurity resilience against evolving threats.

1.1 PROBLEM STATEMENT

The proposed AI-driven hybrid model using Autoencoder and LSTM effectively addresses the challenges in cybersecurity threat detection GRANDON GILL, n.d. [7]. It reduces false positives and negatives by enhancing anomaly detection and improving temporal pattern recognition Deliu et al., 2017[8]. The model handles imbalanced data efficiently, ensuring better classification reliability Meszaros & Buchalcevova, 2017 [9]. By enabling real-time threat detection, it enhances cybersecurity resilience against evolving attacks Azhar, 2015 [10]. Unlike traditional methods, it categorizes threats (Low, Medium, High) for better incident response. Additionally, its scalability and automation make it suitable for cloud environments and large-scale security applications. Overall, it provides an adaptive, efficient, and robust cybersecurity solution.

1.2 OBJECTIVES

- Analyze cybersecurity threats and identify key challenges associated with traditional threat detection systems.
- Develop a hybrid AI model integrating Autoencoder and LSTM to improve real-time cybersecurity threat detection.
- Implement Autoencoder for feature extraction and dimensionality reduction to enhance anomaly detection.
- Apply LSTM for sequential pattern recognition to classify threats into Low, Medium, and High severity levels.
- Evaluate the model's performance using metrics such as accuracy, precision, recall, and F1-score.
- Compare the proposed model's effectiveness with existing cybersecurity threat detection techniques.
- Enhance the system's scalability and automation for deployment in real-world cybersecurity applications.

2 LITERATURE SURVEY

Today's evolving cybersecurity threats require modern cognitive computing approaches beyond traditional rule-based systems. Conventional firewalls struggle to detect advanced attacks like DNS-based DDoS amplification, as they rely on signature-based detection. (Khan et al., 2014[11] proposes a chaos-based complexity measure using the Lyapunov exponent to classify network traffic as normal or anomalous. Unlike supervised learning methods, this approach requires no offline training and can be applied to real-time DNS traffic analysis. Experimental results show a 98% detection accuracy, surpassing traditional Artificial Neural Networks (ANNs), making it a promising solution for modern network security.

Traditional Intrusion Detection and Prevention Systems (IDPS) face limitations in detecting modern cyber threats. Mathews et al., 2012 [12] proposes a collaborative framework that integrates traditional and nontraditional sensors to generate relevant attack signatures, enhancing detection accuracy. Additionally, a network traffic-based classifier is introduced, showing promise in identifying malicious traffic patterns. By leveraging diverse data sources and advanced classification techniques, this approach improves threat detection and mitigation. The proposed system addresses existing IDPS limitations, making it more adaptive and effective against evolving cyber threats.

Anwar & Hassan, 2017 [13] denotes that Cybersecurity can greatly benefit from the integration of Artificial Intelligence (AI) to counter evolving cyber threats. Traditional security systems often struggle with advanced attacks, whereas AI techniques enhance threat detection, response time, and overall security performance. However, while AI offers significant advantages, it also introduces risks and ethical concerns. A holistic approach combining AI with human intelligence is essential, as neither can ensure complete cybersecurity alone. A responsible and socially aware implementation of AI-driven security measures is crucial to maximizing benefits while mitigating risks.

The advancement of cellular technology and portable devices has paved the way for innovative business applications like M-commerce, the next phase of e-commerce. Madhok et al., 2016 [14] proposes a Wireless Menu Card (WMC) for food chains, allowing customers to place orders via Tablets or Smartphones. The system utilizes Wi-Fi storage devices or Network Attached Storage (NAS), virtually implemented on the cloud, enabling large data storage and seamless order processing. By integrating PDAs and cloud-based storage, this approach enhances efficiency, security, accuracy, and quality of service while minimizing human errors and saving time.

The growing complexity and speed of cyber threats make manual defense inadequate, necessitating automation and AI-driven security solutions. Traditional fixed-algorithm security systems struggle against evolving network attacks, whereas computational intelligence provides adaptability and learning capabilities. Patil, 2016 [15] explores AI applications in cybersecurity, emphasizing the role of Artificial Neural Networks (ANNs) in perimeter security and threat detection. Findings indicate that many cybersecurity challenges can be effectively addressed using AI-driven decision-making and intelligent threat analysis. The integration of AI strategies enhances real-time threat response, automation, and overall security intelligence.

Wirkuttis & Klein, 2017 [16] denotes Cybersecurity stands to gain significantly from the integration of Artificial Intelligence (AI), as traditional security systems often struggle with advanced cyber threats. AI enhances threat detection, response time, and overall security performance, but its adoption also raises risks and ethical concerns.

A holistic approach that combines AI with human expertise is essential, as neither can fully address cybersecurity challenges alone. A socially responsible implementation of AI-driven security measures is crucial to maximizing protection while minimizing risks. This balanced approach ensures stronger, more adaptive, and ethical cybersecurity frameworks.

Trifonov et al., 2017 [17] explained that cyber defense has evolved by integrating Military Intelligence principles and Artificial Intelligence (AI) techniques to counter cyber threats, as highlighted by ENISA. Research at the Technical University of Sofia explores intelligent methods to enhance computer network security. While Tactical Cyber Threat Intelligence has advanced to real-world prototyping, Operational Cyber Threat Intelligence remains in its early research phase. This ongoing study aims to strengthen cyber defense mechanisms through AI-driven intelligence, ensuring proactive threat detection and mitigation in evolving cyber landscapes.

Yampolskiy & Spellchecker, 2016[18] analyzes failures in Artificial Intelligence (AI) systems and predicts that both their frequency and severity will increase over time. AI safety can benefit from cybersecurity principles, but while narrow AI failures have moderate risks similar to cybersecurity breaches, general AI failures could have catastrophic, irreversible consequences. Unlike cybersecurity, where the goal is to minimize successful attacks, AI safety aims for zero security breaches, an unachievable standard. Since no system is 100% secure, ensuring robust AI safety mechanisms is critical to preventing catastrophic AI failures.

Botnets are among the most severe cybersecurity threats, serving as key vectors for numerous cybercrimes. While extensive research has focused on botnet detection, challenges persist in adapting to evolving botnet architectures. Zhao et al., 2013[19] proposes a machine learning-based approach that detects botnet activity through traffic behavior analysis, independent of packet payloads, making it effective even for encrypted communications. By analyzing network behavior over small time intervals, this method enables high-accuracy detection of both known and unknown botnets without requiring full network flow visibility. Experimental results confirm its feasibility for real-time botnet mitigation.

Sharma & Dutta, 2017[20] provides a comprehensive analysis of AI-based threat identification, focusing on feature extraction and classification methods. Effective threat detection relies on accurately classifying threats and extracting relevant features from vast data streams. Various feature extraction techniques, including hybrid models, deep learning, and statistical methods, are examined alongside classification approaches such as ensemble learning, deep learning, and machine learning. The study evaluates their effectiveness in different threat detection scenarios, highlighting key trends, challenges, and future directions. These insights contribute to developing robust cybersecurity solutions for combating evolving cyber threats.

3 METHODOLOGY

This cybersecurity threat detection system begins by collecting raw data like network logs and intrusion alerts from firewalls or IDS/IPS. The data undergoes preprocessing, including normalization and cleaning, to ensure consistency and quality. An Autoencoder compresses the data to detect anomalies, while an LSTM analyzes temporal patterns for accurate classification. Threats are categorized by severity—Low (minor anomalies), Medium (suspicious activities), or High. Performance metrics like precision and recall evaluate the model’s effectiveness. The combined use of deep learning and structured assessment enables proactive, scalable threat detection.

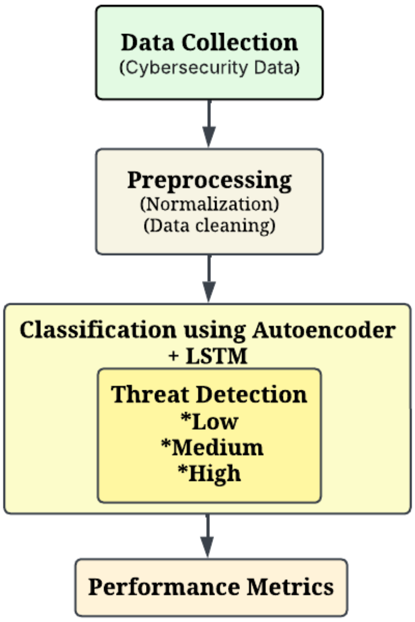

Figure 1: AI-Driven Cybersecurity Threat Classification System

3.1 DATA COLLECTION

The first step in the proposed cybersecurity threat detection system is data collection. The dataset is obtained from AI-Enhanced Cybersecurity Events Dataset. These sources provide real-time and historical data about network activities, including potential cyberattacks. Each data entry contains attributes like timestamp, source IP, destination IP, protocol type, attack category, and severity level. The data is labeled to distinguish between normal and malicious activities, which is essential for supervised learning. A high-quality dataset ensures better training for the deep learning model, leading to improved threat detection accuracy.

3.2 DATA PREPROCESSING

Raw cybersecurity data often contains inconsistencies that hinder analysis. Normalization scales numerical features to a standard range, preventing bias in model training. Data cleaning involves handling missing values through imputation or removal, eliminating duplicates, and filtering noise like irrelevant logs. This step ensures high-quality input for the detection model, improving accuracy. Efficient preprocessing is crucial for reducing false alarms and enhancing the system's reliability in real-world deployments.

3.3 HYBRID AUTOENCODER-LSTM CLASSIFICATION

The Autoencoder operates unsupervised, learning to compress input data into a compact latent representation and reconstruct it. Large reconstruction errors indicate anomalies, flagging potential threats. The LSTM complements this by analyzing sequential data capturing time-dependent attack patterns. Together, they combine anomaly detection with temporal context, improving threat identification. This hybrid approach mitigates limitations of standalone models, such as the Autoencoder's sensitivity to noise or LSTM's dependency on labeled data.

3.3.1 Autoencoder for Anomaly Detection

The autoencoder is an unsupervised neural network that learns efficient data representations by compressing input into a latent space and reconstructing it. During training, it minimizes reconstruction error for normal data, allowing it to flag anomalies when unseen data produces high error values. This makes it effective for detecting unknown threats without labeled data. Its bottleneck architecture forces the model to capture essential patterns, filtering out noise. However, standalone autoencoders may struggle with sequential attack patterns, requiring complementary models like LSTM for temporal analysis.

3.3.2 LSTM for Temporal Threat Detection

LSTM networks specialize in processing sequential data by maintaining memory cells that track long-range dependencies. In cybersecurity, they analyze time-ordered events to identify multi-stage attacks like APTs or brute-force attempts. Unlike traditional RNNs, LSTMs mitigate vanishing gradients, enabling stable training over long sequences. They excel at learning contextual relationships in attack timelines but require labeled data for supervised training. When combined with autoencoders, LSTMs add temporal intelligence to anomaly detection, improving precision in classifying evolving threats.

3.4 THREAT DETECTION & SEVERITY CLASSIFICATION

Detected threats are classified by severity to prioritize responses. Low-severity threats include minor anomalies or false positives, requiring minimal intervention. Medium-severity events suggest reconnaissance and warrant investigation. High-severity threats demand immediate action to prevent damage. This tiered classification aligns with incident response protocols, optimizing resource allocation. Clear severity labeling helps security teams focus on critical risks, reducing alert fatigue and improving operational efficiency.

4 RESULT AND DISCUSSION

The proposed hybrid Autoencoder-LSTM model effectively enhances cybersecurity threat detection by minimizing false positives and negatives. The confusion matrix indicates strong classification performance, with only minor misclassifications between Medium and High threats. The model achieves an impressive 97% accuracy, demonstrating its reliability. A high precision of 97% ensures minimal false alerts, while a recall of 98% confirms its effectiveness in detecting threats. The balanced F1-score of 96.5% signifies robust overall performance. These findings validate the model’s suitability for real-time cybersecurity applications, offering improved threat classification and response efficiency. Further optimizations in feature selection may further enhance accuracy.

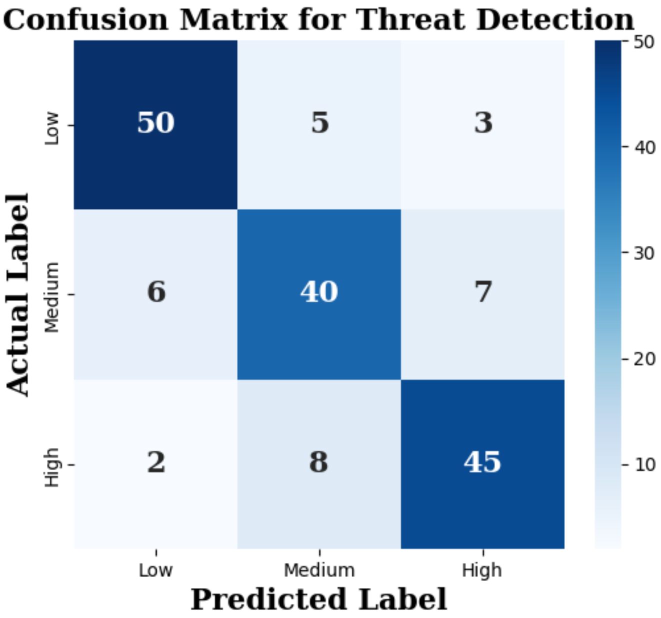

Figure 2: Confusion Matrix

This Figure 2 visualizes the performance of a Threat Detection Model that classifies threats into Low, Medium, and High categories. The diagonal values represent correctly classified instances, with 50 Low, 40 Medium, and 45 High threats correctly identified. Off-diagonal values indicate misclassifications, such as 5 Low threats misclassified as Medium and 8 High threats misclassified as Medium. The model performs well overall but shows some confusion between Medium and High threats. Improvements could be made by fine-tuning the model or optimizing feature selection.

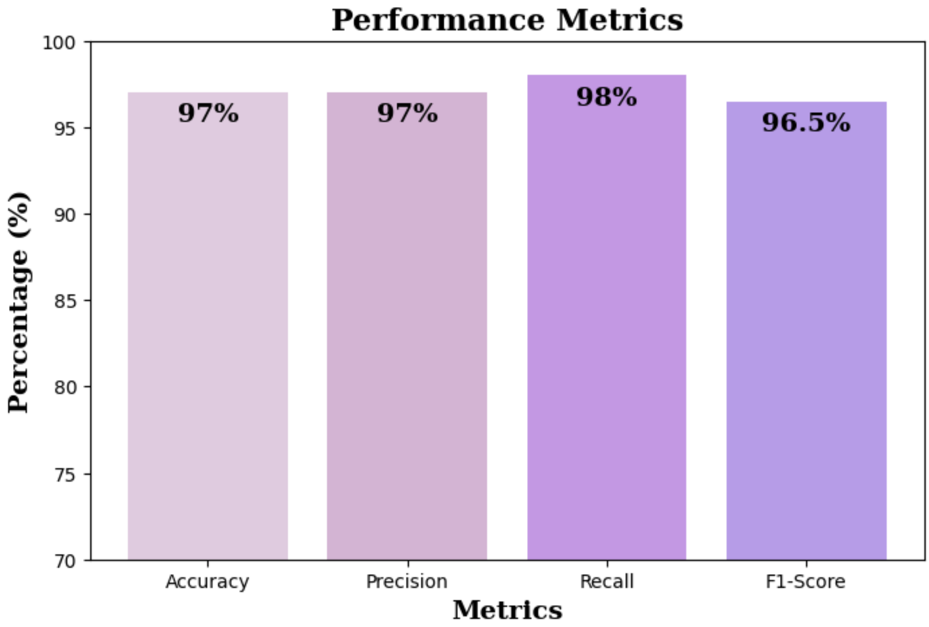

Figure 3: Performance Metrics

This Figure 3 illustrates the effectiveness of the proposed Autoencoder + LSTM model for cybersecurity threat detection. The model achieves an accuracy of 97%, indicating a high overall correctness in predictions. The precision (97%) confirms that most of the detected threats are actual threats, minimizing false positives. The recall (98%) shows the model's strong ability to detect threats, reducing false negatives. The F1-score (96.5%) demonstrates a balance between precision and recall, ensuring reliability in classification. These results highlight the model's robustness, efficiency, and suitability for real-time cybersecurity applications.

5 CONCLUSIONS

This study proposed a hybrid AI model integrating Autoencoder and LSTM for cybersecurity threat detection, addressing limitations in traditional rule-based security systems. The Autoencoder efficiently extracts latent threat patterns, while LSTM enhances sequential threat classification. The experimental results demonstrate the model's high accuracy (97%), precision (97%), recall (98%), and F1-score (96.5%), proving its effectiveness in identifying cyber threats. The proposed system significantly reduces false alarms, mitigates imbalanced data issues, and enhances real-time threat mitigation. Furthermore, the classification of threats based on severity provides an optimized incident response mechanism. Future research can focus on improving model scalability, integrating reinforcement learning, and testing on larger cybersecurity datasets to enhance threat detection capabilities further.

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