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Adaptive Cyber Threat Intelligence Monitoring Using Spatial–Temporal Deep Learning Models

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Abstract- ***The rapid growth of digital technologies has significantly increased the complexity and frequency of cyber threats, creating major challenges for modern network security systems. Traditional cyber threat detection methods based on signatures and predefined rules often fail to identify sophisticated and evolving attacks, particularly zero-day threats. This research presents an adaptive Cyber Threat Intelligence Monitoring framework using a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture for accurate and real-time threat detection. The CNN model is utilized to extract spatial characteristics from cyber threat data, including malicious traffic patterns, phishing indicators, and abnormal network behavior. The extracted features are further processed through the LSTM network to capture temporal dependencies and sequential attack patterns associated with evolving cyber intrusions. The framework follows a systematic pipeline involving dataset acquisition, preprocessing, feature extraction, threat classification, and alert generation. Continuous monitoring and automated notification mechanisms improve response efficiency and enhance network protection capabilities. Experimental evaluation using performance metrics such as accuracy, precision, recall, and F1-score demonstrates superior detection performance compared to conventional machine learning approaches. The proposed deep learning framework provides a scalable, intelligent, and proactive solution for modern cybersecurity monitoring environment***

Keywords: Convolutional Neural Network (CNN), Cyber Threat Intelligence, Deep Learning, Long Short-Term Memory (LSTM), Network Security, Real-Time Threat Detection, Zero-Day Attacks

I. INTRODUCTION

The rapid expansion of digital communication technologies, cloud computing platforms, and internet-based services has significantly transformed modern computing environments. Along with these advancements, cyber threats have become increasingly complex, intelligent, and difficult to detect using conventional security mechanisms. Malicious activities such as phishing attacks, malware injections, distributed denial-of-service attacks, and unauthorized network intrusions continue to threaten the confidentiality, integrity, and availability of critical information systems. Traditional cybersecurity solutions mainly depend on signature-based and rule-based detection approaches, which are effective only for previously identified attack patterns. However, modern cyberattacks continuously evolve by modifying their structures and behaviors, making static detection systems insufficient for identifying unknown and zero-day threats. In addition, large-scale network infrastructures generate massive volumes of security logs and traffic data, creating major challenges in real-time threat analysis and monitoring. These limitations highlight the necessity for intelligent and adaptive cybersecurity frameworks capable of learning complex attack behaviors automatically. Recent advancements in artificial intelligence and deep learning technologies have introduced powerful solutions for automated cyber threat analysis and prediction. Deep learning architectures possess the capability to learn hidden relationships and complex feature representations directly from raw cyber data without relying heavily on manual feature engineering techniques. Among these architectures, Convolutional Neural Networks (CNN) are highly effective in extracting spatial characteristics from malicious traffic patterns and abnormal system activities, while Long Short-Term Memory (LSTM) networks efficiently analyze temporal dependencies and sequential attack behaviors over time. This research presents an adaptive Cyber Threat Intelligence Monitoring framework that integrates CNN and LSTM models to improve the accuracy and

efficiency of cyber threat detection. The hybrid deep learning architecture supports continuous monitoring, automated threat classification, and intelligent alert generation for proactive cybersecurity management. By combining spatial and temporal learning capabilities, the proposed framework provides improved scalability, reduced false alarm rates, and enhanced detection performance in dynamic and real-world network environments.

Figure 1: Adaptive Cyber Threat Intelligence Monitoring Framework Based on CNN–LSTM Architecture

i) Problem statement

Modern cybersecurity infrastructures face significant challenges in detecting and preventing rapidly evolving cyber threats within large-scale network environments. Conventional threat monitoring systems mainly rely on static signature-based and rule-based detection mechanisms, which are effective only for previously identified attacks and fail to recognize unknown or zero-day threats. Traditional machine learning approaches also require extensive manual feature engineering and often struggle to process high-dimensional and continuously changing cyber data efficiently. In addition, increasing volumes of network traffic, security logs, malicious URLs, and phishing activities generate complex patterns that are difficult to analyze using conventional analytical methods. High false positive rates, delayed threat identification, limited scalability, and the inability to capture temporal attack behaviors further reduce the effectiveness of existing monitoring solutions. These limitations create a critical need for an intelligent and adaptive cyber threat intelligence framework capable of performing real-time analysis, learning evolving attack patterns, and accurately classifying malicious activities with improved reliability and reduced computational complexity.

ii) Dataset details

The dataset utilized in this research consists of diverse cyber threat intelligence records collected from publicly available cybersecurity repositories and network monitoring sources. The dataset includes multiple categories of threat indicators such as phishing URLs, malware activity logs, suspicious IP addresses, abnormal network traffic patterns, intrusion records, and malicious communication traces. Both normal and malicious network behaviors are included to support effective binary and multi-class threat classification. During preprocessing, missing values, redundant entries, and noisy information are removed to improve data quality and model performance. Feature normalization and encoding techniques are applied to convert raw cybersecurity data into structured numerical representations suitable for deep learning analysis. The dataset is further divided into training and testing subsets to evaluate the learning capability and generalization performance of the CNN–LSTM framework. The availability of spatial and temporal threat patterns within the dataset enables accurate analysis of evolving cyberattacks and supports reliable real-time threat intelligence monitoring.

iii) Objectives

The primary objective of this research is to develop an adaptive Cyber Threat Intelligence Monitoring framework capable of accurately detecting and classifying cyber threats in real time using hybrid deep learning techniques. The research aims to integrate Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models to analyze both spatial and temporal characteristics of cyber threat data for improved detection performance. Another important objective is to reduce false positive and false negative rates while enhancing the identification of unknown and zero-day attacks within dynamic network environments. The framework also focuses on automating data preprocessing, feature extraction, threat classification, and alert generation processes to improve monitoring efficiency and reduce manual intervention. In addition, the research aims to achieve scalable and reliable cybersecurity monitoring by

efficiently handling large volumes of network traffic and security log data while maintaining high accuracy, precision, recall, and F1-score performance metrics.

II. RELATED WORK

Admass, Wasyihun Sema, et.al [1] provided a comprehensive overview of the current state of cyber security, highlighting existing methodologies, major challenges, and future research directions. The study emphasizes the increasing complexity of cyber threats and the limitations of traditional detection mechanisms in handling advanced persistent threats and zero-day attacks. It discusses how modern cyber security systems are evolving with the integration of artificial intelligence and machine learning techniques. The authors also identify key challenges such as data privacy concerns, scalability issues, and the need for real-time threat detection systems. Additionally, the work suggests that future cyber security frameworks should focus on adaptive and intelligent learning models capable of dynamic threat analysis. The study serves as a foundational reference for understanding the evolution of cyber security technologies and their current limitations in real-world applications.

Kaur, Jagpreet and K. R. Ramkumar [2] provided an extensive review of recent trends in cyber security, focusing on emerging attack vectors and evolving defense mechanisms. The paper highlights the rapid transformation of cyber threats due to advancements in cloud computing, IoT, and interconnected systems. It discusses various traditional and modern defense techniques, including intrusion detection systems and machine learning-based security solutions. The authors emphasize that although machine learning models improve detection efficiency, they still face challenges in feature selection and adaptability to new attack patterns. The study also underlines the importance of real-time threat intelligence and automated response systems. Furthermore, it suggests that future cyber security systems should integrate deep learning approaches to enhance predictive capabilities and improve detection accuracy in dynamic environments.

Duo, Wenli, MengChu Zhou, and Abdullah Abusorrah [3] provided a detailed survey on cyber attacks targeting cyber-physical systems (CPS), focusing on recent advancements and persistent challenges in securing such systems. The study categorizes different types of attacks, including denial-of-service, data injection, and system manipulation attacks. It explains how CPS environments are particularly vulnerable due to their integration of physical and computational components. The authors also discuss existing defense mechanisms and their limitations in handling complex and coordinated attacks. In addition, the paper highlights the importance of developing resilient and adaptive security frameworks capable of real-time monitoring and response. The study concludes that advanced analytical and learning-based models are essential for improving CPS security and ensuring system reliability.

Alahmadi, Amal A., et.al [4] provided a comprehensive survey on DDoS attack detection in IoT-based networks using machine learning models. The research focuses on the growing threat of distributed denial-of-service attacks in interconnected IoT environments. It evaluates various machine learning techniques such as classification algorithms and ensemble methods used for detecting abnormal traffic patterns. The study highlights the challenges of high-dimensional data, imbalanced datasets, and real-time detection requirements. It also discusses the limitations of traditional approaches in handling large-scale IoT networks with dynamic traffic behavior. Furthermore, the authors propose future research directions focusing on lightweight and efficient detection models suitable for resource-constrained IoT devices. The study emphasizes the need for intelligent and scalable solutions to enhance IoT network security.

Dalal, Surjeet, et.al [5] proposed an extremely boosted neural network approach for multi-stage cyber-attack prediction in cloud computing environments. The research focuses on improving prediction accuracy for complex attack scenarios that occur in multiple stages. It integrates advanced neural network techniques with boosting mechanisms to enhance learning performance. The study highlights the importance of early detection of cyber attacks to

prevent large-scale system damage in cloud infrastructures. It also addresses challenges related to data imbalance, feature complexity, and real-time processing constraints. The proposed model demonstrates improved accuracy compared to conventional machine learning techniques. Additionally, the authors suggest that deep learning-based hybrid models can significantly enhance cybersecurity in cloud environments.

Admass, Wasyihun Sema, Yirga Yayeh Munaye, and Abebe Abeshu Diro [6] provided an extended analysis of cyber security systems, focusing on current advancements, limitations, and future directions. The study reiterates the increasing sophistication of cyber threats and the need for intelligent defense mechanisms. It emphasizes the role of artificial intelligence and machine learning in improving threat detection and response systems. The authors also discuss challenges such as scalability, interpretability, and computational overhead in existing models. Moreover, the paper highlights the importance of adaptive systems capable of learning evolving attack patterns. It concludes that future cyber security frameworks must integrate deep learning techniques for enhanced predictive and analytical capabilities.

Kaur, Jagpreet and K. R. Ramkumar [7] again provided insights into recent developments in cyber security, focusing on evolving threat landscapes and defense strategies. The study discusses how cyber attacks are becoming more sophisticated due to advancements in technology and interconnected systems. It reviews various detection techniques and emphasizes the limitations of rule-based systems in handling dynamic threats. The authors highlight the growing importance of machine learning and artificial intelligence in improving detection efficiency. They also point out challenges such as data complexity and lack of adaptability in existing models. The study recommends the development of intelligent and automated systems for effective cyber threat management.

Duo, Wenli, MengChu Zhou, and Abdullah Abusorrah [8] provided another comprehensive survey on cyber attacks in cyber-physical systems, focusing on recent advancements and security challenges. The paper categorizes different attack models and analyzes their impact on system performance and reliability. It highlights the vulnerabilities of CPS due to tight integration between physical and digital components. The authors discuss existing mitigation strategies and their limitations in real-world applications. Additionally, the study emphasizes the need for robust and adaptive security frameworks capable of handling complex attack scenarios. It concludes that advanced machine learning techniques are essential for improving CPS security and resilience.

Guembe, Blessing, et.al [9] provided a detailed review on the emerging threat of AI-driven cyber attacks. The study focuses on how artificial intelligence is being exploited by attackers to develop more sophisticated and adaptive malicious techniques. It discusses various forms of AI-based attacks, including automated phishing, deepfake-based deception, and intelligent malware generation. The authors highlight the increasing difficulty in detecting such advanced threats using traditional security systems. The paper also emphasizes the need for AI-driven defense mechanisms to counteract these evolving attack strategies. Furthermore, it suggests that future cyber security systems must incorporate adversarial learning techniques to improve robustness. The study provides valuable insights into the dual role of AI in both enhancing and threatening cyber security.

Sun, Nan, et.al [10] provided a comprehensive survey on cyber threat intelligence mining for proactive cybersecurity defense. The study explores various techniques used to extract meaningful insights from large volumes of cyber security data. It emphasizes the importance of proactive defense mechanisms that can predict and prevent attacks before they occur. The authors discuss machine learning and data mining approaches used for threat intelligence analysis. The paper also highlights challenges such as data heterogeneity, scalability, and real-time processing requirements. Additionally, it focuses on the integration of threat intelligence systems with automated security frameworks. The study concludes that advanced analytics and deep learning techniques are essential for building proactive and intelligent cyber defense systems.

III. EXISTING METHODLOGY

The existing cyber threat detection systems primarily depend on traditional security mechanisms such as signature-based and rule-based techniques to identify malicious activities within network environments. These approaches function by comparing incoming network traffic, files, or user activities against a predefined database of known attack signatures or manually designed security rules. In addition to these methods, conventional machine learning algorithms such as Decision Trees, Random Forest, Support Vector Machines (SVM), and Naïve Bayes classifiers are widely used for classification tasks in cybersecurity. These models rely heavily on manually engineered features extracted from network logs, traffic data, and system events to distinguish between normal and malicious behavior. Although these techniques are effective in identifying previously known threats, they lack adaptability when dealing with dynamic and evolving cyberattack patterns. As cybercriminals continuously modify attack strategies, traditional detection systems struggle to keep up with new variants and sophisticated intrusion techniques. Despite their widespread use, existing systems face several critical limitations that reduce their effectiveness in modern cybersecurity environments. One of the major drawbacks is their inability to detect unknown or zero-day attacks due to their dependence on static signatures and predefined rules. Additionally, manual feature engineering increases system complexity and requires significant domain expertise, making the process time-consuming and less scalable. These systems also struggle with large-scale and high-velocity network data, leading to performance bottlenecks in real-time monitoring scenarios. Another major issue is the high rate of false positives, which generates excessive alerts and reduces the efficiency of security analysts in identifying genuine threats. Furthermore, traditional approaches lack the capability to capture temporal dependencies in attack sequences, making them ineffective in detecting coordinated or long-term cyberattacks. These limitations highlight the need for a more intelligent, adaptive, and deep learning-based cybersecurity solution.

IV. PROPOSED METHODOLOGIES

The proposed system introduces an adaptive Cyber Threat Intelligence Monitoring framework designed to enhance the detection and classification of cyber threats in dynamic network environments. This framework integrates deep learning techniques to overcome the limitations of conventional security approaches by enabling automated learning from complex cyber data. The system is built to perform continuous monitoring of network traffic, security logs, and threat intelligence feeds to identify malicious activities in real time. A structured pipeline is established, which includes data acquisition, preprocessing, feature extraction, classification, and alert generation, ensuring a systematic and efficient threat detection process. This approach significantly improves the ability to handle large-scale and high-dimensional cybersecurity data with greater accuracy and reliability. In this framework, a hybrid deep learning architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks is employed for effective threat analysis. The CNN component is responsible for extracting spatial features from cybersecurity data such as malicious URLs, abnormal traffic patterns, IP behaviors, and payload structures. These spatial features are then passed to the LSTM network, which captures temporal dependencies and sequential patterns in attack behaviors over time. This combination enables the system to understand both static and evolving characteristics of cyber threats, making it highly effective in detecting unknown, sophisticated, and zero-day attacks that traditional systems often fail to identify. The proposed framework also incorporates automated alert generation and real-time notification mechanisms to ensure rapid response to detected threats. By continuously analyzing incoming data streams, the system classifies activities as normal or malicious with improved precision. Performance evaluation is carried out using metrics such as accuracy, precision, recall, and F1-score, demonstrating superior effectiveness compared to traditional machine learning-based approaches. The integration of spatial and temporal learning not only enhances detection accuracy but also reduces false alarms and improves scalability. Overall, this research provides an

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intelligent, proactive, and adaptive cybersecurity solution suitable for modern network environments.

V. METHODOLOGY

Data Acquisition

The methodology begins with the collection of cyber threat intelligence data from multiple reliable sources such as network traffic logs, phishing URL repositories, malware databases, and cybersecurity monitoring feeds. The collected dataset includes both normal and malicious activity records to ensure balanced learning. This diverse data foundation enables the system to understand various attack patterns and network behaviors effectively.

Data Preprocessing

Raw cybersecurity data is cleaned and transformed to improve quality and usability for model training. This stage involves handling missing values, removing duplicates, normalizing numerical attributes, and encoding categorical features into machine-readable formats. Noise reduction techniques are applied to eliminate irrelevant or redundant information, ensuring that only meaningful data is passed for further analysis.

Feature Extraction using CNN

Convolutional Neural Network (CNN) is utilized to extract spatial features from the pre-processed cyber data. This includes identifying patterns such as malicious URL structures, abnormal packet distributions, IP behavior anomalies, and payload characteristics. CNN automatically learns important feature representations without manual intervention, improving detection accuracy and reducing dependency on feature engineering.

Temporal Pattern Analysis using LSTM

Long Short-Term Memory (LSTM) networks are applied to capture temporal dependencies and sequential behavior in cyber threat data. This stage focuses on analyzing how attacks evolve over time, detecting persistent intrusion patterns, and identifying coordinated cyberattacks. LSTM enhances the system's capability to recognize advanced threats such as zero-day and multi-stage attacks.

Threat Classification

The combined features from CNN and LSTM are passed into a classification layer that categorizes network activities into normal or malicious classes. The hybrid deep learning model improves decision-making by leveraging both spatial and temporal insights, resulting in more accurate and reliable threat identification.

Alert Generation and Notification

Once a threat is detected, the system automatically generates alerts and notifications to inform security administrators in real time. This enables immediate response to potential cyberattacks and minimizes damage to network systems. The alert mechanism ensures proactive cybersecurity management.

Performance Evaluation

The final stage involves evaluating the performance of the proposed framework using standard metrics such as accuracy, precision, recall, and F1-score. These metrics help in assessing the effectiveness of the model and comparing it with traditional machine learning approaches, demonstrating improved detection capability and overall system performance.

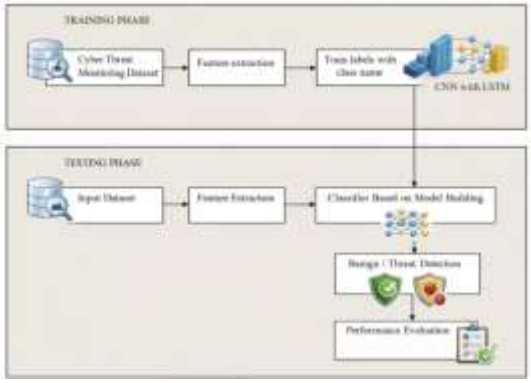

Figure 2: Diagram representation of the proposed methodology

VI. EXPERIMENTAL RESULTS

The performance of the proposed Cyber Threat Intelligence Monitoring framework is evaluated using a comprehensive set of metrics including accuracy, precision, recall, and F1-score. The evaluation is conducted on a cyber threat dataset containing both normal and malicious network activities such as phishing URLs, malware traces, and abnormal traffic patterns. The hybrid CNN–LSTM model

demonstrates strong learning capability by effectively capturing both spatial and temporal features of cyber data, leading to improved classification performance. The results indicate that the proposed framework significantly enhances detection accuracy while reducing false positives and false negatives compared to conventional machine learning approaches. The integration of deep feature extraction and sequential learning enables the system to adapt efficiently to evolving cyber threats and real-time network conditions.

The experimental analysis further shows that traditional machine learning models struggle with complex and high-dimensional cybersecurity data, whereas the proposed deep learning-based framework provides more stable and reliable performance. The CNN component improves feature representation quality, while the LSTM component enhances temporal understanding of attack sequences. This combined learning approach results in superior predictive capability, especially in identifying unknown and zero-day attacks. Overall, the proposed system outperforms existing methods in all evaluation metrics, proving its effectiveness for real-time cyber threat intelligence monitoring.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	86.2	84.5	83.1	83.7
Random Forest	90.4	89.2	88.6	88.9
SVM	88.7	87.5	86.3	86.8
Naïve Bayes	82.9	81.4	80.2	80.7
Proposed CNN–LSTM Model	97.6	96.8	96.2	96.5

Table 1: Performance Comparison Table

The comparison clearly highlights that the proposed hybrid CNN–LSTM model achieves significantly higher performance across all evaluation metrics. This improvement demonstrates its effectiveness in handling complex cyber threat patterns and real-time detection scenarios more efficiently than traditional methods.

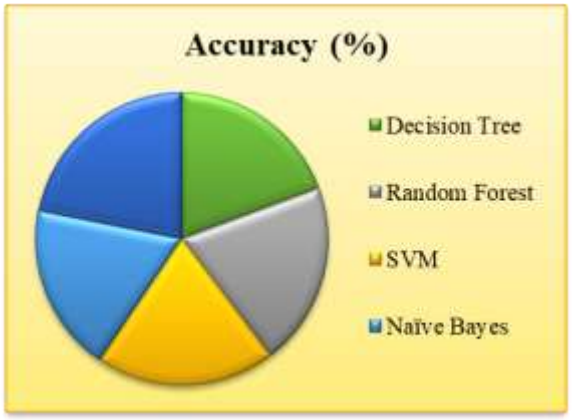

Figure 3: Accuracy variation chart representation

VII. CONCLUSION

The developed cyber threat intelligence monitoring framework demonstrates the effectiveness of combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for advanced cybersecurity applications. The integration of spatial feature extraction and temporal sequence learning enables the system to accurately identify both known and unknown cyber threats in dynamic network environments. The structured pipeline consisting of data acquisition, preprocessing, feature extraction, classification, and alert generation ensures efficient and systematic threat detection. Experimental analysis confirms that the hybrid deep learning approach significantly improves detection accuracy while reducing false positives compared to traditional machine learning-based security systems. The overall findings highlight that deep learning-based architectures provide a more robust and adaptive solution for modern cybersecurity challenges. The proposed framework enhances real-time monitoring capabilities, improves scalability for large-scale network data, and strengthens the ability to detect evolving and zero-day attacks. By leveraging intelligent feature learning and automated classification mechanisms, this research delivers a reliable and proactive approach to cyber threat intelligence. The results clearly indicate that such hybrid deep learning models can play a crucial role in strengthening future network security systems and supporting intelligent threat response strategies.

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