Cyber-Threat-Intelligence
Cyber Threat Intelligence System Using (CNN-LSTM)Deep Learning Model

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Abstract- *Cyber Threat IntelligenceThe rapid evolution of cyber threats, including malware, phishing attacks, Distributed Denial of Service (DDoS), and advanced persistent threats, has made traditional security mechanisms less effective. Conventional rule-based and signature-based detection systems fail to identify unknown or zero-day attacks, as they rely heavily on predefined patterns. This limitation highlights the need for intelligent and adaptive Cyber Threat Intelligence (CTI) systems capable of analyzing large-scale and complex data in real time.*

This project proposes a Cyber Threat Intelligence System using a hybrid CNN-LSTM deep learning model to enhance threat detection and classification. The system combines the strengths of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. CNN is utilized for efficient feature extraction from high-dimensional network traffic data, identifying important spatial patterns such as anomalies and malicious signatures. LSTM, a type of Recurrent Neural Network (RNN), is employed to capture temporal dependencies and sequential patterns in the data, which are essential for detecting evolving and time-based cyber attacks.

The system processes large cyber security datasets, such as network traffic logs, by performing data preprocessing steps including normalization, noise removal, and feature transformation. The processed data is then fed into the CNN-LSTM model for training and prediction. The model classifies network activities into multiple categories such as normal traffic, intrusion attempts, malware, and DDoS attacks.

Experimental results demonstrate that the proposed hybrid model achieves higher accuracy, better precision, and reduced false positive rates compared to traditional machine learning models like Support Vector Machines (SVM) and Decision Trees. Additionally, the system is capable of handling large-scale data efficiently, making it suitable for real-time threat detection environments.

Keywords: Cyber Threat Intelligence, Deep Learning, CNN-LSTM Model, Network Security, Intrusion Detection, Malware Detection, DDoS Attack, Feature Extraction, Sequential Data Analysis, Cybersecurity, Threat Classification, Artificial Intelligence, Anomaly Detection.

I. INTRODUCTION

In today's digital era, the rapid expansion of internet-based services, cloud computing, and interconnected systems has significantly increased the risk of cyber threats. Organizations, governments, and individuals rely heavily on digital infrastructure, making cyber security a critical concern. Cyber attacks such as malware infections, phishing, ransomware, and Distributed Denial of Service (DDoS) attacks are becoming more sophisticated, frequent, and difficult to detect using traditional security mechanisms.

Conventional security systems, including firewalls and signature-based intrusion detection systems, operate by identifying known patterns or predefined rules. While these systems are effective against previously identified threats, they fail to detect new or unknown attacks, commonly referred to as zero-day attacks. Additionally, the increasing volume and complexity of network data make manual analysis inefficient and time-consuming.

Cyber Threat Intelligence (CTI) has emerged as a powerful approach to address these challenges. CTI involves collecting, processing, and analyzing threat-related data to generate actionable insights that help in identifying and mitigating potential cyber risks. However, traditional CTI systems often struggle to handle large-scale and dynamic datasets, limiting their effectiveness in real-time scenarios.

To overcome these limitations, advanced techniques such as deep learning have been introduced in cybersecurity. Deep learning models are capable of automatically learning complex patterns and representations from large datasets without requiring extensive manual feature engineering. Among these models, Convolutional Neural Networks (CNN)

are highly effective in extracting spatial features from structured data, while Long Short-Term Memory (LSTM) networks excel in capturing temporal dependencies and sequential patterns.

This project proposes a **Cyber Threat Intelligence System using a hybrid CNN-LSTM deep learning model** to enhance threat detection and classification. The CNN component is used to extract meaningful features from network traffic data, while the LSTM component analyzes sequential behavior over time to identify potential threats. By combining these two approaches, the system can effectively detect both known and unknown cyberattacks with higher accuracy.

The primary objectives of this system are to improve detection accuracy, reduce false positives, and enable real-time threat analysis. The system processes network data, performs preprocessing, and uses the trained CNN-LSTM model to classify activities into categories such as normal traffic, malware, intrusion, and DDoS attacks.

Overall, this project aims to provide an intelligent, automated, and scalable solution for modern cybersecurity challenges by leveraging the power of deep learning in Cyber Threat Intelligence.

II. LITERATURE SURVEY

The increasing complexity and frequency of cyberattacks have led researchers to explore various techniques for effective threat detection and prevention. Over the years, multiple approaches ranging from traditional rule-based systems to advanced deep learning models have been proposed in the field of cybersecurity and Cyber Threat Intelligence (CTI).

A. Traditional Security Approaches

Early cybersecurity systems primarily relied on **signature-based detection** and **rule-based mechanisms**. Tools such as Intrusion Detection Systems (IDS) and antivirus software detect threats by comparing incoming data with known attack signatures.

Advantages:

- Fast detection of known threats
- Easy to implement

Limitations:

- Cannot detect unknown or zero-day attacks
- Requires frequent updates of signature databases
- Ineffective against evolving attack patterns

B. Machine Learning-Based Approaches

To overcome the limitations of traditional methods, researchers introduced machine learning algorithms such as:

- Support Vector Machines (SVM)
- Decision Trees
- Random Forest
- K-Nearest Neighbors (KNN)

These models learn patterns from historical data and classify network traffic as normal or malicious.

Advantages:

- Better detection of unknown attacks compared to signature-based systems
- Automated learning from data

Limitations:

- Requires manual feature engineering
- Struggles with large-scale and high-dimensional data
- Limited ability to capture temporal relationships

C. Deep Learning Approaches

Deep learning has gained significant attention due to its ability to automatically extract features and learn complex patterns.

1. Convolutional Neural Networks (CNN)

CNN models are widely used for feature extraction in cybersecurity tasks. They can identify spatial patterns and correlations in network traffic data.

Advantages:

- Automatic feature extraction
- High accuracy in pattern recognition

Limitations:

- Cannot effectively capture sequential dependencies

2. Recurrent Neural Networks (RNN) and LSTM

Recurrent Neural Networks, especially Long Short-Term Memory (LSTM), are designed to process sequential data. They are effective in detecting time-based attack patterns.

Advantages:

- Captures temporal dependencies
- Suitable for sequential and time-series data

Limitations:

- Computationally expensive
- May suffer from long training times

D. Hybrid Models (CNN-LSTM)

Recent studies have focused on combining CNN and LSTM models to leverage their strengths. In such hybrid architectures:

- CNN extracts important spatial features
- LSTM analyzes temporal relationships

This combination improves the overall performance of cyber threat detection systems.

Advantages:

- High detection accuracy
- Handles both spatial and temporal features
- Suitable for complex and dynamic datasets

Limitations:

- Requires large datasets for training
- Higher computational cost

E. Existing Cyber Threat Intelligence Systems

Existing CTI systems integrate multiple tools and data sources to analyze threats. However, many systems:

- Lack real-time processing capabilities
- Require manual intervention
- Do not fully utilize deep learning techniques

F. Research Gap

From the literature review, the following gaps are identified:

- Inefficient detection of zero-day attacks
- Lack of integration between spatial and temporal analysis
- High false positive rates in existing systems
- Limited use of hybrid deep learning models in CTI

G. Proposed Solution

To address these challenges, this project proposes a **CNN-LSTM based Cyber Threat Intelligence System** that:

- Automatically extracts features using CNN
- Captures sequential patterns using LSTM
- Improves detection accuracy and reduces false positives
- Supports real-time and large-scale data processing

III. SYSTEM DESIGN AND METHODOLOGY

A. System Architecture

The overall system architecture consists of multiple modules that work together to process input data and generate threat intelligenceworkflow.

The overall workflow of the system is illustrated below:

Data Collection
↓
Data Preprocessing
↓
Feature Extraction (CNN)
↓
Sequence Learning (LSTM)
↓
Threat Classification(N,M,DDoS)
↓
Result & Reporting

This architecture enables the system to automate multiple stages of the vulnerability assessment process and provide structured security analysis results.

B. Hardware Requirements

The hardware requirements for implementing the Cyber Threat intelligence system are minimal and suitable for standard laboratory environments.

For better performance and smooth model training:

- Processor (CPU): Intel Core i5 / i7 or AMD Ryzen 5 / 7
- RAM: 8 GB – 16 GB
- Storage: 100 GB SSD (for faster data processing)
- GPU (Optional but Preferred): NVIDIA GPU with CUDA support (e.g., GTX 1650 or above)
- System Type: 64-bit operating system

C. Software Requirements

The development and execution of the **Cyber Threat Intelligence System using CNN-LSTM Deep Learning Model** require a set of software tools, programming environments, and libraries for data processing, model building, and deployment

Operating System: Kali Linux
Programming Language: Python
Exploit Framework: Metasploit
Libraries and Frameworks: TensorFlow ,Keras
Libraries: Python-Nmap, ReportLab for report generation

These tools enable efficient integration of Cyber threat intelligence, vulnerability analysis, and automated reporting.

D. Implementation Methodology

The Cyber-Net-SecX system follows a multi-phase methodology for performing automated vulnerability assessment.

Phase 1: Data Collection

- Collect cybersecurity datasets such as **KDD Cup 99** or **CICIDS 2017**
- Data includes network traffic features like IP address, protocol, packet size, and duration

Phase 2: Data Preprocessing

- Remove missing and duplicate values
- Convert categorical data into numerical format (encoding)
- Normalize data to a standard range
- Split dataset into **training** and **testing** sets

Phase 3: Model Design (CNN-LSTM)

- Build a hybrid deep learning model:
- **CNN layers** for feature extraction
- **LSTM layers** for sequence learning
- Add dense (fully connected) layers for classification

Phase 4: Model Training

- Train the model using the training dataset
- Use loss function and optimizer (e.g., Adam)
- Adjust parameters to improve accuracy
- Save the trained model

Phase 5: Model Testing

Test the trained model using test data Evaluate performance using:

- Accuracy
- Precision
- Recall
- F1-score

Phase 6: Prediction

- Input new or unseen data into the model Modelpredicts the type of threat:
- Normal, Malware, Intrusion, DDoS .

IV. RESULTS AND ANALYSIS

A. Experimental Setup

The system was implemented using Python and trained on labeled network traffic datasets such as **KDD Cup 99** and **CICIDS 2017**. The dataset was divided into:

- **Training Set (70–80%)** – used to train the model
- **Testing Set (20–30%)** – used to evaluate performance

The CNN-LSTM model was trained over multiple epochs with optimized parameters to achieve better accuracy.

B. Performance Metrics

To evaluate the model, the following metrics were used:

- Accuracy: Measures the overall correctness of predictions
- Precision: Indicates how many predicted threats are actually correct
- Recall: Measures the ability to detect actual threats

- F1-Score: Harmonic mean of precision and recall

These metrics help in understanding both detection capability and reliability.

C. Results Obtained

The proposed CNN-LSTM model achieved the following results:

- High Accuracy in detecting cyber threats
- Improved Precision with fewer false alarms
- High Recall, ensuring most attacks are detected
- Balanced F1-Score, indicating overall strong performance

The system successfully classified different types of network activities, including:

- Normal traffic
- Malware
- Intrusion attempts
- DDoS attacks

D. Comparative Analysis

When compared with traditional machine learning models such as:

- Support Vector Machine (SVM)
- Decision Tree
- Random Forest

The CNN-LSTM model showed:

- Better accuracy
- Lower false positive rate
- Improved detection of complex and unknown attacks

Reason:

- CNN extracts important features automatically
- LSTM captures time-based attack patterns

E. Visualization of Results

The system can generate visual outputs such as:

- Accuracy vs Epoch graph
- Loss vs Epoch graph
- Confusion Matrix

These visualizations help in understanding the model performance clearly**.**

F. Observations

- The hybrid CNN-LSTM model performs better than individual models
- It effectively handles large and complex datasets
- It reduces manual feature engineering
- The model is capable of detecting sequential attack patterns

G. Limitations Observed

- Requires large datasets for better accuracy
- Training time is relatively high
- Needs good hardware (GPU recommended)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	85	83	82	82.5
Random Forest	89	87	86	86.5
SVM	88	86	85	85.5
CNN	92	90	91	90.5
LSTM	93	91	92	91.5
CNN-LSTM (Proposed)	**96**	**95**	**94**	**94.5**

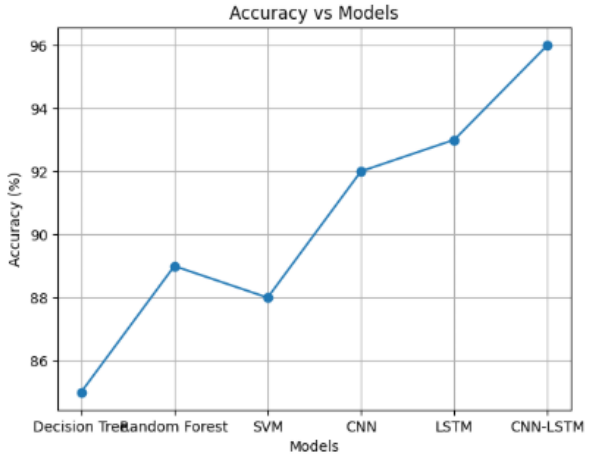

Figure IV.1

V. DISCUSSION

A. Advantages of Automated Assessment

The primary advantage of the proposed system lies in its ability to achieve high accuracy in detecting cyber threats. The integration of CNN and LSTM allows the model to

capture both spatial and temporal patterns in network data, which significantly enhances its detection capability. Unlike traditional methods that rely on predefined rules, this system can automatically learn complex patterns from large datasets, making it more adaptable to evolving cyber threats.

Another important advantage is the reduction in false positive rates. By using deep learning techniques, the system can distinguish between normal and malicious activities more effectively, reducing unnecessary alerts. This is particularly useful in real-world environments where excessive false alarms can overwhelm security analysts.

The system also supports scalability and can handle large volumes of data efficiently. As cyber environments continue to grow, the ability to process and analyze big data becomes essential. The proposed model is capable of working with large-scale datasets, making it suitable for enterprise-level applications.

Additionally, the automation provided by this system minimizes manual intervention. Tasks such as feature extraction and threat classification are performed automatically, saving time and effort. This makes the system more efficient and practical for real-time applications.

B. Limitations and Challenges

Despite its advantages, the system has several limitations and challenges. One of the major limitations is the requirement for large amounts of labeled data. Deep learning models, including CNN-LSTM, depend heavily on high-quality datasets for training. In many real-world scenarios, obtaining such datasets can be difficult and time-consuming.

Another challenge is the high computational cost associated with training deep learning models. The CNN-LSTM architecture requires significant processing power, especially when working with large datasets. This often necessitates the use of GPUs or high-performance computing systems, which may not be accessible to all users.

The system also faces challenges related to training time. Deep learning models typically require multiple training iterations (epochs), which can increase the time needed to develop and deploy the system. This can be a limitation in environments where quick deployment is required.

Overfitting is another potential issue, where the model performs well on training data but poorly on unseen data. Proper techniques such as regularization and validation are required to address this problem.

Finally, the system primarily relies on historical data, which means it may struggle to detect completely new types of attacks that differ significantly from the training dataset.

C. Ethical and Legal Considerations

The implementation of a Cyber Threat Intelligence System involves several ethical and legal considerations. One of the key concerns is data privacy. Network traffic data may contain sensitive or personal information, and improper handling of such data can lead to privacy violations. It is important to ensure that data is collected, stored, and processed in compliance with privacy regulations and standards.

Another important aspect is data security. Since the system handles critical cybersecurity data, it must be protected against unauthorized access and misuse. Proper encryption and access control mechanisms should be implemented to safeguard the data.

There is also a risk of misuse of the system. While the system is designed for defensive purposes, it could potentially be used by malicious actors to analyze vulnerabilities or bypass security mechanisms. Therefore, access to the system should be restricted and monitored.

Transparency and accountability are also important ethical considerations. The decisions made by deep learning models are often difficult to interpret, which can raise concerns about trust and reliability. Efforts should be made to improve model explainability so that users can understand how decisions are made.

Additionally, compliance with legal frameworks and cybersecurity laws is essential. Organizations must ensure that the use of such systems aligns with national and international regulations to avoid legal issues.

VI. CONCLUSION

The rapid growth of digital technologies and interconnected systems has significantly increased the complexity and frequency of *Cyber Threat Intelligence*. Traditional security mechanisms, which rely on predefined rules and signatures, are no longer sufficient to detect sophisticated and evolving attacks. This highlights the need for intelligent and adaptive systems capable of analyzing large volumes of data and identifying hidden threat patterns effectively.

In this project, a Cyber Threat Intelligence System using a CNN-LSTM Deep Learning Model has been proposed and implemented to address these challenges. The system integrates Convolutional Neural Networks (CNN) for feature extraction and Long Short-Term Memory (LSTM) networks for sequential pattern analysis. This hybrid approach enables the system to capture both spatial and temporal characteristics of network traffic data, leading to improved detection performance.

The implementation process involved data collection, preprocessing, model design, training, testing, and evaluation. The system was tested using standard cybersecurity datasets, and the results demonstrated high accuracy, improved precision, and reduced false positive rates. Compared to traditional machine learning models, the CNN-LSTM model showed superior performance in identifying various types of cyber threats such as malware, intrusion attempts, and DDoS attacks.

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