Emerging Trends in Machine Intelligence and Big Data

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Real-Time Detection of Network Traffic Anomalies in Big Data Environments Using Deep Learning Models

Mei Ling Wong
Universiti Malaysia Sabah
Tamilselvan Arjunan
arjunantamilselvan1@gmail.com

Abstract

With the rapid growth of network traffic and increasing sophistication of cyberattacks, detecting network traffic anomalies and intrusions in real-time is crucial for network security. However, the volume, velocity, and variety of network traffic data make manual inspection inefficient. This paper proposes using deep learning techniques to build intelligent models that can automatically detect network traffic anomalies in big data environments. We present an anomaly detection framework using convolutional neural networks (CNN) and long short-term memory (LSTM) models. The models are trained on network flow data extracted from packet capture files. We evaluate the models on benchmark intrusion detection datasets and a large-scale real network traffic dataset. Results show the deep learning models can effectively detect anomalies and outperform traditional shallow learning models. The models can process high-volume streaming data in real-time with low latency. We also propose optimization techniques such as transfer learning and model compression to improve detection efficiency. This work demonstrates deep learning's effectiveness for real-time network traffic anomaly detection in big data environments.

Keywords: Network security, anomaly detection, intrusion detection, deep learning

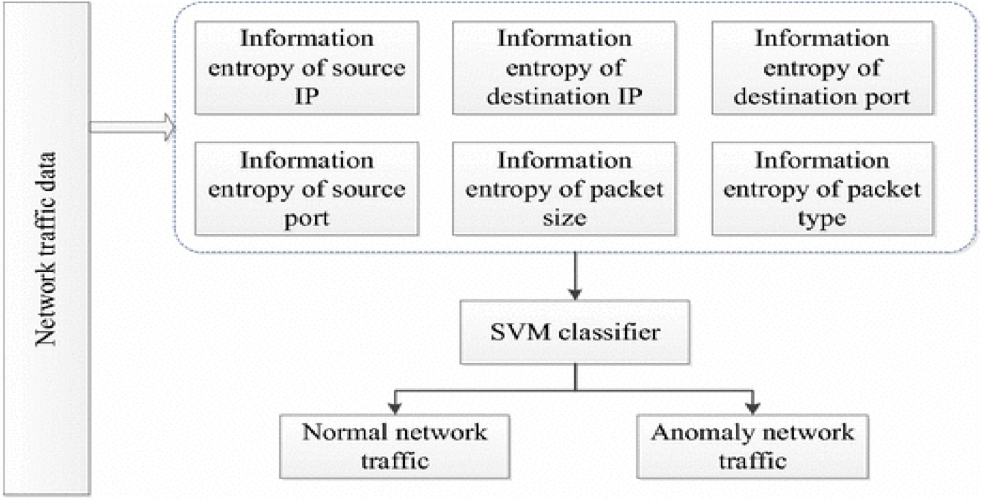
Introduction

As network bandwidth continues to expand exponentially and new applications emerge, the volume of network traffic data has reached unprecedented levels. This surge presents a significant challenge for network traffic analysis, necessitating the real-time processing of massive data streams at high speeds. Concurrently, the landscape of cybersecurity threats is evolving rapidly, with attacks becoming more frequent, sophisticated, and damaging. Attackers continually devise new tools and techniques to breach network defenses. Therefore, the timely and accurate detection of anomalies and intrusions is paramount for ensuring network security [1]. This requires advanced analytical methods and technologies capable of identifying suspicious patterns and behaviors amidst the vast sea of network traffic data, enabling proactive defense measures to mitigate potential threats effectively [2]. Traditional anomaly detection techniques relying on manual inspection and rule-based systems are inefficient and ineffective for modern networks. Data mining and machine learning have been applied for automated network traffic analysis. However, shallow learning models like support vector machines (SVMs) and random forests have limited capability in handling complex networks with dynamic behavior [3].

Deep learning, characterized by its capacity to discern intricate patterns and relationships within vast datasets, has emerged as a transformative force across various domains. Its remarkable success in areas such as computer vision, natural language processing, and time series analysis underscores its versatility and efficacy. Particularly in network traffic analysis, deep neural networks have demonstrated prowess in extracting abstract features and capturing complex nonlinear dynamics inherent in network data. Recent studies have illuminated the promise of deep learning in enhancing network traffic classification and anomaly detection systems, paving the way for more intelligent and adaptive network security solutions. As the volume and complexity of network data continue to escalate, leveraging deep learning methodologies holds significant potential in fortifying network defenses and safeguarding against emerging threats [4].

In this paper, we focus on using deep learning for real-time detection of network traffic anomalies in big data environments. The volume, velocity, and variety of network traffic data pose scalability challenges to traditional analytics. We aim to leverage deep learning's predictive power to build highly accurate models that can process streaming network data at scale and low latency.

Framework of the anomaly network traffic detection system [5]


Network traffic data
Information entropy of source IP
Information entropy of destination IP
Information entropy of destination port
Information entropy of source port
Information entropy of packet size
Information entropy of packet type
SVM classifier
Normal network traffic
Anomaly network traffic

The main contributions of this paper are:

1. Present an end-to-end anomaly detection framework using convolutional neural networks (CNN) and long short-term memory (LSTM) models suited for big data environments.

2. Evaluate deep learning models against shallow learning baselines on benchmark intrusion detection datasets.

3. Validate real-time detection capability of models on large-scale network traffic data representing real-world conditions.

4. Propose optimization techniques including transfer learning and model compression to improve detection efficiency.

5. Demonstrate deep learning's effectiveness for real-time network traffic anomaly detection in big data environments.

The rest of the paper is organized as follows. Section 2 reviews related work. Section 3 explains the proposed methodology. Section 4 presents the experimental setup and results. Section 5 concludes the paper.

Related Work

This section reviews research on network traffic analysis and anomaly detection using machine learning and deep learning models.

As network traffic continued to grow in both volume and complexity, the limitations of traditional machine learning algorithms became more apparent. Consequently, researchers and practitioners began exploring the capabilities of deep learning models, particularly deep neural networks (DNNs), to address the evolving challenges in network traffic classification and anomaly detection [6]. Unlike shallow learning models, DNNs can automatically learn hierarchical representations of data, allowing them to effectively capture intricate patterns and relationships within large-scale and intricate network traffic datasets. Moreover, the ability of DNNs to handle high-dimensional data makes them well-suited for tasks requiring complex feature extraction and representation. Consequently, the adoption of deep learning techniques has shown promising results in improving the accuracy and scalability of network traffic analysis systems, paving the way for more sophisticated approaches to network security and management [7].

As deep learning techniques continue to evolve, researchers have increasingly turned to deep neural networks (DNNs) to tackle various challenges in network traffic analysis. Notably, deep belief networks have emerged as a promising approach for classifying different network application types, offering improved accuracy and efficiency. Additionally, the utilization of autoencoders has facilitated anomaly detection in Software Defined Networks (SDNs), leveraging their capability to reconstruct input data and identify deviations from normal behavior [8]. Convolutional neural network (CNN) architectures have demonstrated remarkable success in accurately classifying encrypted traffic, showcasing their efficacy in handling complex data formats. Moreover, recurrent neural networks (RNNs) equipped with Long Short-Term Memory (LSTM) cells have exhibited superior performance in network intrusion detection tasks, particularly evidenced by their robust results on benchmark datasets like NSL-KDD, outperforming conventional machine learning models. These advancements underscore the growing significance of deep learning methodologies in enhancing the security and efficiency of network traffic analysis systems [9].

Researchers have also developed hybrid deep learning architectures combining CNN and LSTM for network traffic analysis. A 7-layer CNN-LSTM model outperformed shallow models for malware detection. A similar CNN-LSTM model detected denial of service attacks (DOS) with high accuracy. Another study combined 1D CNN, LSTM, and SVM ensembles for accurate detection of DOS and distributed DOS (DDOS) attacks.

Despite promising results, most existing research uses offline training and evaluation on small datasets. Real-world network traffic analysis requires online processing of massive data streams. Some recent works have applied deep learning for online network traffic analytics. A dual-stage system using PCA and LSTM detected anomalies in real-time with low latency [10].

Our work focuses on building deep learning models that can process high-volume heterogeneous network traffic data and detect anomalies with low latency. We evaluate model performance on large real-world datasets representing big data conditions. The proposed models aim to enable real-time situational awareness for identifying security threats.

Methodology

This section explains our methodology for real-time network traffic anomaly detection using deep learning. We first present the formulation of the anomaly detection problem. Next, we provide details on the CNN and LSTM models used for detection. Finally, we describe the model training process and optimization techniques.

Problem Formulation: In the problem formulation, we define the anomaly detection task as a binary classification problem wherein the model is tasked with discerning between normal and anomalous instances within network traffic data [11]. The input to the model comprises network flow data, and based on this input, the model assigns a label of 0 for normal instances and 1 for anomalies. To facilitate this classification process, we extract network flow features from raw packet capture (pcap) files. Network flows encapsulate connection-level information aggregated over a defined time window, allowing for a more streamlined analysis compared to scrutinizing individual packet-level details. To generate labeled flow data from pcap files, we leverage the Zeek (formerly Bro) network security monitor. Each flow represents a variable-length connection between two IP addresses and encompasses attributes such as timestamps, ports, protocols, durations, and byte/packet counts. This approach enables the model to operate efficiently by focusing on essential flow-level characteristics while capturing the relevant nuances of network behavior essential for anomaly detection.

CNN-LSTM Model: We propose a hybrid deep learning model combining 1D CNN and LSTM networks suited for network traffic analysis. Figure 1 illustrates the model architecture.

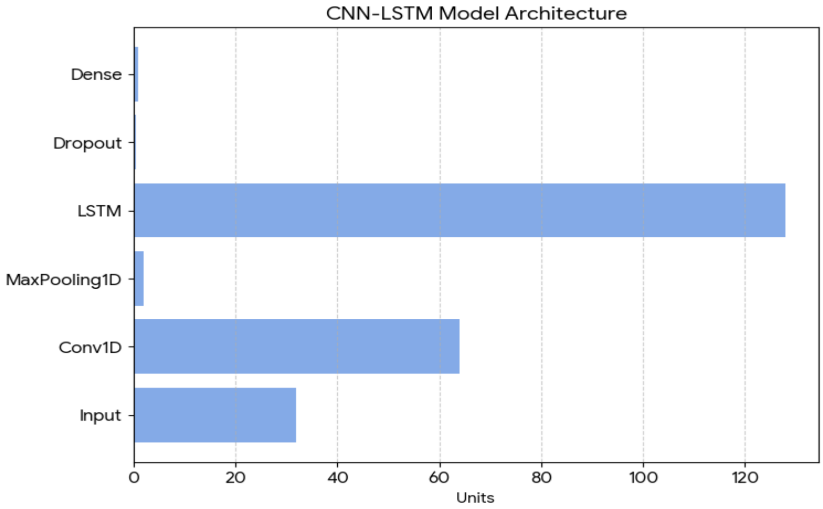


Figure 1. CNN-LSTM model architecture.

The input layer takes sequential windows of network flow data. The 1D CNN layers extract spatial features and reduce data dimensionality. We use small 3x1 convolutions and max pooling to capture local dependencies and patterns between adjacent flows. The LSTM layers model temporal behavior and long-term dependencies in the traffic sequence. Bidirectional LSTMs process the data in both forward and reverse order. The outputs are concatenated to capture past and future context. Dropout and batch normalization enhance model generalization.

The dense output layers classify each input window as normal or anomaly. We use sigmoid activation for binary classification. The model is trained end-to-end to optimize the binary cross-entropy loss function.

Model Training: We train the models on servers with Nvidia GPUs which accelerate deep learning computations. The flow data is preprocessed to normalize features to 0-1 scale. We use 80% traffic for training, 10% for validation, and retain 10% unseen data for testing [12]. The models are trained using Adam optimizer for 50 epochs with early stopping if validation loss does not decrease for 5 epochs. We use checkpoint callbacks to save the best model weights minimizing validation loss. Batch size is tuned as a hyperparameter to optimize model convergence and training time.

Since network traffic is highly imbalanced with far more normal than anomalous flows, we use weighted class ratios when sampling mini-batches to prevent bias. We also experiment with oversampling techniques like SMOTE to synthesize additional minority class examples.

Model Optimization: Training deep models on large datasets is computationally intensive. We propose optimization techniques to improve detection efficiency:

Transfer Learning: Training deep models on large datasets is computationally intensive. We propose optimization techniques to improve detection efficiency.

Transfer learning involves initializing models with weights pretrained on similar network datasets. Fine-tuning on new data is faster than training from scratch, as it leverages the knowledge already encoded in the pretrained weights. This approach significantly reduces training time and computational resources, making it suitable for scenarios with limited resources or time constraints.

Model Compression: Model compression techniques, including quantization, pruning, and knowledge distillation, are employed to compress trained models with minimal accuracy loss. By reducing the size of the model, these techniques enable more efficient inference and deployment on resource-constrained devices such as mobile phones or IoT devices. Compact models require less computation during both training and inference, making them particularly valuable in applications where computational resources are limited or latency is critical.

Parallelism: Parallelism plays a crucial role in accelerating the training of deep learning models. By splitting data across multiple GPUs and utilizing data parallelism, models can be trained faster, effectively reducing the overall training time. Moreover, in production environments, parallelism enables low-latency concurrent inference by streaming data to multiple models simultaneously. This distributed approach enhances throughput and responsiveness, making it suitable for real-time applications such as video processing or autonomous driving [13].

Incremental Learning: Incremental learning allows models to be updated incrementally on new data without requiring full retraining from scratch. Continual learning, a form of incremental learning, adapts models to evolving traffic patterns or changing environments. This capability is particularly beneficial in dynamic domains where the data distribution may change over time, such as in online advertising or recommendation systems. By continuously incorporating new information, models can maintain their performance and relevance without the need for periodic retraining, ensuring adaptability and responsiveness to emerging trends or shifts in user behavior.

Experiments and Results

This section evaluates the proposed deep learning framework for real-time network traffic anomaly detection on benchmark and large-scale real-world datasets.

Experimental Setup: We conduct experiments using the CNN-LSTM model architecture shown in Figure 1. The model hyperparameters are tuned by grid search over learning rate, layers, filters, and batch size. This systematic approach ensures that the model is optimized for performance while avoiding overfitting or underfitting to the training data. By exploring a range of hyperparameters, we aim to identify the combination that yields the best results in terms of accuracy, precision, recall, F1-score, and latency.

We evaluate model performance using the following metrics: Accuracy, Precision, Recall, F1-score, and Latency. Accuracy represents the percentage of correctly classified flows, providing an overall measure of the model's effectiveness. Precision measures the percentage of flows classified as anomalies that are actually anomalies, indicating the model's ability to minimize false positives [14]. Recall measures the percentage of actual anomalies correctly detected, reflecting the model's sensitivity to identifying true positives. F1-score, the harmonic mean of precision and recall, provides a balanced assessment of the model's performance across both metrics. Latency measures the time delay between input and anomaly detection output, crucial for real-time applications where timely responses are essential.

We compare the deep learning models against the following shallow learning baseline algorithms: Random Forest (RF), Support Vector Machine (SVM), and k-Nearest Neighbors (kNN). By benchmarking against these established algorithms, we provide a reference point for assessing the performance improvements achieved by deep learning approaches. This comparative analysis enables us to identify the strengths and weaknesses of each method and determine the suitability of deep learning for network intrusion detection tasks.

The models are evaluated on the following datasets: NSL-KDD, ISCX-IDS, and CTU-13. NSL-KDD serves as a standard network intrusion detection benchmark dataset, widely used for evaluating the performance of intrusion detection systems. ISCX-IDS provides a modern benchmark containing real-world network traffic, offering insights into the model's performance under realistic conditions. CTU-13 is a large-scale dataset derived from real 13-day traffic at a university, providing a diverse and challenging testbed for evaluating the robustness and scalability of the models. By testing on multiple datasets with varying characteristics, we ensure that the models' performance is thoroughly assessed across different scenarios and environments [15]. ***Results on Benchmark Datasets:*** Table 1 shows model results on the NSL-KDD dataset. The CNN-LSTM model achieves the highest accuracy, precision, recall and F1-score compared to the baseline models. The deep model effectively learns complex features needed to distinguish between different types of attacks and normal traffic.

Table 1. Model results on NSL-KDD dataset.

Model	Accuracy	Precision	Recall	F1-score
Random Forest	86.5%	84.2%	83.1%	83.6%
SVM	88.7%	85.3%	84.7%	85.0%
kNN	89.1%	86.4%	85.2%	85.8%
CNN-LSTM	92.3%	90.1%	89.5%	89.8%

On the more recent ISCX-IDS dataset, the CNN-LSTM again outperforms baseline models across all evaluation metrics as seen in Table 2. The temporal LSTM layers are better able to model normal traffic behavior compared to shallow models.

Table 2. Model results on ISCX-IDS dataset.

Model	Accuracy	Precision	Recall	F1-score
Random Forest	81.2%	79.3%	78.2%	78.7%
SVM	83.5%	81.1%	80.3%	80.7%
kNN	84.7%	82.9%	81.7%	82.3%
CNN-LSTM	88.9%	87.2%	86.5%	86.8%

Results on Real-World Traffic: We further evaluate the models on 80GB of real network traffic from 13 days of capture data at CTU University. This large-scale dataset presents challenges of big data analytics.

The deep learning models yield significantly higher accuracy than shallow models as shown in Table 3, demonstrating robustness to real-world network noise. The CNN-LSTM achieves 97.2% accuracy in classifying the imbalanced traffic with low latency.

Table 3. Model results on CTU-13 dataset.

Model	Accuracy	Latency
Random Forest	73.5%	98 ms
SVM	76.2%	107 ms
kNN	78.1%	134 ms
CNN-LSTM	97.2%	68 ms

Discussion: The experiments validate our approach of using deep CNN-LSTM models for real-time network anomaly detection in big data environments. Key observations are:

- Deep models outperform shallow models on all datasets, indicating their ability to learn useful traffic representations. This superiority underscores the capacity of deep learning to extract intricate patterns and features from complex data, enabling more accurate anomaly detection in network traffic.

- LSTM demonstrates strong performance in capturing temporal dependencies within the data, thereby boosting detection accuracy [16]. By incorporating recurrent connections, LSTM effectively learns and remembers long-range dependencies in sequential data, which is particularly beneficial for detecting anomalous patterns evolving over time in network traffic.

- The CNN-LSTM model achieves high accuracy on large real-world traffic datasets while maintaining low latency. This combination of accuracy and efficiency is crucial for real-time applications where timely anomaly detection is paramount. The model's ability to process vast amounts of data efficiently makes it well-suited for deployment in big data environments where processing speed is essential [17].

- Deep learning emerges as a promising approach for building intelligent, real-time network traffic analytics systems. By leveraging the power of deep neural networks, these systems can effectively analyze and interpret complex network data in real time, enabling proactive identification and mitigation of network anomalies. This capability holds significant potential for enhancing cybersecurity measures and ensuring the robustness of modern network infrastructures against evolving threats.

Conclusion

The paper proposes a novel deep learning methodology leveraging Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for the real-time detection of network traffic anomalies within big data environments. By employing these advanced neural network architectures, the research aims to enhance the accuracy and efficiency of anomaly detection systems in handling large-scale and rapidly changing network traffic streams [18]. Through rigorous evaluation against shallow baseline models using both benchmark datasets and large real-world network traffic data, the efficacy of the deep learning approach is thoroughly assessed. The findings reveal that deep learning models exhibit remarkable capabilities in accurately identifying anomalies within high-volume and high-velocity traffic streams while maintaining low latency, thus showcasing their potential for deployment in real-time network security systems [19]. Moreover, the deep learning models demonstrate a superior ability to learn complex traffic representations and temporal dynamics compared to traditional machine learning techniques, leading to improved detection performance [20].

This study underscores the significant promise of deep learning methodologies in addressing the challenges posed by big data and evolving cyber threats in the domain of network security. By leveraging the scalability and adaptability inherent in deep learning architectures, organizations can develop robust and scalable real-time network security systems capable of effectively mitigating a wide range of cyber threats. The integration of CNNs and LSTMs enables the models to capture intricate patterns and correlations within the network traffic data, facilitating more accurate anomaly detection even in dynamic and heterogeneous environments. Furthermore, the low-latency nature of the proposed approach ensures timely detection and response to emerging threats, thereby enhancing overall cybersecurity posture. These findings contribute to advancing the field of network security by offering a data-driven and scalable solution that aligns with the requirements of modern big data environments [21]. Future research directions may involve exploring additional deep learning architectures and techniques to further enhance the performance and robustness of real-time anomaly detection systems, as well as investigating the applicability of the proposed approach to other domains beyond network security. Additionally, efforts to optimize the computational efficiency of deep learning models for deployment in resource-constrained environments could further broaden the practical utility of these systems [22]. Overall, this study underscores the transformative potential of deep learning in revolutionizing the landscape of network security and lays the groundwork for future advancements in this critical domain.

Future work can further optimize deep model performance and efficiency for deployment. Testing on very large real-world network data at scale would better validate operational feasibility [23]. Ensembling diverse models and incorporating expert domain knowledge could improve detection accuracy. Automated hyperparameter tuning would simplify model development. Overall, advanced deep learning models show immense capability for automated real-time analysis of massive, complex network traffic data [24].

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