An Advanced Intrusion Detection System for SDVNs Using Deep Learning Techniques

Research Project Seminar

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Outline

Evolution: From VANETs to SDVNs

VANET Architecture

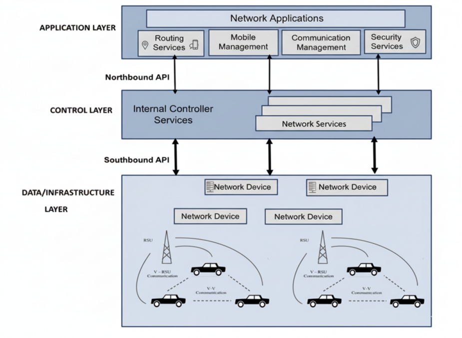

Figure 1: Traditional VANET

SDVN Architecture

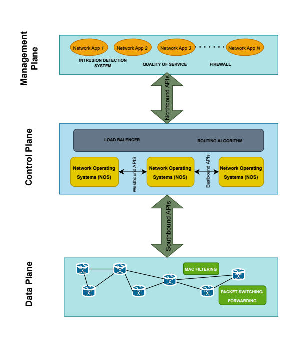

Figure 2: Software-Defined VANET

Introduction

Key Points

- Vehicular Ad-hoc Networks (VANETs) enable vehicle-to-everything (V2X) communication for Intelligent Transportation Systems (ITS)
- Traditional VANETs face challenges: decentralized nature, scalability issues, complex security management
- Software-Defined Vehicular Networks (SDVN) provide centralized control through SDN paradigm
- SDVN separates control plane from data plane for better network management
- **Critical Challenge:** Centralized controller becomes single point of failure and prime target for cyberattacks (e.g., DDoS)
- Need for sophisticated, intelligent Intrusion Detection System (IDS) to protect SDVN infrastructure

Motivation

Why Advanced IDS for SDVNs?

- **Centralized Control Advantage:** SDN controller has global network view - ideal platform for intelligent, data-driven IDS
- **Limitation of Traditional Methods:** Signature-based detection cannot identify zero-day attacks
- **ML/DL Superiority:** Machine learning and deep learning can learn normal behavior patterns and detect anomalies
- **Critical for ITS:** Security is paramount for safety-critical vehicular applications
- **Emerging Threat Landscape:** Sophisticated attacks targeting SDVN controller require advanced detection mechanisms

Problem Statement

Research Gap

- **Current Limitation:** Most existing IDS treat intrusion detection as static classification problem
- Traditional models aggregate traffic features over time windows, losing temporal information
- **Critical Loss:** Sequence of events and evolution of traffic patterns are discarded
- **Vulnerability:** Static models fail against time-dependent attacks:
  - Low-and-slow attacks
  - Port scanning sequences
  - Multi-stage intrusions
- **Key Challenge:** Mismatch between static models and time-dependent nature of real-world attacks

SDVN Architecture Overview

Three-Plane Architecture

- **Data Plane**
  - OBUs (vehicles)
  - RSUs (roadside units)
  - Forward traffic per controller rules
- **Control Plane**
  - Centralized SDN controller
  - Global network view
  - Routing decisions
- **Application Plane**
  - Network applications
  - ITS services

Threat Landscape

- **Data Plane Attacks**
  - Man-in-the-Middle
  - Sybil attacks
- **Control Plane Attacks**
  - DDoS on controller
  - Resource exhaustion
- **Application Plane**
  - Malicious applications
  - Policy manipulation

Intrusion Detection Approaches

Table 1: IDS Classification

Type	Advantages	Limitations
Signature-based	High accuracy for known attacks, Low false positives	Cannot detect zero-day attacks, Requires constant signature updates
Anomaly-based (ML/DL)	Detects unknown attacks, Learns normal behavior patterns	May have higher false positive rates, Requires training data

Focus of This Work

- **Anomaly-based IDS using Deep Learning**
- Specifically: Sequence-aware LSTM networks
- Advantage: Captures temporal dynamics of traffic

Literature Survey

Table 2: Comparative Analysis of Existing ML/DL-Based IDS

S.No.	Reference	Method	Dataset	Accuracy	Limitations
1	Ye et al.	SVM	Simulated	95.24%	No feature selection, static features
2	Tang et al.	DNN	NSL-KDD	75.75%	Only 6 basic features, no temporal analysis
3	Tang et al.	GRU-RNN	NSL-KDD	89%	Limited features, controller overhead unaddressed
4	Myint Oo et al.	ASVM	Simulated	97%	Small dataset, lacks temporal context
5	Silva et al.	K-means + SVM	Simulated	88.7%	Resource-intensive, ignores sequential patterns
6	Braga et al.	SOM	Custom	98.61% DR	Aggregated features, no temporal analysis
7	Elsayed et al.	CNN + SD-Reg	InSDN	98.92%	CNN doesn't model long-range temporal dependencies
8	Dey & Rahman	GRU-LSTM	NSL-KDD	87%	Still relies on aggregated statistics

Research Gap Identified

Common Limitations in Literature

1. Heavy reliance on static, aggregated features
2. Loss of temporal sequence information
3. Inability to detect time-dependent attack patterns
4. Models treat each traffic sample independently
5. No analysis of traffic flow evolution over time

Our Solution

Treat intrusion detection as a **time-series classification problem** using sequence-aware LSTM networks

Research Objectives

Primary Objectives

1. **Design and Develop:** A novel IDS framework that analyzes network traffic as temporal sequences
2. **Implement:** A sequence-aware deep learning model using Long Short-Term Memory (LSTM) networks
3. **Capture:** Long-range temporal patterns and behavioral dynamics in SDVN traffic data
4. **Evaluate:** Model performance on standard network traffic dataset
5. **Demonstrate:** Superiority over static classification approaches for intrusion detection

Methodology Overview

Two-Stage Approach

1. **Data Conditioning Pipeline**
   - Data cleaning and preprocessing
   - Feature engineering
   - Normalization
   - Reshaping for sequential analysis

2. **Sequence-Aware LSTM Model**
   - Input layer (3D tensor)
   - LSTM layer (temporal feature extraction)
   - Dense output layer (classification)

Data Conditioning Pipeline

Preprocessing Steps

1. **Data Cleaning**
   - Handle missing values
   - Remove non-informative features
   - Drop: Flow ID, Src IP, Dst IP, Timestamp
2. **Feature Engineering**
   - Label encoding for categorical features
   - Protocol $\rightarrow$ numeric
   - Label $\rightarrow$ numeric classes

Transformation

3. **Normalization**
   - StandardScaler application
   - Prevent feature domination
4. **Reshaping for LSTM**
   - 2D: (samples $\times$ features)
   - $\downarrow$ Transform
   - 3D: (samples, timesteps, features)
   - 79 features per timestep

LSTM Architecture

Network Structure

1. **Input Layer**
   - Shape: (samples, timesteps, 79 features)
2. **LSTM Layer**
   - Processes sequential data
   - Learns long-term dependencies
   - Gates: Forget, Input, Output
3. **Output Layer (Dense)**
   - Softmax activation
   - Multi-class classification
   - Classes: Non-Tor, NonVPN, Tor, VPN

LSTM Cell Operations

$$
\begin{aligned}
f_t &= \sigma(W_f x_t + U_f h_{t-1} + b_f) \\
i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i) \\
\tilde{c}_t &= \tanh(W_c x_t + U_c h_{t-1} + b_c) \\
c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\
o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o) \\
h_t &= o_t \odot \tanh(c_t)
\end{aligned}
$$

Training Configuration

- Optimizer: ADAM
- Loss: Categorical cross-entropy
- Early stopping enabled

Why LSTM for Intrusion Detection?

Advantages of LSTM Networks

- **Memory Capability:** Can remember information over long sequences
- **Temporal Pattern Recognition:** Identifies attack behaviors that evolve over time
- **Gate Mechanisms:** Selectively retain or forget information
  - Forget gate: Removes irrelevant past information
  - Input gate: Decides what new information to store
  - Output gate: Controls what information to output
- **Gradient Flow:** Addresses vanishing gradient problem in traditional RNNs
- **Complex Pattern Learning:** Captures subtle temporal dependencies in network traffic

Dataset: CIC-Darknet2020

Dataset Characteristics

- **Source:** Canadian Institute for Cybersecurity
- **Size:** 158,659 samples
- **Features:** 85 columns (79 used after preprocessing)
- **Traffic Types:** Tor, VPN, Non-Tor, Non-VPN
- **Applications:** Browsing, Chat, Email, File Transfer, P2P, Audio/Video streaming, VoIP

Class Distribution

Class	**Count**	**%**
Non-Tor	110,442	69.6%
NonVPN	23,863	15.0%
VPN	22,919	14.4%
Tor	1,392	0.9%

Data Split

- Training: 80%
- Testing: 20%

Classification Results

Overall Performance

Test Accuracy: 96.59%

Table 3: Detailed Classification Report

Class	**Precision**	**Recall**	**F1-score**	**Support**
Non-Tor	1.00	1.00	1.00	18,655
NonVPN	0.91	0.90	0.90	4,752
Tor	0.98	0.86	0.91	282
VPN	0.90	0.91	0.91	4,608
Macro Avg	0.95	0.92	0.93	28,297
Weighted Avg	0.97	0.97	0.97	28,297

Confusion Matrix Analysis

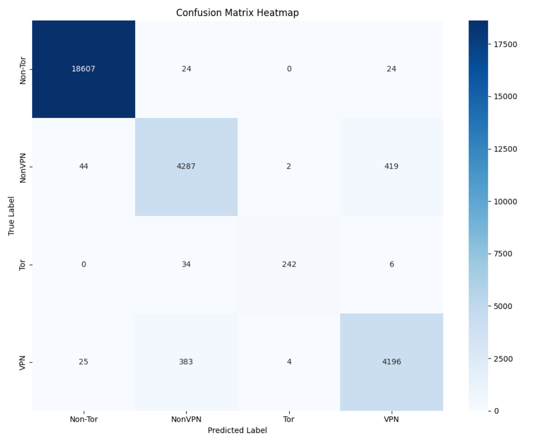

Figure 3: Confusion Matrix

Key Observations:

Training Performance

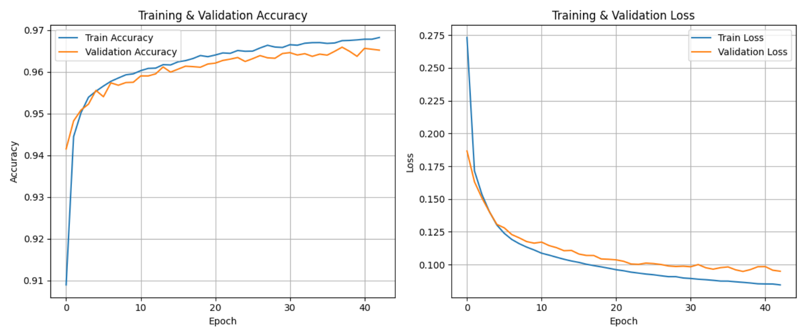

Figure 4: Training and Validation Accuracy/Loss

- **Training stopped at epoch 43** (early stopping)
- No signs of overfitting
- Smooth convergence of both accuracy and loss

Per-Class Performance Metrics

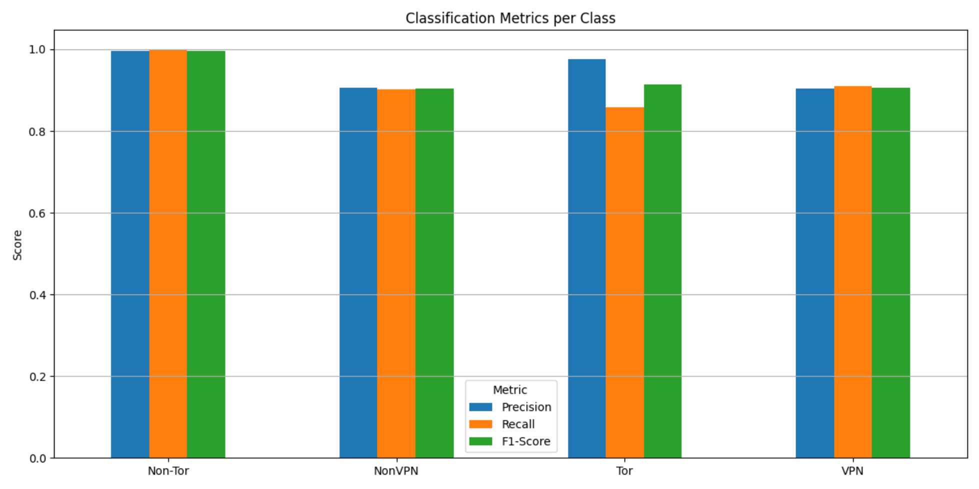

Figure 5: Precision, Recall, and F1-Score by Class

Result Discussion

Key Findings

1. **Excellent Overall Performance:** 96.59% accuracy demonstrates effectiveness of sequence-aware approach
2. **Balanced Metrics:** Macro avg (0.95, 0.92, 0.93) shows consistent performance across classes
3. **Class-Specific Insights:**
   - Non-Tor: Perfect classification (likely due to distinct patterns and large sample size)
   - Tor: High precision but lower recall (small sample size effect)
   - VPN/NonVPN: Slight confusion expected due to encryption similarity
4. **Training Stability:** Early stopping at epoch 43 with no overfitting indicates good generalization

Conclusion

Summary of Contributions

- Successfully demonstrated **sequence-aware deep learning framework** for intrusion detection
- Overcame limitations of static classification methods by treating traffic as **time series**
- Achieved **96.59% accuracy** on CIC-Darknet2020 dataset
- Proved effectiveness of LSTM networks in capturing temporal dynamics of network traffic
- Established foundation for advanced IDS in SDVN environments
- Model shows strong generalization with balanced precision-recall trade-offs

Key Takeaway

Temporal sequence modeling is essential for robust intrusion detection in dynamic vehicular networks

Future Work

Immediate Next Steps

1. **Domain-Specific Dataset Evaluation**
   - Test on VeReMi (vehicular dataset)
   - Evaluate against vehicle-specific attacks (position falsification, misbehavior)
2. **Architectural Enhancement**
   - Integrate attention mechanisms with LSTM
   - Enable dynamic focus on most critical traffic features
   - Improve interpretability of model decisions

Future Work (continued)

Extended Research Directions

3. **Comprehensive Benchmarking**
   - Compare with traditional ML (Random Forest, SVM)
   - Evaluate against non-sequential DL (CNN, standard DNN)
   - Quantify benefits of sequence-aware modeling
4. **Real-Time Performance Optimization**
   - Measure and minimize inference latency
   - Ensure suitability for low-latency vehicular applications
   - Deploy in SDVN controller for practical validation
5. **Integration with SDVN Infrastructure**
   - Develop controller-integrated IDS
   - Enable automated threat response
   - Build resilient intelligent transportation ecosystem

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Dissemination I

Current Work Status

- **Proof-of-Concept:** Successfully demonstrated sequence-aware LSTM framework for network intrusion detection
- **Dataset Used:** CIC-Darknet2020 (general network traffic) with 96.59% accuracy achieved
- **Publication Plan:** Manuscript preparation in progress for submission to IEEE Transactions on Intelligent Transportation Systems or similar venue
- **Next Phase:** Evaluation on vehicular-specific datasets (VeReMi) and integration with SDVN controller
- **Future Enhancements:** Attention mechanism integration and real-time performance optimization

Thank You

Questions?