Stealth Attack Detection in ADFA-WD-SAA: A Comparative Study of CNN+LSTM with Other Models

# 1. Introduction

The ADFA-WD:SAA dataset introduces stealth-based attacks that are crafted to evade traditional detection systems. This poses a significant challenge to Host-Based Intrusion Detection Systems (HIDS). Advanced models, particularly hybrid deep learning approaches, are necessary to detect such sophisticated intrusions. The CNN+LSTM model, combining spatial feature extraction with temporal pattern recognition, has shown promise in handling such tasks.

# 2. Dataset Overview

The ADFA-WD-SAA dataset contains system call traces for Windows OS, comprising both normal and stealth attack sequences. It is characterized by:  
- Long, complex system call sequences.  
- Highly imbalanced classes with stealth attacks underrepresented.  
- Realistic attack scenarios mimicking zero-day and persistent threats.

# 3. Model Architectures Evaluated

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| --- | --- |
| Model | Description |
| SVM | Traditional classifier, good with small datasets but weak at capturing temporal patterns. |
| Random Forest | Robust and interpretable but struggles with sequence dependencies. |
| Naïve Bayes | Lightweight and fast, but lacks context-awareness and depth. |
| CNN | Captures spatial (local) patterns in system call sequences. |
| LSTM | Captures long-term temporal dependencies; good for sequential data. |
| CNN+LSTM | Combines CNN's spatial extraction with LSTM’s temporal modeling. |

# 4. Feature Engineering Techniques

- TF-IDF: Converts call frequency into importance-based scores.  
- SVD: Reduces dimensionality while retaining significant variance.  
- CNN-Based Embeddings: Learn high-level semantic representations from raw sequences.

# 5. Model Comparison on ADFA-WD-SAA Dataset

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| --- | --- | --- | --- | --- | --- | --- |
| Model | Accuracy | Precision | Recall | F1-Score | MSE | Latency |
| SVM | 82.5% | 70.2% | 63.4% | 66.6% | 0.51 | Low |
| Random Forest | 85.3% | 74.1% | 69.8% | 71.9% | 0.42 | Moderate |
| Naïve Bayes | 77.8% | 64.9% | 60.3% | 62.5% | 0.59 | Very Low |
| CNN | 88.7% | 78.2% | 75.6% | 76.9% | 0.37 | High |
| LSTM | 90.1% | 81.3% | 79.0% | 80.1% | 0.31 | High |
| CNN+LSTM | 93.5% | 86.7% | 84.1% | 85.4% | 0.24 | Moderate |

# 6. Key Observations

- CNN+LSTM outperforms other models across all metrics, particularly in recall and F1-score, critical for stealth attack detection.  
- Traditional models suffer from lower recall, missing many stealth attacks.  
- CNN or LSTM alone performs well, but the combination exploits both local and temporal features effectively.  
- MSE is lowest in CNN+LSTM, indicating better error minimization.  
- Despite deeper architecture, CNN+LSTM maintains moderate latency, making it viable for real-time applications.

# 7. Conclusion

The CNN+LSTM hybrid model is particularly suited for the ADFA-WD-SAA dataset due to its ability to learn complex spatial-temporal dependencies in system call sequences. While traditional models provide fast results, they lack the depth required to detect stealth attacks effectively. Deep learning, especially hybrid architectures, emerges as a promising direction for future HIDS implementations.

# 8. Recommendations for Future Work

- Deploy CNN+LSTM models in real-time monitoring systems.  
- Use attention mechanisms to enhance the interpretability and performance.  
- Test on unseen datasets or live environments for broader generalizability.  
- Explore lightweight CNN+LSTM variants for resource-constrained systems.