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# Hybrid Deep Learning Models for Intrusion Detection in Cloud Networks: A Benchmark-Based Comparative Study

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**ABSTRACT:** The increasing complexity of cyber threats targeting cloud infrastructures demands advanced and adaptive intrusion detection systems (IDS). This study explores the application of deep learning (DL) models—Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and a hybrid CNN+BiLSTM architecture—for detecting network intrusions using benchmark datasets CIC-IDS2017 and UNSW-NB15. This study contributes by demonstrating how hybrid CNN+BiLSTM architectures enhance intrusion detection accuracy on benchmark datasets, offering low latency and improved recall for rare attack classes, thereby validating their suitability for real-time cloud security deployment. Results show that hybrid CNN+BiLSTM models outperform standalone CNN and LSTM architectures in detection performance, achieving accuracies up to 97.4% on CIC-IDS2017 and 96.85% on UNSW-NB15, while maintaining acceptable latency for real-time deployment. The hybrid model also demonstrates superior F1-scores for rare attack classes and lower false positive rates. The discussion highlights the importance of dataset quality, feature engineering, and the role of adversarial training and model optimization in enhancing robustness. In conclusion, this work affirms the value of hybrid DL architectures for cloud-based IDS and suggests future directions in federated learning, adaptive retraining, and deployment in edge environments.

**Keywords:** Intrusion Detection, Cloud Computing, Deep Learning, CNN, LSTM, Hybrid Architecture, Network Security, IDS Evaluation.



## INTRODUCTION

The rapid evolution of cloud computing infrastructure has introduced a range of sophisticated security vulnerabilities. As organizations increasingly migrate sensitive operations and data to the cloud, the necessity for effective security mechanisms becomes paramount. Cloud environments are inherently dynamic, hosting large volumes of network traffic and virtualized workloads.

Consequently, they are exposed to an array of cyber threats, from Distributed Denial-of-Service (DDoS) attacks and data breaches to complex Advanced Persistent Threats (APTs). Traditional Intrusion Detection Systems (IDS), while foundational in network security architectures, struggle to address the scale, agility, and heterogeneity of cloud-based threats.

DDoS attacks remain a common threat in cloud environments, aiming to overload network and application resources (Abdalgawad et al., 2022). Meanwhile, misconfigured cloud storage or insider breaches frequently expose sensitive data (Rehman et al., 2022; Wei & Shangguan, 2023). Additionally, the integration of Internet of Things (IoT) technologies with cloud platforms has further broadened the attack surface, enabling automated exploitation through interconnected devices (Ferrag et al., 2020). The use of social engineering and phishing tactics also adds complexity to threat detection (Tareq et al., 2024), and disruptions caused by such attacks can impact both service availability and consumer trust (Toldinas et al., 2021). In this landscape, rapid detection and adaptive security responses are essential, positioning IDS as a critical component in the cloud security stack (Al-Hawawreh et al., 2019).

However, conventional IDS, especially those rooted in rule-based or signature-based methodologies, have proven insufficient in detecting sophisticated or novel threats. Signature-based IDS are limited by their dependence on predefined attack patterns, rendering them ineffective against zero-day exploits and polymorphic threats (Manjunatha et al., 2023). Moreover, high false positive rates and the burden of maintaining extensive signature databases hinder their application in real-time and large-scale settings (El-Sayed et al., 2024; Zhong et al., 2020). The static nature of traditional models also clashes with the elastic and decentralized nature of cloud infrastructure (Tang et al., 2016), necessitating a shift toward more dynamic detection approaches.

Deep learning (DL) has emerged as a powerful solution, capable of autonomously extracting features and recognizing complex attack patterns across diverse datasets (Elsaeidy et al., 2020; Hnamte et al., 2023). CNNs, for instance, are adept at spatial pattern recognition, while RNNs, including LSTMs, capture temporal dependencies in traffic data (Aliabadi & Jalalian, 2023; Ullah & Mahmoud, 2022). Hybrid models combining CNN and recurrent architectures demonstrate further performance enhancements in terms of detection accuracy and false alarm reduction (Vembu & Ramasamy, 2022). These systems also facilitate rapid retraining on limited labeled data, allowing for near real-time adaptability (Tang et al., 2016).

Benchmark datasets play a crucial role in evaluating and training DL-based IDS. Although KDD Cup 1999 is a foundational benchmark, it has been largely superseded by more comprehensive datasets like UNSW-NB15 and CICIDS2017, which offer realistic and diverse attack scenarios (Priya & Kumar, 2023; Ferrag et al., 2020). For instance, CICIDS2017 includes updated features and traffic patterns, simulating real-world conditions more accurately. IoT-specific datasets such as IoT-23 further expand research applicability to emerging domains (Abdalgawad et al., 2022).

Despite the advancements, deploying IDS in large-scale or real-time cloud settings presents multiple challenges. High data volume, virtualization dynamics, and workload migration complicate traffic monitoring and anomaly detection (Laghrissi et al., 2021). Computational

resource constraints also hinder real-time analysis, especially when applying deep models with large parameter sets (Tareq et al., 2024). Moreover, coordination between cloud service providers and customers is necessary for incident response, yet often lacks clarity in responsibilities (Teuffenbach et al., 2020). Finally, regulatory frameworks such as GDPR introduce additional considerations related to privacy and data handling (Kumar & Alqahtani, 2023).

Given these challenges, there is a pressing need to examine the role of deep learning in enhancing IDS capabilities, especially through hybrid models that combine spatial and temporal feature learning. This study aims to evaluate and compare the performance of CNN, LSTM, and hybrid CNN+BiLSTM architectures on public benchmark datasets (CICIDS2017 and UNSW-NB15). The goal is to identify whether hybrid deep learning architectures provide superior detection performance while maintaining acceptable computational efficiency and adaptability to evolving threat landscapes. The scope of this research encompasses model design, preprocessing strategies, performance evaluation, and deployment implications—contributing to both academic understanding and practical applications of IDS in cloud computing.

## METHOD

This chapter outlines the experimental framework for assessing the effectiveness of deep learning models CNN, LSTM, and CNN+BiLSTM in detecting network intrusions within cloud environments. It details the datasets used, preprocessing strategies, model architectures, training setup, and evaluation metrics.

### Datasets

Two widely-used benchmark datasets were employed in this study:

- CIC-IDS2017**:** Contains ~3 million network traffic records with 78 features, including benign and 15+ attack classes. It is comprehensive and simulates realistic traffic patterns.
- UNSW-NB15**:** Comprises ~2.5 million records across 49 features with 9 diverse attack types. Offers modern traffic profiles suitable for DL experimentation.

Both datasets were selected for their richness, diversity, and wide usage in IDS research.

### Preprocessing

Preprocessing plays a vital role in preparing data for deep learning models:

- Normalization**:** All numerical features were scaled using MinMaxScaler and StandardScaler to a uniform range, accelerating convergence and improving learning consistency.
- Dimensionality Reduction: PCA and ExtraTreesClassifier were used to retain only the most informative features, reducing training time and overfitting risk.
- Feature Extraction: Deep models were allowed to learn hierarchical features directly; however, exploratory feature analysis was also conducted to identify salient attributes
- Categorical Encoding: Protocols and services were one-hot encoded to transform them into numerical inputs.
- Class Imbalance Handling: SMOTE oversampling was employed to boost minority class representation, improving detection of underrepresented attacks.

### Deep Learning Model Architectures

Three architectures were examined:

- CNN: Utilized 1D convolutions across features. Its spatial feature extraction and pooling layers make it efficient for non-sequential inputs, with reduced parameter count and faster training.
- LSTM: Designed for time-series analysis, LSTM networks model long-term dependencies in sequential data. They use memory cells and gating mechanisms, making them computationally intensive.
- Hybrid CNN+BiLSTM: CNN layers extract spatial features, which are then passed to BiLSTM units for temporal modeling. This integration enhances detection of complex, multi-phase attacks at the cost of increased computational load.

**Training Setup**

- Data Split: 70% training, 15% validation, 15% testing.
- Optimizer & Loss Function: Adam optimizer with categorical cross-entropy loss.
- Regularization: Dropout (0.2) applied to mitigate overfitting.
- Early Stopping: Monitored validation loss with patience of 10 epochs.
- Hardware: All models were trained on GPU-enabled environments.

**Evaluation Strategy**

To ensure robust and fair evaluation:

- Cross-Validation: K-fold (k=5) validation used to reduce variance and improve generalization (Kumar & Alqahtani, 2023).
- Hyperparameter Tuning: Grid search conducted for batch size, learning rate, and neuron counts (Thakkar & Lohiya, 2021).
- Class Imbalance Consideration: Stratified sampling and metric sensitivity checks were performed to ensure balanced assessments (Javeed et al., 2023).
- Evaluation Metrics:
  1. Accuracy
  2. Precision
  3. Recall
  4. F1-score
  5. ROC-AUC

These metrics were selected to comprehensively capture model performance in both binary and multiclass intrusion detection contexts (Alaghbari et al., 2023).

**Adaptability and Monitoring**

In line with real-world deployment standards, all models were designed with adaptability in mind. Retraining mechanisms were planned to accommodate updated datasets, reflecting evolving cyber threats (Javeed et al., 2023).

This methodological design aims to provide a replicable, scalable, and fair foundation for comparing DL models in the context of intrusion detection within cloud infrastructures.

## RESULT AND DISCUSSIONS

This chapter presents the performance outcomes of CNN, LSTM, and hybrid CNN+BiLSTM architectures applied to CIC-IDS2017 and UNSW-NB15 datasets. It is organized into three key dimensions: model accuracy, confusion matrix analysis, and efficiency evaluation.

**Model Accuracy & Metrics**

Deep learning-based IDS models demonstrate high performance on both datasets. CNN and LSTM perform well individually, while the hybrid CNN+BiLSTM architecture yields superior results.

- CIC-IDS2017 Accuracy: CNN: 96.55%, LSTM: 96.25%, Hybrid: 97.40%
- UNSW-NB15 Accuracy: CNN: 94.80%, LSTM: 95.25%, Hybrid: 96.85%

The improved accuracy of the hybrid model over baseline CNN and LSTM architectures (e.g., 97.4% on CIC-IDS2017) underscores the benefit of integrating spatial and temporal learning, surpassing existing benchmarks in DL-based IDS research (Alsumaidaee et al., 2023).

F1-Score for Rare Attacks:

- Hybrid models achieve higher F1-scores (above 85%) for infrequent attack classes compared to CNN or LSTM alone, which often drop below 70% (Jin et al., 2024).

Trade-offs:

- CNNs offer faster training and lower resource demand.
- LSTMs capture sequential dependencies more effectively.
- Hybrid models balance both but at the cost of higher computational requirements (Tian et al., 2024).

Dataset Quality Impact: High-quality datasets (e.g., CIC-IDS2017, UNSW-NB15) significantly enhance model performance, generalization, and class-wise balance (Shang et al., 2023).

**Confusion Matrix Analysis**

False Positive Rates:

- DL-IDS systems show 2%–10% FPRs on average.
- Hybrid models reduce FPR by up to 30% versus single-model architectures.

Recall in Minority Classes:

- Enhanced via SMOTE, ensemble training, and hyperparameter tuning.

Confusion Matrix Trends:

- Persistent low recall for specific attacks prompts architectural refinements or retraining.

- Misclassification insights guide feature and parameter adjustments.

**Latency & Efficiency**

Latency Ranges:

- Inference times of 18ms–23ms were achieved.
- Acceptable for real-time detection (within the 20–200ms threshold).

Impact of Model Complexity:

- LSTM and hybrid models incur longer training and inference times due to depth and gating structures (Zhao et al., 2024).
- CNNs remain optimal for low-latency deployment.

Optimization Techniques:

- Quantization, pruning, model distillation reduce latency while preserving accuracy (Chung et al., 2023).
- Ensemble methods and model parallelism enhance efficiency.

Resource Utilization:

- CNNs: lower memory and computational demand.
- LSTMs: higher resource consumption but better sequential understanding.
- Selection depends on operational constraints and detection precision needs

Overall, the hybrid CNN+BiLSTM architecture achieves the best trade-off between detection performance and operational viability, making it a strong candidate for cloud-based IDS applications.

The findings from this study reinforce the value of deep learning—especially hybrid CNN+BiLSTM architectures—in developing robust intrusion detection systems (IDS) for cloud computing environments. While benchmark datasets such as CIC-IDS2017 and UNSW-NB15 provide a strong foundation for model evaluation, their use is not without challenges. A major limitation lies in their inability to represent emerging or complex attack vectors like zero-day exploits or advanced persistent threats (APTs) (Devi & Muthusenthil, 2022). Furthermore, the static and imbalanced nature of these datasets can hinder a model's ability to generalize to real-time network scenarios, raising the potential for overfitting (Alshehri et al., 2024). As such, while these datasets serve well for comparative analysis, ongoing updates and supplementary real-world traffic data are essential to ensure operational effectiveness.

Hybrid DL models demonstrate notable potential in adversarial settings. By integrating CNN and LSTM structures, these models capitalize on both spatial and temporal data patterns. However, enhancing their resilience requires specific techniques, such as adversarial training, where models

are exposed to adversarially generated samples during the learning process. Incorporating augmentation strategies like Fast Gradient Sign Method (FGSM) or Projected Gradient Descent (PGD) improves robustness against crafted perturbations (Gamal et al., 2021). Additionally, attention mechanisms or reinforcement learning can further adapt these models to dynamic threat landscapes, improving decision-making in real-time deployments.

Feature selection remains a cornerstone of IDS performance improvement. Effective selection strategies such as Recursive Feature Elimination (RFE) or feature ranking help eliminate noise, reduce dimensionality, and improve interpretability. This process not only enhances detection rates and reduces false positives but also aids cybersecurity teams in understanding which attributes are most critical to threat identification (Abosata et al., 2022; Shukla et al., 2024). In evolving networks, adaptive feature selection based on live feedback can dynamically optimize models to maintain high accuracy under changing data conditions (Liang et al., 2020).

As cloud and edge computing infrastructures expand, emerging trends are reshaping how DL-based IDS are developed and deployed. Federated learning allows distributed model training across decentralized sources without sharing raw data, addressing growing concerns around privacy and compliance (Alsubhi, 2024). Simultaneously, resource-aware DL models are being developed through knowledge distillation and pruning, enabling efficient inference on edge devices (Spadaccino & Cuomo, 2022). This is critical for real-time detection at the network edge, where latency and energy constraints limit the viability of complex models. Moreover, transfer learning facilitates rapid adaptation of pre-trained models to novel attack scenarios, shortening deployment times and enhancing model responsiveness (Véstias et al., 2020).

In conclusion, the study confirms that hybrid DL architectures not only improve detection rates but also offer practical advantages in latency and adaptability, which are critical for real-world deployment in dynamic cloud environments.

## CONCLUSION

This study demonstrates that hybrid deep learning architectures, particularly CNN combined with BiLSTM, offer superior performance in detecting intrusions within cloud-based networks. Through empirical evaluations using CIC-IDS2017 and UNSW-NB15 datasets, the hybrid model consistently achieved higher accuracy and F1-scores compared to standalone CNN and LSTM approaches. The integration of spatial and temporal feature learning allowed for more effective detection of complex and infrequent attack patterns, while maintaining inference latencies suitable for real-time deployment.

Beyond accuracy improvements, the findings highlight the importance of feature selection, class balancing, and dataset quality in enhancing IDS effectiveness. The proposed architecture's adaptability and efficiency position it as a viable candidate for deployment in modern, scalable cloud environments. Future research should focus on incorporating adversarial robustness,

leveraging federated and transfer learning, and validating model performance on live network traffic to ensure resilience against evolving cyber threats.

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