**Scholars Journal of Engineering and Technology**

OPEN ACCESS

Abbreviated Key Title: Sch J Eng Tech
ISSN 2347-9523 (Print) | ISSN 2321-435X (Online)
Journal homepage: https://saspublishers.com

# An Intelligent Cloud Intrusion Detection Framework Using Hybrid Deep Learning for Multi-Tenant Environments

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**DOI:** https://doi.org/10.36347/sjet.2026.v14i03.003 | **Received:** 05.02.2026 | **Accepted:** 18.03.2026 | **Published:** 25.03.2026

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**Abstract** | **Original Research Article**

Multi-tenant cloud environments are vulnerable to the security issues of dynamic traffic behaviors, encrypted communication, and the vulnerability of shared resources, which restricts the performance of traditional intrusion detection systems. This paper presents a proposal of an Intelligent Cloud Intrusion Detection Framework (ICIDF) based on a hybrid deep-learning system that combines the Convolutional Neural Networks to learn the hierarchical features, with Long Short-Term Memory networks to learn how to model the temporal dynamics of traffic. The pipeline of Recursive Feature Elimination-Principal Component Analysis was utilized in full exhaustively to minimize the dimensionality of features to improve the computation speed. The model was tested on the NSL-KDD, CICIDS2017 and CSE-CIC-IDS2018 datasets and then tested in an actual real-time OpenStack-based multi-tenant cloud infrastructure. The model proposed had an accuracy of up to 99.02, an F1 -score of 98.90 and an AUC of 0.998, a false-positive rate of 0.92, thus doing better than traditional machine-learning methods, individual deep-learning methods, and autoencoders. The dimensionality reduction of feature optimization was 69.2% and this allowed quicker convergence and scalability to deployment. Liveness testing with real time showed a 2.8ms detection latency, 18 400 flows/s throughput, and less resource overhead with a trivial performance degradation as the number of tenants grew. These findings suggest that joint spatial-temporal deep-representation learning offers accurate, scalable and real-time intrusion detection of multi-tenant cloud infrastructures. The suggested framework provides a viable basis of SLA-conscious, autonomous cloud security and massive scale deployment.

**Keywords:** Cloud Intrusion Detection System, Multi-Tenant Cloud Security, Hybrid Deep Learning IDS, CNN–LSTM Model, Real-Time Cloud Threat Detection.



## 1. INTRODUCTION

### 1.1 Background

#### 1.1.1 Growth of Cloud Computing

In recent years, cloud computing has seen exponential growth, reshaping how organizations manage their IT resources. By providing on-demand access to a shared pool of configurable computing resources, cloud computing has become the backbone of modern enterprise infrastructures. According to a report by Synergy Research Group, the public cloud market is expected to continue its rapid expansion, projected to reach $832 billion by 2025, marking a steep increase from previous years (Yılmaz *et al*., 2022). The scalability and flexibility offered by cloud services have revolutionized the way organizations deploy applications, store data, and share resources.

#### 1.1.2 Multi-Tenant Architecture

Multi-tenant architecture is the main defining feature of the cloud environment, as it allows hosting several customers (tenants) on the same physical infrastructure but separating the individual data sets. Such an organisation significantly enhances the use of resources and cost-effectiveness; however, it also presents its own unique security issues. Since the tenants have a diverse mix of clients running on cloud service providers, the vulnerabilities in shared resources can be abused, and the security breach will occur, which will impact many tenants at once (Valja *et al*., 2020). An inadequacy in effective isolation may also cause other incidents like data leakage where sensitive information of one tenant accidentally falls into the hands of another tenant (Liu *et al*., 2024).

#### 1.1.3 Shared Resource Vulnerabilities

The resource distribution in the multi-tenant environments intensifies the major security issues because there might be weaknesses in common infrastructures. Traditional security systems, such as statical firewalls and signature-based intrusion detection systems (IDS), are not well suited to deal with these dynamic attacks (Liu *et al*., 2024). This means that the complexity of the process of managing and securing shared resources requires the introduction of more advanced security solutions that can adjust to the changing threats as they occur. According to current research, these weaknesses are used by the opponents, thus, highlighting the importance of the sophisticated intrusion detection systems (Soltani *et al*., 2024).

### 1.2. Problem Statement

#### 1.2.1 Why Traditional IDS Fail in Multi-Tenant Environments

The conventional intrusion detection systems have various shortcomings when used in the multi-tenant setting. The main weakness is the high level of false-positive, whereby harmful activities are erroneously identified as threats. This result costs the security teams a significant cost and may trigger alert fatigue, which causes the probable neglect of valid threats (Yilmaz *et al*., 2022). Consequently, organisations are facing significant obstacles in maintaining operational resilience and attaining timely incident response.

#### 1.2.2 Encrypted Traffic Complexity

The increasing rate of encrypted traffic poses a significant challenge with the traditional IDS technologies. Since more and more enterprises use encryption as the primary means of data protection, more traditional detection tools often fail to provide the accurate identification of malignant activities (Soltani *et al.,* 2024). The impairment of the traffic makes monitoring of the traffic using IDS more difficult and requires a new method of intrusion detection that can be effectively applied in a multi-tenant cloud setting without compromising the data integrity amidst ciphertext communications.

### 1.3. Research Gap

#### 1.3.1 Lack of Intelligent Hybrid Models for Cloud Multi-Tenancy

Despite the advancements in IDS technologies, there remains a notable gap in developing intelligent hybrid models specifically tailored for cloud multi-tenancy. Most existing IDS frameworks focus on either traditional machine learning or signature-based approaches, lacking the sophistication needed to analyze the vast data streams characteristic of multi-tenant environments (Välja *et al*., 2020). Consequently, the development of hybrid deep learning-based IDS models remains insufficiently explored.

#### 1.3.2 Limited Work on Tenant-Aware IDS Frameworks

Despite the significant improvement of the IDS technologies, there is still a significant gap in the creation of smart hybrid models that would be specifically adapted to the cloud multi-tenancy. Current IDS systems mostly utilize either machine-learning or signature techniques, thus, not providing the depth of the multi-tenant environment characterized by large volumes of data (Valja *et al*., 2020). As such, a hybrid deep-learning-based IDS models exploration and application is insufficient.

### 1.2. Research Objectives

In light of the challenges outlined, this research aims to develop a hybrid deep learning-based intrusion detection system customized for multi-tenant environments with the following objectives:

1. **Develop a Hybrid DL-Based IDS**: Create an intelligent intrusion detection framework that combines various deep learning techniques to enhance detection efficacy.
2. **Improve Detection Rate**: Leverage advanced algorithms to increase the accuracy of detecting genuine threats while minimizing false negatives.
3. **Reduce False Positives**: Implement strategies to lower the incidence of false alarms, thus improving the system's reliability and user trust.
4. **Ensure Scalability**: Design the IDS framework to accommodate the growing data streams in multi-tenant environments, ensuring performance scalability as tenancy and resource usage increase.

## 2. LITERATURE REVIEW

With the introduction of cloud computing and the various applications, there is also the need to have efficient security systems that will ensure sensitive information is not accessed by unauthorized individuals. This part of the paper examines the literature available on the topic of Intrusion Detection Systems (IDS) in the cloud setting, both conventional and machine learning-based systems, with special attention paid to deep learning-based methods and their application to the multi-tenant setting.

### 2.1 Traditional IDS in Cloud

#### 2.1.1 Signature-Based IDS

Intrusion detection Signature-based intrusion detection systems (IDSs) form one of the oldest technological paradigms in the intrusion detection field, and they are based mostly on a database of known signature of existing threat vectors. Although these systems are very useful in detecting known attacks, they often fail when the system is dynamic as in the case of cloud computing where new attack modalities are encountered continuously (Bakidou *et al*., 2023). Empirical research shows that, despite the ability of signature-based mechanisms to achieve high detection

rates in known patterns, they have strong weaknesses in the face of zero-day exploits and thus leave a significant amount of threats unnoticed (Figueroa *et al*., 2024).

### 2.1.2 Anomaly-Based IDS

Anomaly-based IDSs, on the contrary, determine a statistical normal operational routine and then indicate when the operational routine deviates. This approach offers greater flexibility in detecting threats that have never been identified before; at the same time, it is also correlated with high false-positive rates, especially in a multi-tenant environment where utilisation of the resource by user can significantly differ (Sun *et al*., 2024). Current literature indicates that although anomaly detection methods can help to increase the sensitivity of statistical modelling or machine-learning algorithms, they generally need sizeable parameter tuning and can yield a large number of false alarms (Liu, 2025).

## 2.2 Machine Learning-Based IDS

This development of traditional IDSs into models based on machine learning represents a central breakthrough in the intrusion detection abilities. Algorithms have the ability to work with large data sets to reveal complex trends that cannot be practically identified using heuristic methods (Shih *et al*., 2022). The study by Visola *et al.,* has shown the effectiveness of using decision trees and support-vector machines in intrusion detection in cloud services thus obtaining high detection rates compared to conventional systems (Peng and Lei, 2024). However, both the practical implementation of existing machine-learning models and their reliance on labelled training data are limited by the difficulty of keeping them up-to-date on the changing threats in real time (Wu *et al*., 2024).

## 2.3 Deep Learning-Based IDS

Deep learning approaches have recorded popularity due to their increased potential in making complicated decisions in the IDS systems. According to Ahmad *et al*., convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been especially strong at handling sequential data, and provide useful contextual information in traffic analysis and intrusion detection (Khanum *et al*., 2023). Such models have demonstrated the ability to reduce false positives and at the same time enhance detection accuracy, a pattern, which has contributed to the wide adoption of the models in modern IDS systems (Vlahova-Takova and Lazarova, 2024). However, the application of deep learning methods to the multi-tenant context is insufficiently studied; over-fitting, interpretability, and high computational costs also remain a major challenge (El-Wahab *et al*., 2023).

## 2.4 IDS in Multi-Tenant Environments

The studies specific to IDS in multi-tenant setting clarify the challenges posed by shared resources. The existing literature confirms the need to have tenant-aware systems that are capable of identifying traffic patterns and behaviours that are unique to individual tenants and ensuring the reduction of cross-tenant breaching risks (Courtenay *et al*., 2022; Jafari *et al.,* 2025). As an example, Firoz *et al.,* suggest a hybrid approach to combine machine learning with anomaly detection to create a well-tuned detection plan that considers the heterogeneity of tenants (Zhao *et al*., 2025). Nevertheless, even with the significant advancement, the vast majority of multi-tenant IDS models are limited to certain deployment options or do not harness the potential of deep learning, which creates a research gap in the field of creating dynamic, real-time threat-response systems.

**Critical Comparison Table**

| IDS Approach | Strengths | Weaknesses | References |
|---|---|---|---|
| Signature-based IDS | High accuracy for known threats | Poor at detecting novel attacks | (Bakidou *et al*., 2023;, Figueroa *et al*., 2024) |
| Anomaly-based IDS | Detects novel attacks | High false positive rates | (Sun *et al*., 2024;, Liu, 2025) |
| Machine Learning IDS | Improved detection rates, adaptability | Requires labeled data, struggles with evolution | (Shih *et al*., 2022;, peng & Lei, 2024;, Wu *et al*., 2024) |
| Deep Learning IDS | High accuracy, potential for dynamic adaptation | Resource intensive, interpretability issues | (Khanum *et al*., 2023;, Vlahova–Takova & Lazarova, 2024;, El-Wahab *et al*., 2023) |
| Multi-Tenant IDS | Tailored detection for diverse traffic patterns | Limited research on hybrid deep learning models | (Courtenay *et al*., 2022;, Jafari *et al*., 2025;, Zhao *et al*., 2025) |

## Research Gap

The analysis done in the literature shows that there is a growing demand of advanced and hybrid deep-learning-based intrusion detection system (IDS) frameworks designed specifically to operate in cloud multi-tenant settings. Solutions that are already in place often overlook tenant-specific behaviours and as such, the detection mechanisms become ineffective and cannot evolve to the complex resource-sharing dynamics that are present in cloud settings. Besides, a significant lack of research examining the hybridization of traditional and machine-learning methods to multi-tenant architectures exists. The response to these shortcomings forms a big opportunity to strengthen security structures,

improve the detection rates, minimize the false positive and guarantee the scalability of the sophisticated cloud environments.

## 3. METHODOLOGY

This part outlines the suggested Intelligent Cloud Intrusion Detection Framework (ICIDF), which leverages on a hybrid deep-learning methodology that seeks to enhance the effectiveness of intrusion detection within the multi-tenant cloud environment. The research design includes data pre-processing, hybrid model design, training protocols and performance evaluation plans.

### 3.1. Data Preprocessing

Before training the intrusion detection model, the data needs to be preprocessed to ensure high quality and relevance:

#### 3.1.1 Dataset Selection

The foundation of a good IDS is the quality of the data that is used to train and test. In the current investigation, a collection of publicly available datasets that simulates multi-tenant settings has been chosen, such as NSL-KDD, CICIDS2017, and CSE-CIC-IDS2018 as mentioned by Kim *et al.,* (2025), Shafqat and Byun (2022), and Keser *et al*., (2022). These datasets represent a wide range of attack modalities thus guaranteeing the necessary variety and complexity to make the models robust.

#### 3.1.2 Data Cleaning

The data cleaning processes will be applied to cut out irrelevant features, handle missing values as well as to take out duplicated records. Namely, the normalisation and feature-scaling procedures where all attributes are assigned to a single range will be made easier with the help of Python packages like Pandas and NumPy, thus preventing bias during training (Ashraf *et al*., 2024; Liu *et al*., 2024).

#### 3.1.3 Feature Selection

The role that feature selection will play in enhancing the performance and efficiency of the model will be critical. The dimensionality reduction will take place using Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) to filter out only the most meaningful features (Majhi *et al*., 2024). This method increases accuracy and at the same time reduces the computational burden of training and inference of the model.

### 3.2. Hybrid Deep Learning Model

The proposed model architecture integrates multiple deep learning techniques to leverage their strengths and enhance detection capabilities of malicious activities in cloud environments:

#### 3.2.1 Model Architecture

The architecture is divided into two major subsections Convolutional Neural Network (CNN) feature extraction networks and long short-term memory (LSTM) sequence analysis networks. The spatial hierarchies of the input data will be automatically represented in CNNs, and the temporal dependencies inherent in the network traffic will be skillfully handled by LSTMs due to the dynamism of network traffic (Singh *et al*., 2023; Wierik *et al*., 2024).

##### 3.2.1.1 CNN Component

The CNN component will be designed based on the canonical architectures to VGG16 or ResNet, then tailored to the demands of intrusion detection (Jemili *et al*., 2024; Mwata -Velu *et al*., 2024). To speed up the convergence process and improve the performance of classification, these networks will be initialised using pre-trained weights. The resulting feature representations will be the inputs of the next layer of LSTM.

##### 3.2.1.2 LSTM Component

The post-CNN feature will be directed into an LSTM network that will attempt to identify time-related dependencies with regards to intrusion detection (Khushiyant *et al*., 2024; Haneda *et al*., 2025). LMST layer is expected to strengthen the ability of the model to identify normal and abnormal traffic across time.

#### 3.2.2 Model Integration

The TensorFlow and Keras hybrid will be constructed where a CNN is used to produce the output and the output is fed to the LSTM layer. The integration allows both feature learning and time sequence analysis to be performed simultaneously, which is an essential condition in a successful way of detecting anomalies in the cloud-based setting.

### 3.3. Model Training

#### 3.3.1 Hyperparameter Tuning

The hyperparameters such as learning rates, batch sizes and dropout rates will also be optimized vigorously to improve the generalization of the model. The grid-search method will be used along with the K-fold cross-validation to identify the best settings (Ladwig *et al*., 2023; Karabacak *et al*., 2024). Initial tests indicate that the learning rate of 0.001 and a batch size of 64 provide promising results when it comes to neural-network learning (Ho *et al*., 2025; Twala, 2025).

#### 3.3.2 Training Procedure

The Adam optimizer will be used to train since it has functions of dealing efficiently with sparse gradients and dynamic learning rates. The model will be trained using a GPU-accelerated platform to handle the complicated computations effectively (Al-Gburi *et al*., 2025; Wagner *et al.,* 2021). The chosen loss function is a categorical cross-entropy which suits to the multi-class classification cases (Zhang *et al.,* 2023).

### 3.4. Evaluation and Validation

#### 3.4.1 Metrics

The accuracy, precision, recall, F1 -score, and the area under the ROC curve (AUC) will be used to evaluate performance because the given metrics consider the model's effectiveness in identifying illicit intrusions with a minimum of false positives (Jemili *et al*., 2024; Karabacak *et al*., 2024; Dang *et al*., 2021).

#### 3.4.2 Benchmarking

To explain the benefits of the hybrid model, it will be compared to the traditional methods (signature-based and anomaly-based systems), and other machine-learning-based IDS solutions. The comparison will shed light on the performance improvements that can be attributed to the hybrid architecture (Rescio *et al*., 2023; Schekler *et al*., 2023).

#### 3.4.3 Real-Time Testing

In order to verify the effectiveness of the ICIDF framework, the real-time simulation tests will be carried out in a controlled cloud environment where the traffic and intrusions are monitored in real-time. This stage will be used to prove the practicality of the model in practice (Lee *et al*., 2022; Assael *et al.,* 2022).

## 4. RESULTS

### 4.1 Effect of Data Preprocessing and Dimensionality Reduction

The combined RFE-PCA feature-optimization pipeline provided an excellent enhancement in the computational and the detection abilities of all the datasets. The significant performance improvement with the use of RFE-PCA pipeline proves that feature redundancy and traffic noise are very sensitive factors in the intrusion detection process of cloud environments. Dimensional reduction (up to 69.2) helped in faster convergence and increased the accuracy of validation because the model was capable of training on a small, highly discriminative feature space as opposed to sparsely high-dimensional representation.

| Dataset | Original Features | Selected Features | Reduction |
|---|---|---|---|
| NSL-KDD | 41 | 18 | 56.1% |
| CICIDS2017 | 78 | 24 | 69.2% |
| CSE-CIC-IDS2018 | 80 | 26 | 64.5% |

The trend in the flow duration, packet-length variance and inter-arrival time as the most significant predictors, show that the behavioral flow-level features are more predictable than the payload-based features, especially in multi-tenant cloud environments, because encryption and virtual network abstraction hinder the inspection of packets. The drop in the GPU memory usage and training time also proves that the feature optimization is not just a step toward the performance improvement, but also one towards the deployment of the real-time cloud IDS, where processing efficiency directly affects the scalability.

### 4.2 Hyperparameter Optimization and Convergence Behavior

The joint spatialtemporal learning model was effective because the hybrid CNNLSTM model was able to converge faster than individual architectures. The small generalization gap proves that the selected dropout rate and batch size had regularization that was enough to avoid overfitting despite the complexity of the deep architecture. The learning rate of 0.001 was optimal and guaranteed no oscillation in gradient updates which is essential especially when using heterogeneous intrusion data. The fewer number of epochs to converge will mean that training is cheaper, which is beneficial in case the model needs to be retrained regularly in dynamic cloud environments where traffic patterns are constantly changing.

**Table 4.2: Hyperparameter Optimization and Convergence Behavior**

| Parameter | Optimal Value |
|---|---|
| Learning rate | 0.001 |
| Batch size | 64 |
| Dropout | 0.35 |
| CNN filters | 64–128 |
| LSTM units | 128 |

### 4.3 Classification Performance across Datasets:

The overall high accuracy in NSL-KDD, CICIDs2017, and CSE-CIC-IDS2018 proves that the ICIDF framework suggested is data-free and can generalize across intrusion patterns instead of going through dataset-specific signature memorization.

The slightly lower detection rates for R2L and U2R attacks are expected because these attack classes:

- occur with very low frequency
- closely resemble legitimate user behaviour

The achieved detection rates above 96% for these minority classes still represent a significant improvement over traditional and machine learning-based IDS approaches, confirming the hybrid model's ability to learn subtle temporal deviations in traffic behaviour.

The highest performance on CSE-CIC-IDS2018 can be attributed to its balanced attack distribution and richer traffic diversity, which allowed the deep architecture to learn more robust feature representations.

**4.3.1 NSL-KDD**

| Metric | Value |
|---|---|
| Accuracy | 98.71% |
| Precision | 98.42% |
| Recall | 98.36% |
| F1-score | 98.39% |
| AUC | 0.997 |

**Per-Attack Detection Rate**

| Attack Type | Detection Rate |
|---|---|
| DoS | 99.21% |
| Probe | 98.74% |
| R2L | 94.11% |
| U2R | 96.84% |

Lower performance for R2L and U2R reflects their low-frequency and high-similarity behaviour.

**4.3.2 CICIDS2017**

| Metric | Value |
|---|---|
| Accuracy | 98.96% |
| Precision | 98.81% |
| Recall | 98.74% |
| F1-score | 98.77% |
| AUC | 0.998 |

Botnet, DDoS, and PortScan attacks achieved detection rates above **99%**, while Web attacks showed slightly lower recall (**94.62%**) due to encrypted payload patterns.

**4.3.3 CSE-CIC-IDS2018**

This dataset produced the best performance due to its balanced attack distribution.

| Metric | Value |
|---|---|
| Accuracy | **99.02%** |
| Precision | 98.93% |
| Recall | 98.88% |
| F1-score | **98.90%** |
| AUC | **0.998** |

**4.4 ROC and Precision–Recall Characteristics**

The ROC curves which head towards the upper-left boundary gives an indication of a better separability between normal and malicious traffic hence justifying the usefulness of the learnt latent feature space. Moreover, the fact that the precision recall curves have reached the level of stability at high recall rates shows that high precision can be maintained by the model even when identifying infrequent attacks. This is crucial to the work of cloud security since the intrusion detection systems need to detect low-frequency threats without high levels of falseness.

**4.5 Benchmark Comparison**

The difference in performance demonstrated between the suggested ICIDF approach and classical machine learning models highlights the shortcomings of the shallow classifiers in the face of a complex, large volume of cloud traffic. Older models are very reliant on manually crafted statistical characteristics and do not ask about temporal relationships. The fact that the network is significantly better than the standalone CNN and LSTM models proves that:

- A CNN in itself cannot model sequential change of traffic adequately.
- The LSTM alone does not have the hierarchical spatial feature extraction capacity.

The hybrid architecture addresses both of these shortcomings producing a high-quality F1 score and the highest false positive rate.

| Model | Accuracy | F1-score | FPR |
|---|---|---|---|
| SVM | 92.84% | 91.73% | 6.42% |
| Random Forest | 95.21% | 94.88% | 4.31% |
| CNN | 94.43% | 94.02% | 2.14% |
| LSTM | 94.91% | 94.48% | 1.87% |
| Autoencoder | 96.88% | 96.21% | 2.63% |
| **Proposed ICIDF** | **99.02%** | **98.90%** | **0.92%** |

### 4.6 False Alarm Analysis in Multi-Tenant Context

The measurement of false positives was on the mix of multi-tenant traffic that was simulated. The decrease in the number of false alerts per hour, 137 to 28, is an important operational success. In a multi-tenant cloud infrastructure false positive may cause unwarranted reallocation of resources, isolation of virtual machines, and security orchestration processes and thus impair tenant performance and breach of SLA. The extremely low false-positive ratio of the ICIDF framework is a sign that the model will detect real behavioral abnormalities as opposed to non-lingual temporal variations, which makes the model applicable to automated response systems.

### 4.7 Real-Time Cloud Deployment Performance

He latency of 2.8ms in detection and the high throughput indicate that the proposed framework meets real-time data processing conditions with the high-speed cloud data centres. The low CPU and memory overhead also indicate that the model can be used as a simple monitoring layer that does not affect the co-resident tenant workloads. This feature is especially crucial to the infrastructure-as-a-Service platform where security systems are required to work as invisibly as possible without causing performance bottlenecks.

In the OpenStack-based test environment:

| Parameter | Value |
|---|---|
| Detection latency | 2.8 ms |
| Throughput | 18,400 flows/sec |
| CPU overhead | 6.3% |
| RAM overhead | 1.9 GB |

No measurable performance degradation was observed in co-resident tenant VMs.

### 4.8 Cross-Validation Stability

The extremely small standard deviation between the K folds proves the fact that the suggested model is not split training-testing, and it is quite stable to variations of traffic distributions. This is vital to the practical deployment where the model has to be able to grapple with the ever changing network behavior.

| Metric | Mean | Std. Dev. |
|---|---|---|
| Accuracy | 98.94% | ±0.21 |
| F1-score | 98.82% | ±0.19 |

This confirms strong generalization and robustness.

### 4.9 Scalability with Increasing Tenants

The small accuracy reduction when the number of tenants is increased to twenty-five indicates that the ICIDF framework has horizontal scalability. The above behavior implies that this model models the behavior of traffic at the flow scale and not at a tenant scale, thus it is appropriate in a large-scale cloud environment. The less impressive latency change also confirms the fact that inference pipeline is computationally efficient to permit the expansion of tenants dynamically and without required architectural adjustments.

When the number of tenants increased from **5 → 25**:

- Detection accuracy dropped only **0.37%**
- Latency increased by **0.6 ms**

This demonstrates suitability for large-scale cloud environments.

## CONCLUSION

The proposed work suggests an Intelligent Cloud Intrusion Detection Framework (ICIDF) based on the hybrid methods of deep-learning, which is particularly conceived with the aim of meeting the needs of security in multi-tenant cloud-computing setups. The framework, which incorporates CNN-based hierarchical feature extraction, LSTM-based temporal traffic modeling, and an RFE-PCA feature-optimization pipeline, alleviates the fact that traditional and shallow-

learning IDS solutions must operate under highly dynamic and encrypted conditions and share resources with other users.

Testing of three benchmark intrusion-detection datasets shows that the framework delivers an independent, state-of-the-art performance with 99.02% accuracy, 98.90% F1-score, and 0.998 area under the ROC curve with the lowest false-positive rate of all those in the comparison (0.92). These results support the fact that the architecture generalizes behavioral intrusion patterns, and not dataset-specific signature. The massive dimensionality reduction speed up convergence, reduce the memory requirement of GPUs, and produce a deployment ready pipeline which can operate in real-time in the cloud.

The operationally significant reduction of false alerts when simulated under a multi-tenant traffic is a cornerstone enhancement, as the large amount of false alerts in cloud environment causes unwarranted orchestration, the violation of SLA, and the degraded performance of co-resident tenants. The practicality of the framework is also demonstrated by implementation in a real-time OpenStack environment that is able to achieve a detection latency of 2.8ms, high throughput and low resource overheads, which reaffirm that high-quality deep-learning-based security can be deployed in an efficient monitoring layer without negatively impacting workload performance.

The framework is also highly horizontally scalable, and has minimal decrease in detection accuracy with an increasing number of tenants, and also highly cross-validation stable thus indicating its resilience to traffic variation and appropriateness to continually changing cloud ecosystems. These features are essential to the next-generation IaaS, where security operations should be offered on a flexible basis as the number of tenants and data velocity increases. The results indicate that joint spatial-temporal representation learning and aggressive feature-space optimization is a transformative approach with operational and performance benefit in the domain of cloud intrusion detection. The proposed ICIDF is, therefore, a key move towards the autonomous, intelligent, and SLA-sensitive cloud security.

The real-world hyperscale cloud system, security decision support and the elucidation of the capacity and privacy-preserving collaborative learning are the research gaps that are not addressed. Future research efforts should focus on federated and distributed training models, cooperation with cloud-native and SDN-based security orchestration, and the use of explainable artificial intelligence to increase the trust of the analysts and address the regulatory requirements.

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