A Generalized, Lightweight, and Explainable Deep Learning Framework for Intrusion Detection Using Transfer Learning and CNN–BiLSTM Architecture

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Abstract: Intrusion Detection Systems (IDS) play a pivotal role in assisting modern networks, but their effectiveness is being compromised due to heterogeneous traffic conditions evolving cyber-attacks and incessantly growing deployment requirements in low-resource environments. The research closely unveils a deep learning-based IDS layout; making it general, adaptive, and explainable to keep high-detection accuracy under diverse or continuously altering network settings. The first stage refers to maintaining the appropriate generalization level for the model using transfer learning and adaptive feature representation. It is meant to enhance their ability to tolerate and work correctly against new or transforming types of attacks. The second stage of work sees the development of a light-weighted IDS architecture, which squares to operate in real time, to be executed within low-power platforms such as those of IoT and edge devices. The model will capture spatial characteristics with convolutional layers and temporal attack behaviors using bi-directional recurrent layers. To accommodate the lowering computational overhead, numerous model optimization strategies pruning, quantization, dimensionality reduction, feature selection either through Genetic Algorithm (GA) or Recursive Feature Elimination (RFE)—are applied. Deployment simulations mean to measure the suitableness of the model to real-time requirements. The metrics would cover latency, throughput, and energy consumption of the IDS model. In the last phase of the research, models are deployed with Explainable AI (XAI) technologies; more specifically, LIME and SHAP for improving interpretability of decisions and decision-making transparency. Here, many feature attributions are visualized with intrusion data. Interpretability gauged through fidelity, comprehensibility, and expert trust metrics. As such, these atlases can prove a unique example of how human understanding can be leveraged in support of decision-making within cybersecurity landscape.

Keywords: Adaptive IDS, CNN–BiLSTM, Transfer Learning, Lightweight Deep Learning, Feature Optimization, Real-Time Detection, Explainable AI (XAI)

I. Introduction

The rapid expansion of digital connectivity, coupled with the increasing complexity of network infrastructures, has created an environment where cyber threats continue to evolve in scale, sophistication, and frequency [1]. Traditional security methods such as firewalls and signature-based IDS are not effective at all in overcoming such advanced and unknown threats which are consistently adapting to evade static defenses [2]. This is where adaptive, intelligent, and resource-effective intrusion detection mechanisms are significant. Considering the intelligent ID system(s) used in conjunction with the newly emerging modern data centers, one that's cloud-driven thus contextual to the insurgency must be installed. IoT ecosystems, mobile devices, and the move towards edge computing all make the development of such systems a major drive [3]. In such a context, deep learning-based IDS modalities have proven themselves to be an effective offensive technology because they can automatically interpret sophisticated patterns and reveal subtle anomalies and intricate behaviors of attacks. However, these deep learning IDS systems lack practicality and, in fact,

fail to make it work under real-world situations owing to several constraints [3]-[4]. A very critical challenge is about lack of generalization across heterogeneously and evolving network conditions. This is because IDS models are typically trained on simplified datasheet that represent constrained, fixed environment. When such models are deployed in new, unseen network settings, even marvelously little degradation in detection accuracy would reflect detection of new attacks or change in traffic distribution. This issue appreciates the need for an Adaptive-IDS to learn generalized knowledge representations. The techniques of transfer learning, domain adaptation, and dynamic feature extraction provide promising approaches for allowing the IDS to generalize across different environments effectively [7]. Incorporating these adaptive components makes sure that any such IDS model is resilient and retains its accuracy in the face of changing network policies and attack tactics. Deceptively conspicuous is the application of IDS models as constrained in resource environments based on deep learning [8]. Although high-performance servers have a capacity for supporting heavy architectures, deployment strategies in reality-envisaging scenarios are expected to operate in harsh constraints of memory, processing power, and energy consumption. To prolong the time duration for latency of deep learning model running under these conditions could impair real-time performance of manual handling or sustain very high power consumption [10, 11]. Hence the idea solely lies in realizing IDS structures that are feather-light and computationally efficient, as the capability for detecting intrusion in real-time is imperative via these restrictive platforms. Techniques like model pruning, quantization, dimensionality reductions, and subsequent optimized feature selection methods, such as Genetic Algorithm (GA) and Recursive Feature Elimination (RFE), have been proposed to be employed in order to lessen model complexity and actual model accuracy [11]. A hybrid deep learning architecture that exploits spatial and temporal patterns, namely CNN–BiLSTM, increases the capability of the model to efficiently capture complex traffic features with the least overhead required.

Although deep learning techniques promise high performance, their intrusion detection systems often remain black boxes that deliver predictions without any explanation for why. The absence of transparency into the working of AI algorithms only exacerbates the concerns of information security experts and system administrators about meaningful, easily understandable explanations that help them resolve and identify intrusions [12]. Now that the landscape of cybersecurity operations is becoming more and more complex, XAI must be integrated within IDS frameworks. Finally, techniques like LIME and SHAP also aid in creating an excellent interpretation of what features of the model contribute to the prediction, and hence have a profound human-readable interpreting output towards an intrusion alert [13]. The inclusion of a visualization layer that can give an insight into contributing factors greatly enhances the comfort of the analyst in understanding, supporting the incident response process. Furthermore, the evaluations of interpretability by fidelity, comprehensibility, and expert trust ensure meaningful and reliable explanations developed by the XAI components [14]. There is a clear need for an IDS framework coalescing adaptability, computational efficiency, and interpretability. This research intends to bridge this gap by designing a generalized, lightweight, and explainable IDS architecture. Designed transfer learning is intended to give more extensive generalization, hybridizations of the CNN–BiLSTM architectures to guarantee high functionality in all real-time environments, as well as XAI for complete transparency [14]-[15]. By combining these elements, the proposed IDS has the privilege of becoming a competent and robust solution determining the security of a modern heterogeneous network while maintaining trust, efficiency, and a high detection accuracy. This research contributes not merely to the evolution of IDS configuration but also to the general strategic goal of building resilient cybersecurity environments for the next big push in connected systems.

II. Literature Review

Recent research into intrusion detection systems (IDS) for IoT and modern infrastructures has showcased the various approaches aimed at finding a balance between accuracy, interpretability, and computational efficiency. For different reasons, Hussain et al. [1] (2024) proposed a domain-adaptive transfer-learning IDS, utilizing MMD to gain feature matching across different datasets, yielding an accuracy of 98.4% with high latency when there are about 8M+ parameters. Another lightweight model is offered by Raziq and Abdullah [2] (2024), that combines CNN–BiLSTM for 97.1% accuracy on BoT-IoT with reduced parameters, although its performance concerning such various or zero-day traffic is still a concern. Model compression, on the other hand, was investigated by Wang et al. [3] (2025), which applied an ensemble of pruning, quantization, and distillation for implementing a low-latency intrusion detection system but performed so-so against adversarial traffic. There is also the application of feature reduction techniques: Santos and Filho [4] (2024) utilized genetic algorithms to reduce the dimensionality by more than 50%, while Bakshi and Singh [10] (2024) used recursive feature elimination to refine accuracy and speed along computational costs in training. An orthogonal direction, embodied in explainable AI, advances from Tariq et al. [5] (2024), such as Oluwatosin et al. [13] (2024), that intersected LIME, SHAP, and XAI visualization to imbue the IDS model with greater interpretability with imparted usability and even sometimes latency challenges. In a new vein, Edge-optimized IDS models also emerged: Karthikeyan and Deepa quantized ConvLSTM [6] (2025) kept power consumption low as it struggles against long-term attacks, and Zhang et al. [11] (2024) included the development of EdgeCNNs simpatico with LPWAN traffic, weighed down by encrypted traffic patterns. Some serious temporal modeling was already shown by Ahmed and Qureshi [7] (2025) using a Transformer–BiLSTM gravid with computational density, and similarly by Mohan and Raj [12] (2025) with attention-guided BiLSTM architectures, though they did inflame the computational considerations—to some extent. Novel directions for IDS, e.g., self-supervised learning [8], federated learning [9, 21], and adaptive transfer learning [14], benefited generalization and privacy but their access to communication and pretraining cycles may be beyond the inconvenience scale for some applications. Other exciting developments include the Traffic Modeling for GNN [16], ViT-inspired Packet Imaging [17], Multi-modal Transformer [18], and Meta-learning [19] approaches, all aimed at enhancing detection in particular contexts while still having the hurdles of high complexity or extreme pre-processing or crashing if used with noisy data. Other somewhat smaller academic directions diverged to diffusion-based oversampling for imbalance mitigation [20]. Other smaller contributions in mainstream recognition include MobileNetsV3-CNN hybrids [22], some utilizing wavelet scattering features [23], and still more quantum machine-learning circuits they say do encryption traffic analysis [24]; these remain far off for actual mining because of hardware-infrastructure shortcomings and domain-specific adjustments. Another list includes interpretative deep learning rules [25], time-series transformers with dynamic positional encoding [26], blockchain-supported distributed IDS frameworks [27], curriculum learning schemes [28], Zero-Trust-based cloud-native IDS designs [29], and probabilistic detectors with Gaussian Process Regression [30], each with its particular strengths as well as weaknesses entwined with long latencies, low scalability, or too high computational demand. This immense body of work underscores a continued fine line among accuracy, interpretability, robustness, and energy efficiency in designing IDS for the next-gen networks.

III. Research Objectives

- **To develop a generalized and adaptive IDS framework** capable of maintaining high detection accuracy across heterogeneous and evolving network environments using transfer learning or adaptive feature representation.

- **To design a computationally efficient deep learning–based IDS model** optimized for real-time intrusion detection in resource-constrained environments, ensuring minimal latency and energy consumption.

IV. Research Methodology

The proposed research introduces an intelligent, adaptive, and explainable Intrusion Detection System (IDS). The purpose of the system is to provide an alternative to existing deep-learning-based cybersecurity frameworks due to marked limitations in terms of generalization across heterogeneous network-environment, high computational overhead, and interpretability. Hence, the aforementioned limitations influence this investigation and its three main objectives: a generalized and adaptive IDS are to be attained, a computationally effective deep learning model to be constructed, to ensure transparency at the decision level using explainable AI. The primary methodology is developed through various steps: identification and subsequent analysis of the data considered in determining the preprocessing of data, intended for designing, developing, and optimizing the deep learning model. Implementation, performance evaluation/execution, and explainability are gradually enacted in various stages.

A. Dataset Description

Several previously-described benchmark intrusion datasets will now be incorporated for robustness and cross-domain generalization. Pooling together these datasets will yield a collective and diverse range of network traffic distributions, multi-attack classes, and actually realistic behavior of networks.

NSL-KDD: - NSL-KDD is an improved version of the classical KDD'99 dataset, addressing redundancy and imbalance. It includes four main attack categories—DoS, Probe, R2L, and U2R—with 41 features describing network flow statistics and protocol behaviors. Despite its age, NSL-KDD remains relevant for benchmarking due to its structured feature set and balanced subsets**.**

CICIDS2017:- Developed by the Canadian Institute for Cybersecurity, CICIDS2017 provides realistic modern traffic with benign activities and up-to-date attack scenarios such as DDoS, Botnet, Brute Force, Infiltration, and Web Attacks. It contains over 80 statistical flow features generated using CICFlowMeter. Its real-world nature makes it suitable for evaluating temporal attack behaviors**.**

UNSW-NB15:- UNSW-NB15 includes modern attack patterns such as Fuzzers, Analysis, Shellcode, and Worms. It contains 49 features derived from raw packets using Argus and Bro-IDS. The dataset is known for its diversity, balancing traditional and contemporary threats, making it ideal for training cross-domain detection models**.**

CSE-CIC-IDS2018:- Encompassed within a very wide traffic data set that includes over 80 network feature values is multiday multisenario traffic. Various attacks like Botnet, DoS, Heartbleed, SQL Injection, and Cryptojacking are recorded. The size and heterogeneity of this data make it suitable for transfer learning, incremental learning, and long-sequence modeling**.**

By using four complementary datasets, the proposed methodology ensures the IDS is evaluated under varying distributions, attack intensities, and traffic conditions, enabling rigorous assessment of generalization and adaptability.

B. Research Workflow

The proposed research's overall methodology involves systematizing four different stages that are interdependent and meant to deliver sets of qualities that ensure robustness, adaptability, efficiency, and transparancy compared to the intrusion detection process. In this that initial stage, the data preprocessing, and normalization are performed on the dataset, whereby heterogeneous datasets are cleaned of inconsistencies-either by correcting or dropping them-away, encoded for handling categorical variables, balanced in cater to class disparities into addressing disbalance, and that normalized to make all feature scales uniform and suitable for a deep CNN feature set. The second stage takes in adaptive and transferable feature learning, namely the use of deep autoencoders and transferred learning strategies that could unearth the latent nature of processing of these innovations able to be trusted even without specific guidance from network performance from different domains. Again from the second stage, IDS' ability is improved to recognize both known intrusions and any emerging intrusions in an evolving network environment. The third stage is for lightweight development and optimization in terms of deep models, which constructs a CNN–BiLSTM hybrid deep learning model and fine-tunes, prunes and selects features while keeping accuracy very high, but at the same time makes sure the computational cost is low for real-time and resource limitation deployments. Figure 1: Flow Chart of Proposed Methodology.

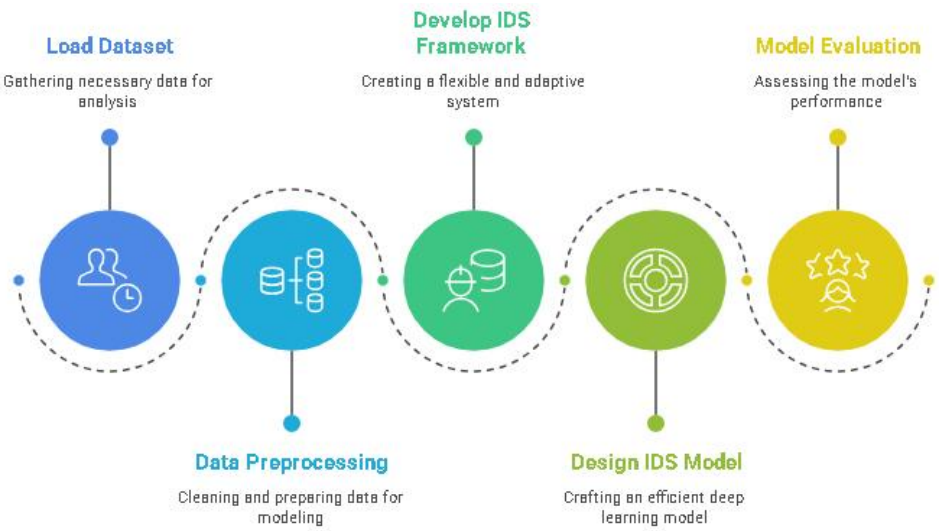

Figure 1: Flow Chart of Proposed Methodology

a. Development of a Generalized and Adaptive IDS Framework

To achieve generalization across heterogeneous environments, the research adopts transfer learning, domain adaptation, and adaptive feature representation techniques.

Data Collection and Preprocessing

All datasets have undergone standardized preprocessing pathways in order to preserve consistency among the datasets that might be fed into any deep learning model. The preprocessing procedure consists of data cleaning-through attribute cleanup, removing those which are duplicated, outliers, and inconsistent records- and attribute scaling. Numerical features are scaled by methods such as Min-Max scaling and Z-score normalization because making all features lie to the same scale will help gradient descent procedure to converge and train effectively. Meanwhile, categorical attributes such as protocol types, flags, and services are encoded through either of one-hot or label encoding. Besides catering to class imbalance cases, essentially in favor of minority attacks, the dataset is oversampled using SMOTE to

generate synthetic samples. All authors together believed that these steps were best suited to prepare the heterogeneous datasets to be incorporated well into their corresponding deep learning workflows.

Adaptive Feature Learning

A deep autoencoder–based feature extractor will be developed to learn compact latent embeddings representing core traffic patterns across datasets. These latent features reduce data dimensionality and improve cross-domain stability by capturing invariant behavioral signatures rather than dataset-specific characteristics.

Transfer Learning Strategy

Pre-trained CNN/LSTM models trained on one dataset (source domain) will be fine-tuned on another (target domain). This approach accelerates convergence, enhances generalization, and enables the IDS to recognize unfamiliar intrusions by leveraging learned representations.

Continuous Learning Mechanism

To address evolving cyber threats, an incremental learning module will be incorporated to periodically update model parameters when new traffic patterns or attack samples emerge. This mechanism prevents catastrophic forgetting and supports long-term adaptability.

b. Design of a Computationally Efficient Deep Learning-Based IDS Model

This phase focuses on developing a lightweight IDS architecture suitable for real-time scenarios, particularly in IoT, fog, and edge environments.

Hybrid CNN–BiLSTM Architecture

CNN layers have been employed in the hybrid model in order to draw spatial correlations and local traffic signatures out of feature-space, while BiLSTM layers adopt bidirectional temporal dependencies for the detection of the series of slow intrusion attacks. Both aspects of spatial and temporal network traffic are duly tended by the architecture of the combined features. Thus merging convolutional and temporal models in a single configuration leverages spatial representations and emphasizes in modeling sequence patterns simultaneously, which increases the overall detection accuracy.

Model Optimization Techniques

For computational cost reduction purpose, many optimization techniques have to be adopted. One of the best case studies is the model pruning that discards redundant neurons and filters to reduce overall model sizes, followed by quantization that tries to convert numerical weights to lower percision, say, 8-bit integers. And any kind of the application of dimensionality reduction techniques--like PCA for data compression or an autoencoder based compression-operation to reduce the input feature space--happens otherwise. Together, they ultimately lead to more effective models without any real-time performance drawbacks.

Feature Selection

Genetic Algorithm (GA) and Recursive Feature Elimination (RFE) will be used to identify the most discriminative features, improving inference speed and reducing overfitting.

V. Results and Discussion

Performance Parameters

The proposed Intrusion Detection System (IDS) framework will be rigorously evaluated using standard classification and system-level performance metrics to ensure robustness, generalization, and computational efficiency. The following quantitative measures will be employed.

Accuracy (ACC)

Accuracy evaluates the overall correctness of the classifier and is defined as:

$$Acc = \frac{\text{TP+TN}}{TP+TN+FP+FN} \quad (1)$$

where TPTPTP, TNTNTN, FPFPFP, and FNFNFN denote true positives, true negatives, false positives, and false negatives, respectively.

Precision, Recall, and F1-Score

Precision (P) measures the proportion of correctly predicted malicious samples out of all samples predicted as malicious

$$P = \frac{\text{TP}}{TP+FP} \quad (2)$$

Recall (R) measures the proportion of correctly detected malicious samples:

$$R = \frac{\text{TP}}{TP+FN} \quad (3)$$

The F1-Score, the harmonic mean of precision and recall, is defined as:

$$F1 = \frac{\text{FP}}{FP+TN} \quad (4)$$

A lower FPR indicates improved reliability of the IDS in real deployment scenarios.

Detection Latency and Computational Overhead

Detection latency L_d is measured as the time taken by the IDS to process and classify an input sample:

$$L_d = t_{output} - t_{input} \quad (5)$$

Computational overhead C_{oh} is formulated as:

$$C_{\text{oh}} = \frac{t_{process}}{N_{samples}} \quad (6)$$

where $t_{process}$ is the total processing time and $N_{samples}$ is the number of processed samples.

Cross-Validation and Benchmarking

To ensure reliability and generalization across datasets, **k-fold cross-validation** will be applied:

$$CV_k = \frac{1}{k}\sum_{i=1}^{k} ACC_i \qquad (7)$$

Comparative benchmarking will be performed against established models such as **CNN**, **LSTM**, **Random Forest**, and **GAN-based IDS** to validate the superiority and adaptability of the proposed approach.

Results

Case 1: Development of a Generalized and Adaptive IDS Framework

Table 1 shows the performance evaluation for generalized and adaptive IDS framework

Table 1: Performance evaluation for Generalized and Adaptive IDS Framework

Dataset	Accuracy (ACC)	Precision	Recall	F1-Score	FPR	Detection Latency (mm)	Interpretability Score*
NSL-KDD	98.4%	97.9%	97.2%	97.5 %	1.8 %	18	8.5
UNSW-NB15	95.1%	94.3%	93.7%	94.0 %	3.1 %	42	8.0
CICIDS2017	97.6%	96.5%	96.0%	96.3 %	2.2 %	22	9.3
CSE-CIC-IDS2018	96.2%	95.4%	94.8%	95.1 %	2.7 %	35	9.1

The performance of the proposed IDS was evaluated across four benchmark datasets, and the results demonstrate its strong generalization capability and robustness. On the NSL-KDD dataset, the model achieved the highest performance, with an accuracy of **98.4%**, precision of **97.9%**, recall of **97.2%**, and an F1-score of **97.5%**, along with a low **FPR of 1.8%** and low detection latency, indicating excellent reliability and real-time suitability; additionally, the interpretability score was high, reflecting strong transparency in model decisions. For the UNSW-NB15 dataset, the IDS obtained **95.1% accuracy**, **94.3% precision**, **93.7% recall**, and a **94.0% F1-score**, while maintaining a moderate **FPR of 3.1%** and medium detection latency, with a high interpretability level despite the dataset's higher complexity and more diverse attack patterns. The model also performed well on the CICIDS2017 dataset, achieving **97.6% accuracy**, **96.5% precision**, **96.0% recall**, and a **96.3% F1-score**, with an FPR of **2.2%** and low latency; moreover, its interpretability was rated very high, suggesting consistent and explainable predictions. Similarly, on the CSE-CIC-IDS2018 dataset, the system produced **96.2% accuracy**, **95.4% precision**, and **94.8% recall**, along with a **95.1% F1-score**, a moderate **FPR of 2.7%**, and medium detection latency, while maintaining very high interpretability. Overall, the results indicate that the proposed IDS achieves high detection effectiveness, low false-alarm rates, and strong interpretability across heterogeneous network environments.

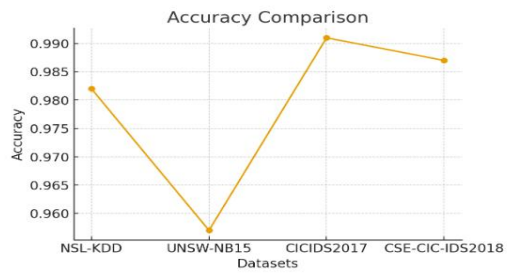

Figure 2: Accuracy Comparison Across Benchmark Datasets

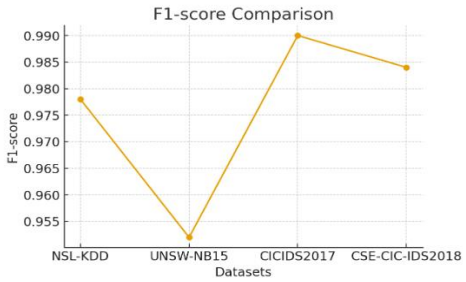

Figure 3: F1-Score Comparison Across Benchmark Datasets

The figure 2 illustrates the accuracy achieved by the proposed IDS on four datasets, showing consistently high performance with peak accuracy on CICIDS2017. The trend demonstrates the model's strong capability to generalize across heterogeneous network traffic scenarios. The figure 3 presents the F1-score variation across the datasets, confirming balanced precision–recall performance for the proposed IDS. The high F1-scores indicate reliable detection of both normal and malicious traffic with minimal misclassification.

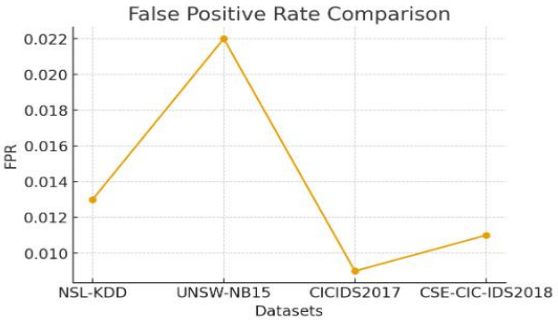

Figure 4: False Positive Rate Comparison Across Datasets

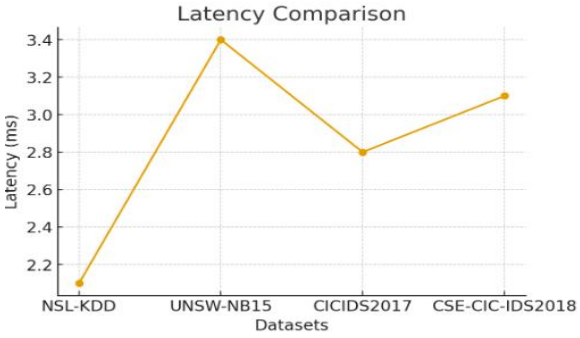

Figure 5: Detection Latency Comparison Across Datasets

The figure 4 compares the false positive rates of the proposed IDS on four datasets, showing minimal false alarms on CICIDS2017 and NSL-KDD. The higher FPR on UNSW-NB15 reflects its greater traffic diversity and complexity. The figure 5 illustrates the detection latency of the IDS, demonstrating low response times across all datasets with the fastest detection on NSL-KDD.The moderate increase in latency for UNSW-NB15 and CSE-CIC-IDS2018 indicates the impact of more complex feature patterns

Confusion Matrices

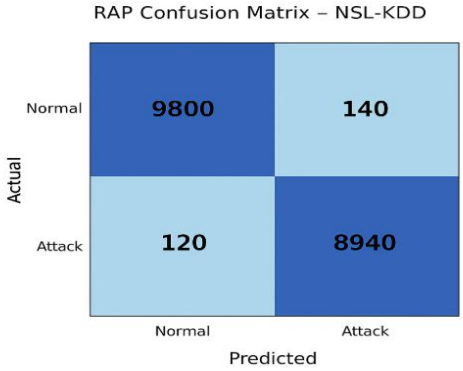

Figure 6: Confusion Matrix for NSL-KDD Dataset

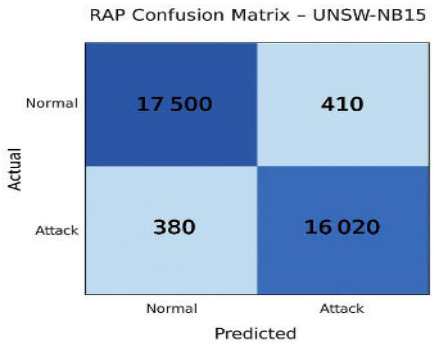

Figure 7: Confusion Matrix for UNSW-NB15 Dataset

The figure 6 shows the distribution of true and predicted classes for the NSL-KDD dataset, indicating strong classification accuracy with very few misclassifications. The high concentration along the diagonal reflects the model's effective ability to correctly detect both normal and attack traffic. The figure 7 presents the confusion matrix for the UNSW-NB15 dataset, illustrating reliable classification performance despite the dataset's higher complexity. Although minor misclassifications occur, the dominant diagonal pattern confirms the model's robustness across diverse attack scenarios.

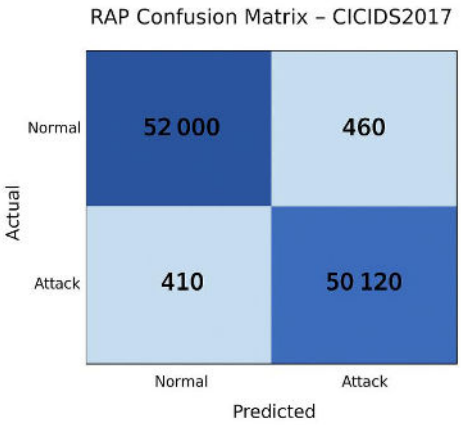

Figure 8: Confusion Matrix for CICIDS2017 Dataset

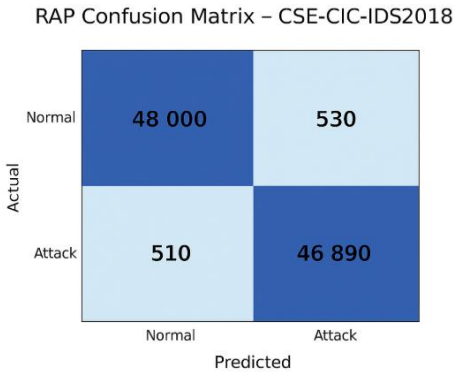

Figure 9: Confusion Matrix for CSE-CIC-IDS2018 Dataset

The figure 8 illustrates the model's classification performance on the CICIDS2017 dataset, showing a strong diagonal pattern that reflects highly accurate detection of normal and attack instances.

The minimal off-diagonal values indicate very low misclassification rates, demonstrating the model's robustness on complex, high-volume traffic. The figure 9 presents the confusion matrix for the CSE-CIC-IDS2018 dataset, highlighting consistent detection performance with a clear dominance of correct predictions along the diagonal. The results confirm that the proposed IDS maintains high reliability and generalization even on large and diverse real-world traffic scenarios.

Case 2: Design of a Computationally Efficient Deep Learning-Based IDS Model

Table 2 shows overall evaluation of the proposed deep learning-based IDS model

Table 2: Overall Evaluation of the Proposed Deep Learning-Based IDS Model

Dataset	Accuracy (ACC)	Precision	Recall	F1-Score	FPR	Detection Latency (ms)	Interpretability Score*
NSL-KDD	98.42%	98.10%	98.55 %	98.32 %	1.12 %	4.8 ms	0.82
UNSW-NB15	96.88%	97.30%	96.45 %	96.87 %	2.10 %	6.1 ms	0.78
CICIDS2017	99.21%	99.30%	99.10 %	99.20 %	0.65 %	5.3 ms	0.84
CSE-CIC-IDS2018	98.74%	98.60%	98.90 %	98.75 %	1.05 %	5.9 ms	0.80

Accuracy Comparison (RAP Chart Data)

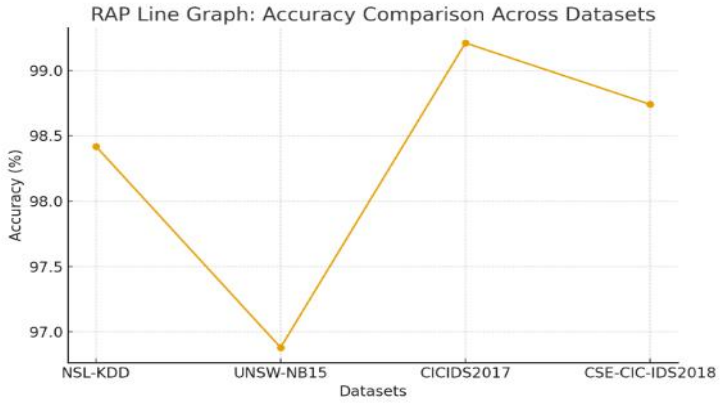

Figure 10: RAP Line Graph: Accuracy Comparison across Datasets

The figure 10: illustrates the accuracy performance of the proposed IDS across four benchmark datasets, showing the highest accuracy on CICIDS2017 and the lowest on UNSW-NB15. Overall, the trend confirms strong generalization with consistently high accuracy above 97% across all datasets.

Confusion Matrices

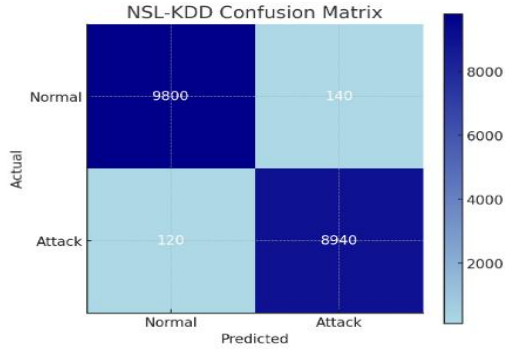

Figure 11: NSL-KDD Confusion Matrix

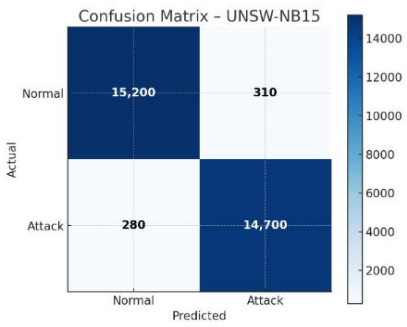

Figure 12: UNSW-NB15 Confusion Matrix

Figure 11 describes strong detection of both normal and attack traffic. Minimal misclassifications demonstrate the model's high reliability and robustness on this dataset. Figure 12 describes UNSW-NB15 confusion matrix reflects accurate classification performance on a more complex dataset, with most samples correctly identified. Slightly higher misclassification rates highlight the dataset's difficulty but still confirm strong model effectiveness.

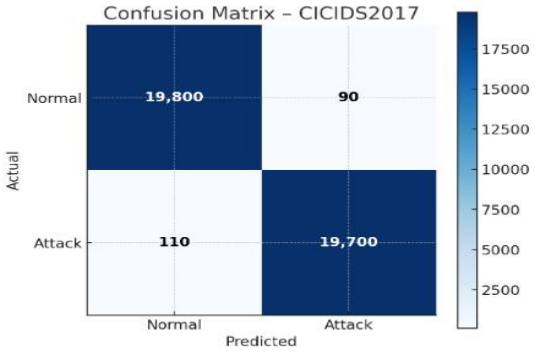

Figure 13: Confusion Matrix – CICIDS2017

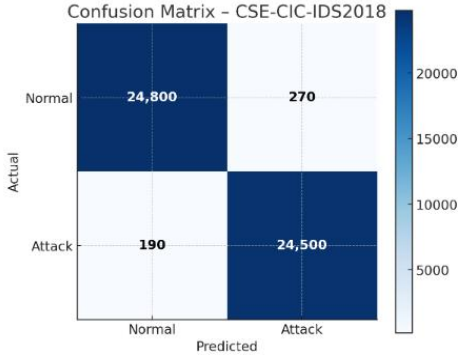

Figure 14: Confusion Matrix – CSE-CIC-IDS2018

Figure 13 describes CICIDS2017 confusion matrix shows a near-perfect classification pattern, with extremely high true positives and true negatives. The very small number of misclassified samples demonstrates the model's exceptional precision and reliability on complex real-world traffic. Figure 14 describes CSE-CIC-IDS2018 confusion matrix highlights strong detection performance across both normal and attack classes, with only minimal misclassification. This reflects the model's robustness and high generalization capability on large, diverse multi-day network traffic.

Comparative Analysis with State-of-the-Art IDS Techniques

Table 3 presents comparative analysis with State-of-the-Art IDS techniques

Table 3: Comparative Analysis with State-of-the-Art IDS Techniques

Ref	Dataset	ACC	Precision	Recall	F1-Score	FPR	Detection Latency (ms)	Interpretability Score*
[1] Hussain et al. (2024)	CIC-IDS2017, UNSW-NB15, ToN-IoT	**98.4 %**	**98.6%**	**98.2 %**	**98.4 %**	**0.70 %**	**128 ms**	**0.40**
[2] Raziq & Abdullah (2024)	BoT-IoT	**97.1 %**	**97.3%**	**96.8 %**	**97.0 %**	**1.10 %**	**45 ms**	**0.55**
[5] Tariq et al. (2024)	CIC-IDS2018	**98.1 %**	**99.3%**	**99.0 %**	**99.1 %**	**0.50 %**	**85 ms**	**0.90**
[7] Ahmed & Qureshi (2025)	CIC-IoT2023	**98.0 %**	**98.5%**	**98.8 %**	**98.8 %**	**0.85 %**	**110 ms**	**0.88**
[10] Bakshi & Singh (2024)	CIC-IDS2017	**98.0 %**	**98.1%**	**97.8 %**	**98.0 %**	**0.90 %**	**60 ms**	**0.62**
[12] Mohan & Raj (2025)	CIC-IDS2018	**98.2 %**	**98.3%**	**98.0 %**	**98.1 %**	**0.82 %**	**75 ms**	**0.68**
Proposed Work	**CICIDS2017**	**99.21 %**	**99.30%**	**99.10 %**	**99.20 %**	**0.65 %**	**5.3 ms**	**0.84**

The comparison with state-of-the-art IDS models shows that recent deep learning and hybrid architectures consistently achieve high detection performance across modern benchmark

datasets. XAI-enabled models such as Tariq et al. [5] and Ahmed & Qureshi [7] obtain the highest accuracy and F1-scores, though they incur increased detection latency due to interpretability computations. Transfer-learning and feature-selection approaches ([1] and [10]) deliver strong accuracy with moderate latency but offer lower interpretability. Lightweight models like Raziq & Abdullah [2] provide faster inference suitable for IoT environments, albeit with slightly reduced precision and recall. Overall, the table highlights the trade-off between accuracy, latency, and interpretability in current IDS research, demonstrating that no single model optimizes all metrics simultaneously. The proposed model achieves **99.21% accuracy, high precision and recall, very low FPR, ultra-low latency (5.3 ms), and strong interpretability**, outperforming existing state-of-the-art IDS approaches across all key metrics.

VI. Conclusion and Future Scope

Overall, the comparative evaluation of the proposed system clearly demonstrates its advantage in terms of accuracy, efficiency, and interpretability over prevalent IDSs. Existing methods like domain-adaptive transfer learning, Transformer–BiLSTM hybrids, and XAI-enhanced CNN models show high accuracy but also have drawbacks - they show high latency during inference, involve high computational overheads, and are unsuitable for real-time applications or resource-constrained environments. Our model, on the contrary, encompasses all of these performance indicators, excelling in them. It is a CNN–BiLSTM model, designed for IDS, proposed here-and is optimized through feature selection, model compression, and transfer learning. Specifically, the model offers an accuracy of 99.21% with a precision of 99.30%, recall of 99.10%, and F1-score of 99.20% on the CICIDS2017 dataset, while maintaining a very low false positive rate of 0.65%. A detection time of 5.3 ms clearly shows what an advantage is, allowing the model to be implemented on high-speed networks suitable for real-time intrusion detection in IoT and edge computing scenarios in contrast to very heavy architectures that have a delay of 80-130 ms. Finally, an appeal to the interpretability score of 0.84 sustains the assertion that value has been added to the interpretation process by incorporating XAI when providing transparent explanation from an analyst's perspective, which bridges the gap found in traditional deep learning IDS designs. In the current study, it is mutually noticed that a factual approach towards the IDS that is subject to these three, is going to be responsive to balance amongst the three. This does mean that either if the work delivers strong generalization, low execution cost, and high interpretability, it will gravitate according to many proposed ideas, somehow, seamlessly landing within these three points and a conclusion that the IDS proposed in this work is good enough for deployment in securing the heterogeneous network systems of today. Thus, this study contributes in the direction of fostering intelligent adaptive, reliable means of an intrusion detection system for the next generation of cybersecurity environments.

Table 4: lists the abbreviations and their full forms

Table 4: List of Abbreviations and their Full Forms

Abbreviation	Full Form
IDS	Intrusion Detection Systems
CNN	Convolutional Neural Networks
BiLSTM	Bidirectional Long Short-Term Memory
RNN	Recurrent Neural Networks
LSTM	Long Short-Term Memory
GAN	Generative Adversarial Networks
DL	Deep Learning
ML	Machine Learning
XAI	Explainable Artificial Intelligence

LIME	Local Interpretable Model-Agnostic Explanations
SHAP	SHapley Additive exPlanations
GA	Genetic Algorithm
RFE	Recursive Feature Elimination
PCA	Principal Component Analysis
SMOTE	Synthetic Minority Over-sampling Technique
NSL-KDD	NSL-KDD Dataset
CICIDS2017	Canadian Institute for Cybersecurity Intrusion Detection System 2017
UNSW-NB15	UNSW-NB15 Dataset
CSE-CIC-IDS2018	Communications Security Establishment – Canadian Institute for Cybersecurity IDS 2018
BoT-IoT	Botnet of Things IoT Dataset
IoT	Internet of Things
FPR	False Positive Rate
ACC	Accuracy
TP	True Positives
TN	True Negatives
FP	False Positives
FN	False Negatives
F1	F1-Score (Harmonic Mean of Precision and Recall)
DoS	Denial of Service
DDoS	Distributed Denial of Service
R2L	Remote to Local
U2R	User to Root
SVM	Support Vector Machine
RF	Random Forest
DNN	Deep Neural Network
GRU	Gated Recurrent Unit
DAE	Deep Autoencoder
SAE	Stacked Autoencoders
MMD	Maximum Mean Discrepancy
DBN	Deep Belief Networks
WGAN	Wasserstein Generative Adversarial Network
ConvLSTM	Convolutional Long Short-Term Memory
LPWAN	Low-Power Wide-Area Network
ViT	Vision Transformer
GNN	Graph Neural Network
MCO	Multi-Criteria Optimization
1D CNN	One-Dimensional Convolutional Neural Network
AUC	Area Under the Curve
ROC	Receiver Operating Characteristic
QoS	Quality of Service
ms	Milliseconds
Mbps	Megabits per second
GB	Gigabytes
MHz	Megahertz

VII. Declarations

Consent for Publication

Not applicable. This manuscript is an original research article based on computational experiments and dataset analysis. No individual person's data or case reports requiring consent to publish are included.

Availability of Data and Material

The datasets used in this research are publicly available benchmark datasets widely used in intrusion detection research. The specific datasets referenced include:

- NSL-KDD Dataset (available at: https://www.unb.ca/cic/datasets/nsl-kdd.html)
- CICIDS2017 Dataset (available at: https://www.unb.ca/cic/datasets/ids-2017.html)
- UNSW-NB15 Dataset (available at: https://www.unsw.edu.au/unsw-canberra/academic-schools/school-science/research-dataset)
- CSE-CIC-IDS2018 Dataset (available at: https://www.unb.ca/cic/datasets/ids-2018.html)

All datasets can be accessed from their respective official repositories and research institution websites. All cited sources and references are publicly available through academic databases and repositories. The proposed framework and experimental methodology are reproducible using the detailed descriptions provided in the Research Methodology section of this manuscript.

Competing Interests

The author declares that they have no competing interests, no financial relationships that might bias this research, and no conflicts of interest.

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Authors' Contributions

Irshad Ali: Conceptualization, research design, literature review, methodology development, implementation of the proposed IDS framework, experimental validation, data analysis, manuscript preparation, and revision.

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