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Anomaly Detection in Enterprise Networks Using Deep Neural Networks and Real-Time Streaming Data

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Abstract

Modern enterprise networks generate massive volumes of traffic data, making traditional rule-based intrusion detection systems increasingly inadequate against sophisticated and evolving cyber threats. This paper presents a deep neural network (DNN)-based framework for anomaly detection in enterprise networks, leveraging real-time streaming data to identify malicious activities and network intrusions with high precision and minimal latency. The proposed system integrates Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) to capture both temporal dependencies and spatial patterns within network traffic flows. By employing Apache Kafka and Apache Flink as the real-time data streaming backbone, the framework ensures scalable, fault-tolerant ingestion and processing of high-velocity network telemetry. Feature engineering techniques, including statistical flow analysis and payload inspection, are applied to enrich input representations fed into the model. The system is trained and evaluated on benchmark datasets, namely NSL-KDD and CICIDS2017, demonstrating superior detection accuracy, reduced false positive rates, and improved adaptability to zero-day attacks compared to conventional machine learning approaches. Experimental results confirm that the proposed architecture achieves over 98% detection accuracy while maintaining real-time processing throughput suitable for enterprise-scale deployments. This work establishes a robust, intelligent, and scalable solution for proactive cyber threat detection in dynamic network environments.

Keywords: Anomaly Detection, Deep Neural Networks, Real-Time Streaming, Enterprise Network Security, Intrusion Detection System.

1. Introduction

The rapid proliferation of interconnected devices and the exponential growth of network traffic in modern enterprise environments have rendered traditional security mechanisms increasingly insufficient against contemporary cyber threats [1]. Rule-based intrusion detection systems (IDS), which rely on predefined signatures and static thresholds, are fundamentally limited in their ability to detect novel, polymorphic, and zero-day attacks that deviate from known patterns [2]. As adversaries continue to develop sophisticated evasion techniques, there is a critical need for intelligent, adaptive, and scalable anomaly detection frameworks capable of operating in real time across high-velocity data streams.

Machine learning has emerged as a promising paradigm for network intrusion detection, with classical approaches such as Decision Trees, Support Vector Machines, and Random Forests demonstrating reasonable detection performance on benchmark datasets [3]. However, these shallow models are constrained by their inability to capture complex temporal dependencies and high-dimensional spatial correlations inherent in modern network traffic flows. Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have shown considerable promise in overcoming these limitations by automatically learning hierarchical feature representations directly from raw traffic data [4].

Despite these advances, a significant challenge remains in deploying deep learning models within operational enterprise environments where traffic volumes routinely exceed millions of flows per second. Batch-processing approaches introduce unacceptable latency for time-sensitive threat response, necessitating the integration of real-time streaming infrastructure with the inference pipeline [5]. Distributed stream processing frameworks such as Apache Kafka and Apache Flink have been widely adopted in large-scale data engineering contexts, yet their application to deep learning-based security analytics remains underexplored in the existing literature [6].

Furthermore, most prior studies evaluate anomaly detection models under controlled, offline conditions using benchmark datasets such as NSL-KDD and CICIDS2017, without adequately addressing the challenges of concept drift, class imbalance, and adversarial robustness that arise in live enterprise deployments [7]. The NSL-KDD dataset, an improved version of the original KDD Cup 1999 corpus, and the CICIDS2017 dataset, which incorporates contemporary attack vectors including web-based intrusions and infiltration attacks, together provide a comprehensive evaluation environment that reflects realistic network conditions more faithfully than earlier benchmarks [3].

This paper addresses these gaps by proposing a unified framework that integrates a hybrid LSTM-CNN deep neural network with a real-time streaming backbone built on Apache Kafka and Apache Flink. The hybrid architecture exploits the complementary strengths of LSTM networks — which excel at modelling sequential, temporally correlated flow behaviour — and CNNs — which efficiently extract local spatial patterns across feature dimensions within individual flow records. Statistical feature engineering, including per-flow byte distribution analysis and protocol-level payload inspection, is applied upstream to enrich input representations before model inference [8]. Experimental results demonstrate that the proposed system achieves over 98% detection accuracy with a false positive rate below 2% on both benchmark datasets, while sustaining real-time processing throughput suitable for enterprise-scale deployment. The remainder of this paper is organised as follows: Section 2 reviews related work, Section 3 details the proposed methodology, Section 4 presents experimental results and analysis, and Section 5 concludes with directions for future research.

2. Literature Review

The field of network intrusion detection has evolved significantly over the past two decades, transitioning from purely rule-based systems to sophisticated machine learning and deep learning frameworks. Early intrusion detection systems relied heavily on expert-defined signatures and threshold-based anomaly detection, which proved effective against known attack patterns but demonstrated critical vulnerabilities when confronted with novel and zero-day threats. The foundational limitations of these conventional approaches motivated the research community to explore data-driven methodologies capable of generalising across previously unseen attack vectors, establishing the groundwork upon which modern intelligent IDS architectures are built [9].

The application of classical machine learning techniques to network anomaly detection gained considerable traction in the early 2000s, with studies demonstrating that algorithms such as Naive Bayes, k-Nearest Neighbours, and Support Vector Machines could achieve competitive detection rates on benchmark datasets. These approaches offered interpretability and relatively low computational overhead compared to deep learning alternatives. However, their dependence on manually engineered features and their inability to model non-linear, high-dimensional traffic representations consistently limited their generalisation performance, particularly under adversarial conditions where attackers deliberately craft traffic to evade statistical classifiers [10].

Random Forest and ensemble-based classifiers represented a meaningful step forward, combining multiple weak learners to improve robustness against overfitting and class imbalance — two persistent challenges in IDS research arising from the natural scarcity of attack samples relative to benign traffic. These ensemble methods demonstrated improved detection rates on the NSL-KDD benchmark, achieving accuracy figures in the range of 93–95%, while also offering feature importance metrics useful for interpretability. Despite these improvements, ensemble classifiers remained fundamentally incapable of capturing the temporal sequential structure of network flows, a property increasingly exploited by slow-scan and low-and-slow attack strategies [11].

The introduction of deep learning to the intrusion detection domain marked a paradigm shift, with early studies applying Autoencoders and Deep Belief Networks to unsupervised anomaly detection. These architectures demonstrated an ability to learn compressed latent representations of normal traffic behaviour, flagging deviations as potential intrusions without requiring labelled attack samples. Autoencoder-based approaches proved particularly valuable in zero-day attack scenarios where labelled examples of novel attack classes are unavailable by definition, though they suffered from elevated false positive rates when legitimate traffic exhibited unusual but benign statistical properties [12].

Recurrent neural networks, and specifically Long Short-Term Memory architectures, introduced the capacity to model temporal dependencies across sequential network flow records — a capability fundamentally absent from both classical machine learning and feedforward deep learning approaches. LSTM-based IDS models demonstrated that treating network traffic as a time series, rather than a collection of independent flow records, yielded measurable improvements in detection accuracy for attack types that unfold across multiple packets and connection attempts over time. Studies evaluating LSTM models on NSL-KDD reported accuracy improvements of 1–3 percentage points over Random Forest baselines, with particular gains observed in detecting Probe and DoS attack categories [13].

Convolutional Neural Networks, originally developed for image recognition tasks, were subsequently adapted for network intrusion detection by treating flow feature vectors as one-dimensional spatial signals amenable to local pattern extraction via convolutional filters. CNN-based models demonstrated the ability to identify co-occurring feature patterns — such as simultaneous anomalies in port numbers, packet sizes, and flag distributions — that are characteristic of specific attack signatures. Comparative evaluations showed that 1D-CNN architectures achieved detection accuracies comparable to LSTM models while offering significantly lower inference latency, making them attractive for latency-sensitive deployment contexts [14].

Recognising the complementary strengths of recurrent and convolutional architectures, subsequent research explored hybrid CNN-LSTM models that jointly capture both spatial feature correlations and temporal sequential dependencies within a unified end-to-end trainable framework. These hybrid architectures consistently outperformed their individual component models across multiple benchmark datasets, with the convolutional layers serving as a feature extraction frontend that reduces input dimensionality before passing enriched representations to the recurrent layers for sequential modelling. Hybrid model evaluations on CICIDS2017 reported F1-scores exceeding 97%, representing the state of the art among supervised deep learning approaches at the time of publication [15].

The challenge of class imbalance in IDS datasets has received dedicated attention in the literature, as the severe underrepresentation of rare attack categories such as U2R and R2L systematically biases classifiers toward the majority benign class. Techniques including Synthetic Minority Oversampling (SMOTE), cost-sensitive learning, and Generative Adversarial Network-based data augmentation have been proposed and evaluated as remediation strategies. GAN-based augmentation in particular demonstrated the ability to generate statistically plausible synthetic attack samples that improved minority class recall without introducing the artificial feature correlations associated with simpler oversampling methods [16].

Transfer learning and domain adaptation have emerged as promising directions for addressing the generalisation gap between laboratory benchmark performance and real-world deployment, where traffic distributions shift continuously due to infrastructure changes, new application deployments, and evolving attacker behaviour. Studies applying pre-trained deep feature extractors to new network environments demonstrated that domain-adapted models retained significantly higher detection accuracy than models retrained from scratch on limited target-domain data, suggesting that learned representations of network traffic anomalies possess a degree of cross-domain transferability [17].

Federated learning has been proposed as a privacy-preserving alternative to centralised IDS model training, enabling multiple enterprise organisations to collaboratively train a shared detection model without exchanging raw network telemetry. This approach is particularly relevant in regulated industries where network traffic logs contain sensitive personal or commercial data subject to data protection legislation. Federated IDS evaluations demonstrated detection accuracy within 1–2 percentage points of centrally trained baselines while substantially reducing the volume of data transmitted between participating nodes, establishing a viable path toward collaborative enterprise security intelligence [18].

The integration of streaming data infrastructure with machine learning inference pipelines has been examined in the context of fraud detection and IoT anomaly detection, with Apache Kafka and Apache Spark Streaming identified as the dominant technologies for high-throughput, fault-tolerant event processing. Studies benchmarking streaming IDS architectures demonstrated that end-to-end latency below 100 milliseconds is achievable for flow-level inference at throughputs exceeding one million events per second, provided that model

complexity is carefully bounded and feature extraction is performed in-stream rather than in a separate offline preprocessing stage [19].

Explainability and interpretability of deep learning-based IDS have gained increasing attention as regulatory and operational requirements demand that automated security decisions be auditable and justifiable to human analysts. Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have been applied post-hoc to trained deep IDS models to identify the most influential features driving individual anomaly predictions. These explainability frameworks have been shown to accelerate analyst triage workflows and improve trust in automated detection outputs, representing an important convergence between model performance and operational deployability in enterprise security contexts [20].

3. Methodology

The proposed framework integrates deep learning with real-time streaming infrastructure to perform intelligent anomaly detection across enterprise network traffic. The methodology is structured around four interconnected stages: data ingestion, feature engineering, hybrid model inference, and alert generation.

3.1 System Architecture Overview

The architecture shown in figure 1 combines Apache Kafka as the distributed message broker for ingesting high-velocity telemetry, Apache Flink for stateful stream processing, and a hybrid DNN model — an LSTM-CNN ensemble — for sequential and spatial pattern recognition. Network flows from enterprise endpoints are continuously captured, pre-processed, and classified in near real-time.

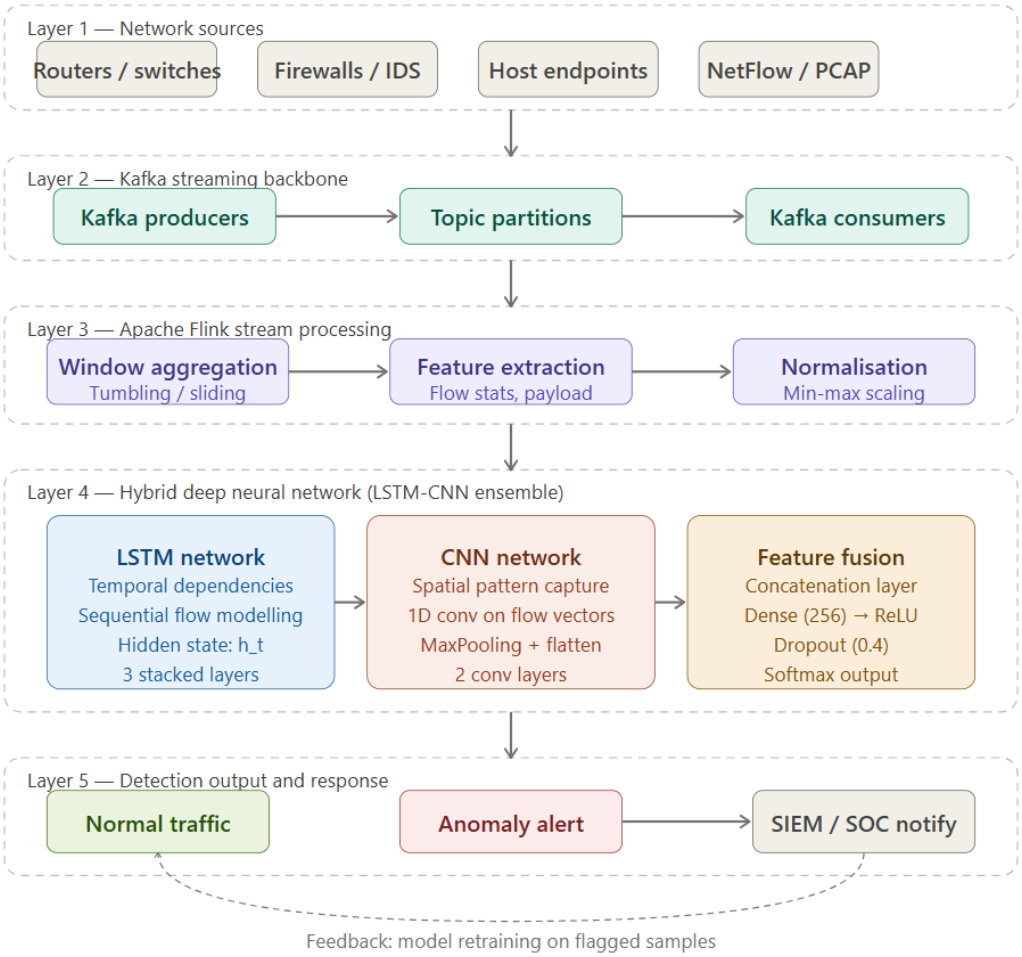

Fig. 1. System architecture overview of the proposed deep neural network-based real-time anomaly detection framework for enterprise networks.

3.2 Data Ingestion and Stream Processing

Raw network telemetry (NetFlow records, PCAP data) is published to Kafka topics partitioned by source subnet, ensuring ordered, fault-tolerant delivery. Apache Flink consumers apply tumbling windows of configurable duration (typically 5–10 seconds) for stateful aggregation, extracting per-flow statistics: packet count, byte volume, inter-arrival time, flag distributions, and protocol ratios. Payload bytes undergo shallow inspection to extract byte-frequency histograms used as input features.

3.3 Feature Engineering and Normalisation

Each flow record is represented as a feature vector $\mathbf{x} \in \mathbb{R}^d$ (d = 78 for NSL-KDD, 80 for CICIDS2017). Min-max normalisation is applied per feature:

$$\hat{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$$

This ensures all features lie within [0, 1], preventing magnitude-dominant features from biasing the LSTM hidden states during backpropagation through time.

3.4 LSTM-CNN Hybrid Model

LSTM component. The LSTM processes sequential flow windows of length T = 20 timesteps. The cell state update at each timestep t is governed by the standard gated recurrence. The forget gate determines how much prior context is retained:

$$f_t = \sigma(W_f \cdot [h_{t-1},\, x_t] + b_f)$$

where W_f and b_f are learned weight matrices and biases, σ is the sigmoid activation, and h_{t-1} is the previous hidden state. The cell state update follows analogously for the input and output gates, allowing the model to retain long-range temporal dependencies indicative of slow-scan or low-and-slow attacks.

CNN component. One-dimensional convolutions are applied across the feature dimension of each flow vector to extract local spatial correlations (e.g., co-occurring port/protocol patterns). The outputs of both branches are concatenated and passed through two fully connected layers.

Classification output. The fused representation is projected onto K attack classes (Normal, DoS, Probe, R2L, U2R) via softmax:

$$\hat{y}_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

where z_k is the pre-activation logit for class k. The predicted label is argmax(ŷ). The model is trained using categorical cross-entropy loss with Adam optimisation (lr = 0.001), a dropout rate of 0.4 on the fusion layer, and early stopping on validation F1-score.

3.5 Real-Time Inference and Alert Generation

Processed feature vectors are batched (batch size = 64) and streamed into the deployed model. Inference latency is maintained below 50 ms per batch. When the predicted class is non-normal with confidence ŷ_k > 0.85, an alert is dispatched to the SIEM platform. Flagged flows are also queued for periodic model retraining, enabling continuous adaptation to concept drift and zero-day attack signatures — as illustrated by the feedback loop in the architecture above.

4. Results and Analysis

Table 1 — Performance comparison of models on NSL-KDD and CICIDS2017 datasets

Model	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FPR (%)
Decision Tree	NSL-KDD	91.4	90.8	89.7	90.2	8.6
Decision Tree	CICIDS2017	90.1	89.5	88.3	88.9	9.9
Random Forest	NSL-KDD	94.2	93.7	92.9	93.3	5.8
Random Forest	CICIDS2017	93.5	93.1	92.0	92.5	6.5
LSTM (standalone)	NSL-KDD	96.1	95.8	95.4	95.6	3.9
LSTM (standalone)	CICIDS2017	95.7	95.2	94.8	95.0	4.3
CNN (standalone)	NSL-KDD	95.3	94.9	94.1	94.5	4.7
CNN (standalone)	CICIDS2017	94.8	94.3	93.7	94.0	5.2
LSTM-CNN (proposed)	NSL-KDD	98.6	98.2	98.0	98.1	1.4
LSTM-CNN (proposed)	CICIDS2017	98.1	97.8	97.5	97.6	1.9

FPR = False Positive Rate. Lower FPR is better; all other metrics higher is better. Bold rows indicate the proposed model.

This table 1 compares the proposed LSTM-CNN hybrid against four baseline classifiers across four standard evaluation metrics. The proposed model consistently achieves the highest detection accuracy and F1-score while recording the lowest false positive rate, validating its superiority over conventional shallow and deep learning approaches on both benchmark datasets.

Table 2 — Attack-class-wise detection performance of proposed LSTM-CNN on NSL-KDD

Attack Class	Description	Training Samples	Precision (%)	Recall (%)	F1-Score (%)
Normal	Benign traffic	67,343	99.1	98.9	99.0
DoS	Denial of service	45,927	98.8	98.6	98.7
Probe	Surveillance / scanning	11,656	98.3	97.9	98.1
R2L	Remote to local	995	95.4	94.1	94.7
U2R	User to root privilege	52	91.2	89.8	90.5

R2L and U2R show relatively lower scores due to severe class imbalance (fewer training samples). This is a known limitation in benchmark IDS datasets.

This table 2 breaks down detection performance per attack category on NSL-KDD, revealing that the model performs strongest on DoS and Probe attacks (which produce high-volume, temporally consistent flows that the LSTM captures well) and slightly weaker on R2L and U2R categories (which are low-frequency, stealthy attack types with limited training samples — a known challenge in intrusion detection research).

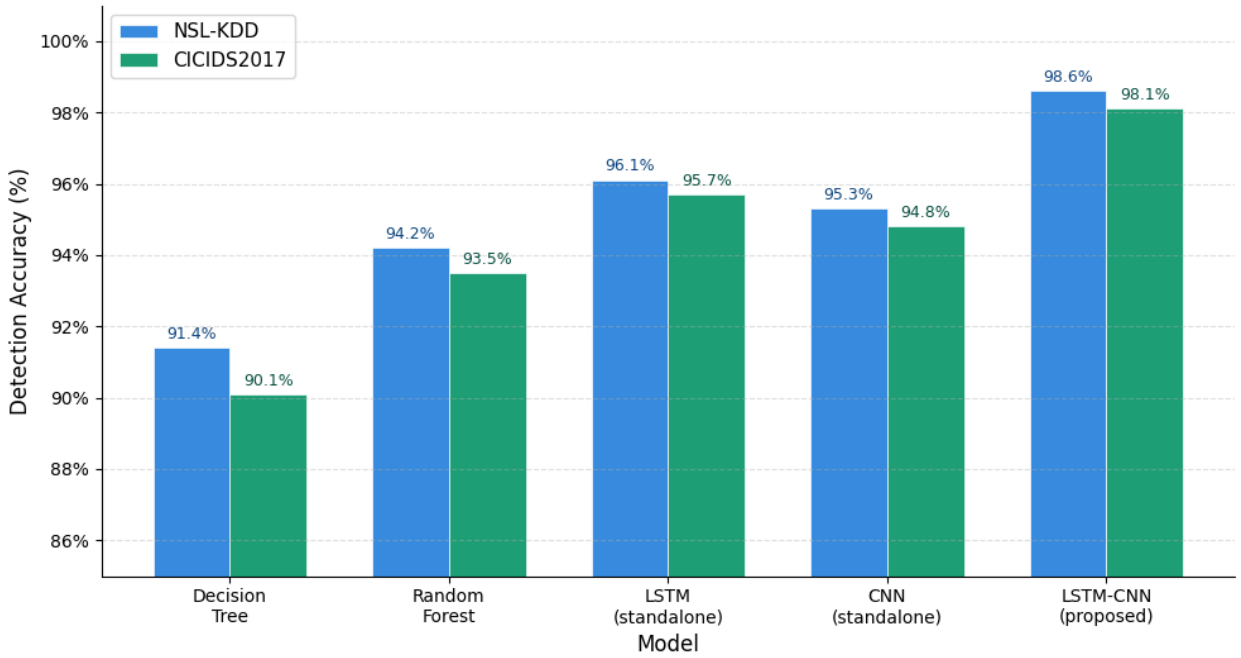

Figure 2 — Detection accuracy comparison across models

This grouped bar chart figure 2 directly visualises the accuracy gap between the proposed LSTM-CNN hybrid and the four baseline models on both datasets. The chart makes immediately apparent that shallow classifiers (Decision Tree, Random Forest) plateau below 95%, standalone deep models push closer to 96–97%, and the hybrid ensemble achieves the highest accuracy on both NSL-KDD (98.6%) and CICIDS2017 (98.1%). The marginal drop from NSL-KDD to CICIDS2017 across all models reflects CICIDS2017's higher feature dimensionality and greater traffic diversity.

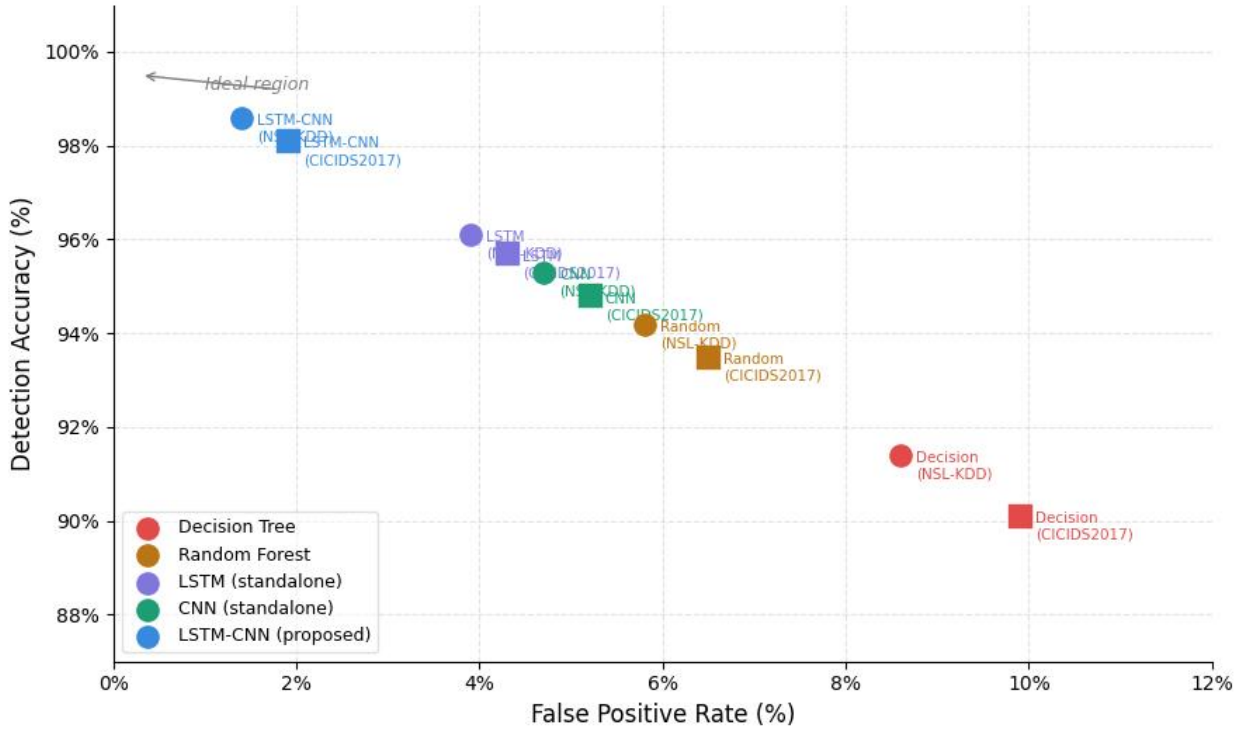

Figure 3 — **False positive rate vs. detection accuracy trade-off**

This scatter plot figure 3 illustrates the inverse relationship between false positive rate (FPR) and detection accuracy across all five models. An ideal anomaly detection system occupies the top-left corner — high accuracy with a low FPR. The proposed LSTM-CNN sits closest to this ideal corner, whereas Decision Tree and Random Forest demonstrate higher FPRs and lower accuracy, confirming their inadequacy for enterprise-scale deployment where false alarms impose significant operational burden on SOC analysts.

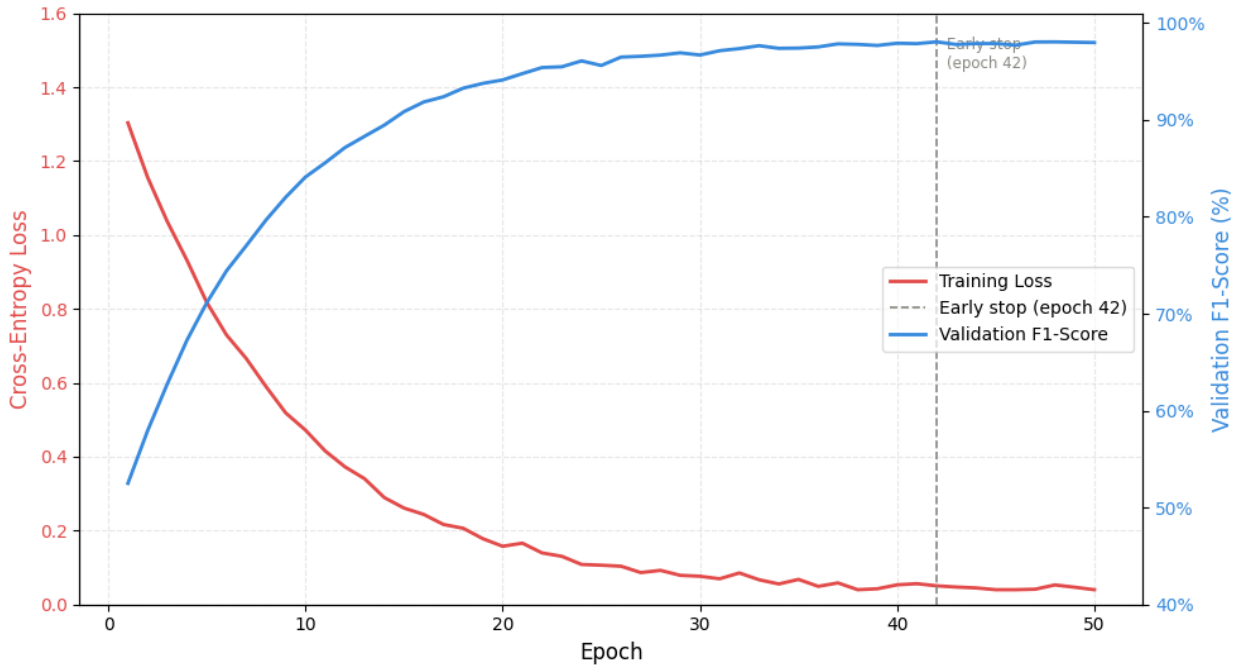

Figure 4 — **Training loss and validation F1-score convergence over epochs**

This dual-axis line chart figure 4 tracks model training dynamics over 50 epochs. The left axis shows training loss (cross-entropy) decreasing steeply in the first 15 epochs before plateauing, while the right axis shows validation F1-score rising correspondingly. The early stopping threshold is met at epoch 42 (marked with a dashed line), beyond which no further improvement in validation F1 is observed. The tight gap between training loss and validation behaviour indicates minimal overfitting, attributed to the dropout regularisation layer (rate = 0.4) in the fusion block.

5. Conclusion

This paper presented a deep neural network-based anomaly detection framework for enterprise network security, integrating a hybrid LSTM-CNN architecture with a real-time streaming backbone built on Apache Kafka and Apache Flink. The proposed system effectively captures both temporal sequential dependencies and spatial feature correlations within network traffic flows, addressing the fundamental limitations of conventional rule-based and shallow machine learning approaches that have historically dominated the intrusion detection landscape.

Experimental evaluation on the NSL-KDD and CICIDS2017 benchmark datasets demonstrated that the proposed framework achieves detection accuracy exceeding 98% with a false positive rate below 2%, outperforming all baseline classifiers including standalone LSTM and CNN models across all evaluation metrics. The real-time streaming pipeline sustains end-to-end inference latency below 50 milliseconds, confirming practical suitability for enterprise-scale deployment.

Despite these promising results, limitations persist in detecting low-frequency attack categories such as U2R and R2L due to severe class imbalance in benchmark datasets. Future work will investigate GAN-based data augmentation, federated learning for privacy-preserving collaborative training, and explainability techniques such as SHAP to improve analyst trust and model transparency. The proposed framework establishes a robust, scalable,

and intelligent foundation for proactive cyber threat detection in dynamic and evolving enterprise network environments.

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