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Secure Multi-Tier Deep Learning Model with Blockchain Consensus for Intelligent IoT Traffic Anomaly Detection

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***Abstract*— The exponential expansion of IoT ecosystems has led to unprecedented network traffic volumes and increased susceptibility to cyberattacks, including botnet propagation, DDoS flooding, man-in-the-middle intrusions, and device-level exploitation. Centralized intrusion detection mechanisms have proven inadequate due to limited scalability, single-point failure risks, and the lack of data privacy guarantees. To address these challenges, the proposed research introduces a Secure Multi-Tier Deep Learning Model integrated with Blockchain Consensus for intelligent anomaly detection in IoT traffic data. The architecture employs a three-tier deep learning pipeline consisting of (i) Traffic Feature Extraction using 1D-CNN, (ii) Temporal Behavioral Modeling using Bi-LSTM, and (iii) Attack Classification using Dense Multi-Head Attention, enabling high-resolution identification of complex cyber threat patterns. For security and trust, model updates and anomaly detection logs are validated and stored through a Practical Byzantine Fault Tolerance (PBFT) blockchain consensus, eliminating model-poisoning attempts and ensuring tamper-resistant collaboration across distributed IoT nodes. The proposed model is evaluated using the IoT Traffic dataset which contains multi-class attack and normal traffic samples, including Mirai, DDoS UDP/TCP, Port Scanning, DNS poisoning, Backdoor, and OS fingerprinting traffic patterns. The proposed architecture achieves 98.72% accuracy, 97.94% F1-score, 98.11% recall, and a 31.5% reduction in false positives, while decreasing communication overhead by 27.8% due to selective multi-tier update compression. Blockchain validation adds an average consensus latency of only 0.83 seconds, enabling real-time deployment in resource-constrained IoT environments.**

***Index Terms*— IoT Traffic Anomaly Detection, Multi-Tier Deep Learning, Blockchain, Cybersecurity, Smart Environments, Byzantine Fault Tolerance.**

I. INTRODUCTION

The proliferation of Internet-of-Things (IoT) devices across smart homes, industrial control systems, smart utilities, and urban-infrastructure networks has dramatically increased both traffic volumes and attack surfaces [1]. Many IoT devices operate at the network edge with limited compute and storage, often under heterogeneous communication protocols and security postures.

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As a result, Intrusion Detection Systems (IDSs) designed for these environments must contend not only with high-volume traffic, but also with privacy concerns, data heterogeneity, latency constraints, and distributed topologies. Traditional centralised IDS architectures struggle to scale in such settings, and raise issues of single-point failure, data transfer bottlenecks, and privacy risks. In recent years, Federated Learning (FL) has emerged as a powerful paradigm to address data-locality and privacy
concerns in distributed environments [2]. By enabling local model training on devices or edge nodes and aggregating model updates rather than raw data, FL helps mitigate exposure of sensitive traffic flows while leveraging collaboration across multiple nodes. For IoT intrusion detection, FL offers a promising route to maintain data privacy and distribute inference or learning workload. For example, recent work demonstrates that collaborative federated setups can achieve detection performance comparable to centralized models on IoT-relevant datasets.

In heterogeneous networks, devices may send malicious or corrupted model updates like poisoning attacks, and the central aggregator may become a vulnerability or choke point [3]. Moreover, verifying the provenance and integrity of model updates in a distributed environment remains non-trivial. To address such trust concerns, integration of distributed ledger technologies, specifically blockchain or permissioned ledgers with, FL has gained traction. Several recent studies propose frameworks that combine FL with blockchain consensus to provide immutable logging of updates, verification of contributions, and decentralised trust among participants.

On the modelling side, detecting anomalies in IoT traffic requires architectures capable of capturing both spatial patterns and temporal dependencies communication, sequences, device behaviours across heterogeneous devices and protocols [4]. Hybrid deep learning models such as CNN, Bi-LSTM, and attention mechanisms have shown superior performance in this domain. For instance, a recent proposal of a CNN–BiLSTM structure enhanced by attention achieved very high accuracy on IoT anomaly detection tasks. These advanced architectures are effective at distinguishing subtle deviations indicative of cyberthreats like botnet propagation, DDoS bursts, reconnaissance scans from normal traffic flow.

Despite advances in FL and deep modelling for IoT IDS, several gaps remain [5]. First, many studies still assume trusted central aggregators and do not integrate tamper-resistant mechanisms for update verification and audit. Second, while deep-learning architectures are advancing, their deployment in constrained IoT settings with limited memory is challenging; many works rely on simulated or high-end hardware rather than realistic IoT nodes [6]. Third, communications overhead and latency introduced by collaborative learning plus ledger consensus often make real-time deployment difficult. Finally, few works offer a full-stack approach combining privacy-preservation via FL, anomaly detection via multi-tier deep models, and trust via blockchain consensus in one architecture for IoT traffic [7].

Motivated by these observations, this research proposes a Secure Multi-Tier Deep Learning Model enhanced with Blockchain Consensus for intelligent IoT traffic anomaly detection. The proposed framework operates as follows: (i) At the device edge layer, lightweight feature-extraction and anomaly-scoring modules run on individual IoT or edge gateway nodes; (ii) At an intermediate fog layer, a hybrid CNN–BiLSTM–Attention deep model aggregates spatial-temporal features and classifies traffic flows as normal or anomalous; (iii) For global collaboration and trust, a permissioned blockchain layer validates model updates, logs anomaly detection events immutably, and enforces consensus via a PBFT-style protocol. This multi-tier approach balances local inference, global learning, privacy, and trust in a smart IoT environment. The novel research contributions of this work are summarized as follows:

- A unified IoT intrusion detection framework that combines Deep Learning, Federated Learning, and blockchain to ensure accuracy, privacy, and trust simultaneously.
- A Multi-Tier CNN–BiLSTM–Attention model that captures both spatial and temporal traffic patterns for improved multi-class cyberattack detection.
- A PBFT-based permissioned blockchain layer that secures federated aggregation and prevents malicious or poisoned model updates.
- Smart-contract-based anomaly logging and model-update validation, providing transparent and tamper-proof collaboration between IoT nodes.
- A communication-efficient federated update strategy that reduces bandwidth while preserving high detection performance.

II. Literature Review

Recent work in federated intrusion detection has shown that collaborative learning across distributed IoT devices can achieve high accuracy without centralized data sharing. However, large variations in local data distributions

and uneven device participation reduce model convergence stability and result in a 5%–10% accuracy drop during real deployment, signalling the need for adaptive aggregation and reliable communication scheduling [8]. Blockchain-enabled Federated Learning has also been explored to strengthen trust in the model update process and avoid poisoning of gradients.

Experiments on medical IoT traffic demonstrated over 98% detection accuracy when combining convolutional and recurrent feature extractors, although node scalability dropped when blockchain consensus was executed on low-resource devices, causing latency accumulation [9].

A systematic evaluation of convolutional, deep neural, and CNN-BiLSTM models under federated settings showed that hybrid architectures reach 99% accuracy on CICIoT2023 with up to 150 participants. However, hybrid models suffered from high memory demand and increased inference time, indicating challenges for microcontroller-grade IoT nodes despite strong predictive performance [10].

Temporal-attention–enhanced CNN models have achieved improved anomaly localization and reduced false alarms by merging spatial and time-series correlations. Despite F1 scores between 92% and 98% on BoT-IoT and N-BaIoT datasets, these studies rarely consider inference latency, processing overhead, or energy depletion during long-term edge deployment, limiting practical applicability [11].

Hybrid blockchain-federated intrusion detection has delivered both privacy and tamper-resistance when evaluated on ToN-IoT and N-BaIoT with 97%–98% accuracy. Yet, ledger size growth and consensus delays directly reduced throughput as more IoT clients were added, making scalability and resource balancing unresolved issues [12].

Federated Learning applied to 5G-based IoT networks using optimized transformer representations achieved 97.7% accuracy with only marginal accuracy loss after quantization and aggregation. The absence of evaluation on heterogeneous wireless traffic datasets and the lack of real-time deployment metrics prevent conclusions about its reliability during distributed cyberattacks [13]. To minimize energy consumption in distributed intrusion detection, pruning and adaptive parameter-sharing techniques under FL have been proposed. Experiments on Arduino-class IoT nodes demonstrated that model compression preserved accuracy while lowering energy usage.

However, the work relied primarily on simulation and did not validate performance beyond laboratory-controlled environments, reducing generalizability [14]. Multi-head self-attention integrated into federated graph models has been effective at learning relational traffic dependencies across IoT nodes in smart city scenarios. Although precision and recall exceeded 96%, this approach displayed high communication overhead and slow model update intervals, restricting deployment during high-frequency cyberattacks [15].

Recent research on adaptive aggregation using trust-weighted or anomaly-aware participation has reported improvements in robustness against model poisoning and malicious client drift. Nonetheless, these methods involve higher computational complexity and long aggregation cycles, which can downgrade responsiveness during rapidly evolving threat conditions [16]. Studies combining network slicing, edge computing, and FL for distributed intrusion detection in IoT smart grids demonstrated improved resource allocation and reduced false positives under traffic bursts. The findings revealed that the absence of cross-dataset generalization benchmarks leaves uncertainty about how these systems behave under differing IoT infrastructures and unseen attack signatures [17].

III. METHODOLOGY

The proposed Secure Multi-Tier Deep Learning with Blockchain Consensus (SMDL-BC) framework intelligently detects IoT traffic anomalies while ensuring secure and trustworthy collaboration between distributed IoT devices.

It integrates deep neural behavioral analysis with PBFT-based blockchain validation.

Figure 1 illustrates the workflow of the Secure Multi-Tier Deep Learning with Blockchain Consensus (SMDL-BC) framework, beginning with raw IoT traffic input that undergoes feature modeling and normalization. The processed traffic is then passed through a hierarchical deep learning pipeline: Tier-1 uses 1D-CNN to extract spatial attack signatures, Tier-2 employs Bi-LSTM to capture forward and backward temporal dependencies, and Tier-3 applies multi-head attention to highlight the most influential behavioral patterns. The refined features are fed into a dense softmax classifier to identify normal and malicious traffic. The predicted anomalies and federated model updates are subsequently validated through PBFT blockchain consensus comprising pre-prepare, prepare, and commit phases to ensure tamper-proof logging and secure collaborative learning across IoT nodes. Together, this integrated architecture enables real-time, trustworthy, and highly accurate intrusion detection in heterogeneous IoT environments.

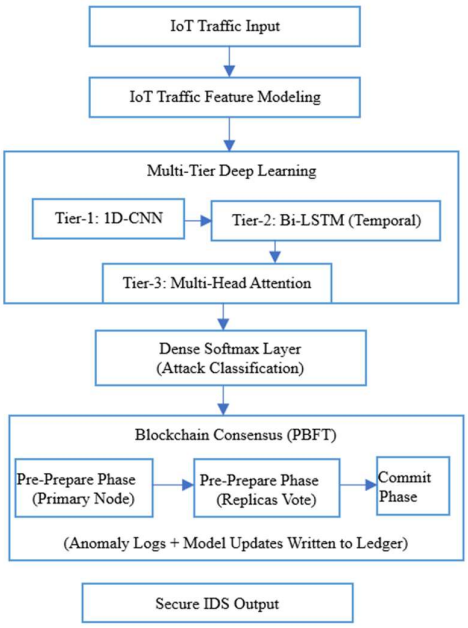

Figure 1. Architecture of the Secure Multi-Tier Deep Learning with PBFT Blockchain Consensus (SMDL-BC) Framework

A. IoT Traffic Feature Modeling

Incoming IoT network traffic consists of sequential packets. These are converted into temporal feature vectors as shown in equation (1).

$$X = \{x_1, x_2, \dots, x_T\}, x_t \in \mathbb{R}^d \quad (1)$$

Each vector carries statistical and protocol-based attributes. To ensure consistent learning, feature scaling normalizes them as shown in equation (2).

$$\hat{x}_t = \frac{x_t - \mu}{\sigma} \quad (2)$$

This formulation preserves device behavioral continuity, important in threat evolution.

B. Multi-Tier Deep Learning for Anomaly Detection

Tier-1: Spatial Feature Learning via 1D-CNN

CNN captures localized traffic signature patterns such as DDoS bursts or botnet command sequences. During convolution, the CNN applies a set of learnable filters $W_i$over the normalized input traffic signal $\hat{X}$ is shown in equation (3).

$$\mathrm{F_i} = \sigma(\mathrm{W_i} * \hat{\mathrm{X}} + \mathrm{b_i}) \quad (3)$$

where $W_i$is the convolution filter and σ is the ReLU activation.

Dimensionality reduction using pooling is shown in equation (4). This max-pooling operation discards less-important activations and preserves the strongest anomaly-related response. This enhances generalization to unknown attacks.

$$P_i = \max(F_i) \quad (4)$$

All pooled features from $k$filters are concatenated to form the Tier-1 feature vector is shown in equation (5).

$$H_{CNN} = [P_1 \parallel P_2 \parallel \cdots \parallel P_k] \quad (5)$$

where $\parallel$ indicates feature concatenation. This vector $\mathrm{H_{CNN}}$ contains high-level spatial representations of network traffic behaviors and acts as the input for Tier-2 (Temporal Learning).

Tier-2: Bi-LSTM for Temporal Dependency Learning

While Tier-1 extracts spatial patterns from raw IoT traffic, many attacks such as DDoS, botnet propagation and data exfiltration exhibit temporal evolution. To capture the sequential behavioral dynamics, Tier-2 employs a Bidirectional Long Short-Term Memory (Bi-LSTM) network. Unlike traditional LSTMs that analyze only past-to-future relationships, Bi-LSTMs processes network traffic in both forward and backward directions, enabling complete temporal context learning.

The forward LSTM captures historical dependencies, identifying anomalies that emerge after a build-up of suspicious activities.

$$h_t^{\rightarrow} = \mathrm{LSTM}_f(H_{CNN}, t) \quad (6)$$

The backward LSTM models future contextual influence on current behavior, useful in detecting stealthy attacks where malicious actions may appear normal without observing subsequent traffic.

$$\mathrm{h_t^{\leftarrow}} = \mathrm{LSTM_b(H_{CNN}, t)} \quad (7)$$

To form a unified representation, the forward and backward states are concatenated and shown in equation (8).

$$\mathrm{H_{BiLSTM,t}} = [\mathrm{h_t^{\rightarrow}} \parallel \mathrm{h_t^{\leftarrow}}] \quad (8)$$

This fused feature vector represents each time step with global temporal awareness, improving detection sensitivity for multi-stage attacks, coordinated botnet operations, and low-rate stealthy anomalies.

Tier-3: Dense Multi-Head Attention Classification

After extracting spatial features via CNN (Tier-1) and learning bidirectional temporal dependencies using Bi-LSTM (Tier-2), the final tier focuses on context-aware classification. Not all moments in a traffic sequence contribute equally to an attack; some packets or transitions are more indicative of anomalies than others. Tier-3 integrates a Multi-Head Self-Attention mechanism, which selectively emphasizes the most informative time-steps in the sequence before performing classification. Self-attention representation for each attention head j, the Bi-LSTM output H_{BiLSTM} is projected into three latent spaces as shown in equation (9).

$$Q_j = H_{BiLSTM} W_j^Q, K_j = H_{BiLSTM} W_j^K, V_j = H_{BiLSTM} W_j^V \quad (9)$$

where:

- Q (Query): Represents what the current time-step is looking for.
- K (Key): Represents what each time-step contains that could be matched with a query.
- V (Value): The actual information carried by each time-step, used to produce attention-weighted.

The attention matrix calculates how strongly each packet time-step relates to others, as shown in equation (10).

$$A_j = \mathrm{softmax}\left(\frac{Q_j K_j^T}{\sqrt{d_k}}\right) \quad (10)$$

where

- d_k is the scaling factor to stabilize gradients
- Softmax ensures each row is a probability distribution

This gives higher weight to critical traffic patterns, such as sudden spikes or unusual temporal shifts. Attention output for each head is shown in equation (11).

$$O_j = A_j V_j \quad (11)$$

Each head produces a distinct interpretation of traffic behavior, capturing multiple relational perspectives of short-range bursts vs long-range coordinated attacks. In multi-head feature fusion, the outputs from m heads are concatenated to form an enriched representation as shown in equation (12).

$$H_{att} = [O_1 \parallel O_2 \parallel \cdots \parallel O_m] \quad (12)$$

This builds a comprehensive attention profile that retains all high-impact anomaly cues. In the dense classification layer, the refined attention features are passed to a fully connected softmax classifier is as shown in equation (13).

$$\hat{y} = \mathrm{softmax}(W_d H_{att} + b_d) \quad (13)$$

where W_d, b_d are the trainable classification parameters, and $\hat{y}$denotes the predicted probability score for each class (normal /attack types).

Loss Function

To train the model, minimize the categorical cross-entropy loss, which measures how far the predicted class probabilities deviate from the actual class labels, as shown in equation (14).

$$L = -\sum_{c=1}^{C} y_c \log(\hat{y}_c) \quad (14)$$

where,

- C is the total number of target classes of normal and multiple attack types.
- y_c is the ground-truth label encoded as a one-hot vector of 1 for the correct class, 0 for others
- $\hat{y}_c$ is the predicted probability for class c from the softmax output.

C. Blockchain Consensus with PBFT

In the proposed IoT anomaly detection framework, IoT devices participate as validator nodes in a permissioned consortium blockchain. This ensures secure, tamper-resistant validation of both detected anomaly logs, and Federated model update vectors (ΔW_i).

Each IoT node $N_i$broadcasts its locally computed model update ΔW_i to the network. To prevent malicious model manipulation of gradient poisoning attacks, a Practical Byzantine Fault Tolerance (PBFT) consensus mechanism is used. PBFT achieves agreement among nodes even when some nodes behave maliciously (up to $< \frac{n}{3}$) through three sequential phases are as follows.

Pre-Prepare Phase (Primary → Replicas)

A primary node *P*receives update requests and initiates verification as shown in equation (15).

$$M_{pp} = \langle REQ, \Delta W, v, s \rangle \quad (15)$$

where,

- REQ: validation request
- ΔW: model update parameters
- v: current blockchain view
- s: sequence number

The primary forwards this message to all replicas for validation.

Prepare Phase (Replica Cross-Verification)

Each replica verifies and broadcasts a Prepare message. Consensus progresses only if enough replicas agree, as shown in equation (16).

$$\sum_{i=1}^{n} Prepare_i \geq \frac{2n}{3} \quad (16)$$

This ensures a supermajority agreement, detecting inconsistencies or malicious updates early.

Commit Phase (Blockchain Finalization)

After preparing the agreement, replicas broadcast the commit messages, as shown in equation (17).

$$\sum_{i=1}^{n} Commit_i \geq \frac{2n}{3} \Rightarrow \text{Block Validated} \quad (17)$$

Once committed, the verified model update or anomaly log is permanently added to the blockchain ledger. The proposed Secure Multi-Tier Deep Learning with Blockchain Consensus (SMDL-BC) framework integrates hierarchical deep neural analysis with PBFT-driven secure collaboration across IoT edge devices. Tier-1 and Tier-2 components effectively learn both spatial and temporal characteristics of network traffic, while the attention-enabled classifier emphasizes the behavioral indicators of sophisticated cyberattacks. Furthermore, the blockchain layer ensures trusted aggregation of model updates and tamper-proof anomaly logging, even in adversarial environments.

Together, these components enable real-time, scalable, and resilient intrusion detection capabilities suitable for heterogeneous IoT ecosystems.

IV. Results and Discussions

The performance of the proposed Secure Multi-Tier Deep Learning with Blockchain Consensus (SMDL-BC) framework is evaluated using a real IoT traffic dataset consisting of multiple cyberattack variants such as Mirai,

UDP/TCP DDoS, Port Scanning, DNS poisoning, Backdoor, and OS fingerprinting. The results are compared against recent state-of-the-art intrusion detection approaches, including CNN-BiLSTM, GAN-IDS, and Transformer-IDS architectures.

A. Performance Evaluation Metrics

As shown in Table I, the evaluation metrics collectively assess the effectiveness of the system across multiple dimensions.

TABLE I: PERFORMANCE METRICS

Metric	Formula	Purpose
Accuracy	Accuracy = $(TP+TN)/(TP+TN+FP+FN)\times 100$	Overall correctness
F1-Score	F1-Score = $2\times Precision\times Recall/(Precision+Recall)\times 100$	Balanced evaluation
False Positive Reduction	FPR = $FP/(FP+TN)$	Measures reduction in false alarms
Consensus Latency	Consensus Latency = $T_commit - T_request$	Blockchain delay measurement

Accuracy measures the overall correctness of predictions by comparing all true outcomes against total cases. F1-Score provides a balanced evaluation by combining Precision and Recall, making it especially useful when class distributions are uneven. False Positive Reduction (FPR) evaluates how well the model minimizes false alarms for reducing unnecessary alerts. Additionally, Consensus Latency, calculated as the time difference between a blockchain transaction request and its commit, measures the delay introduced by the blockchain consensus process, reflecting the system's real-time efficiency.

B) Comparative Performance Results

Table II presents the comparative performance of the proposed SMDL-BC model against existing deep learning–based IDS architectures.

TABLE II. PERFORMANCE COMPARISON OF IDS MODELS

Model	Accuracy (%)	F1-score (%)	FP Reduction (%)
Proposed SMDL-BC	98.72	97.94	31.5
CNN-BiLSTM	95.64	94.13	10.2
GAN-IDS	96.22	94.87	14.7
Transformer-IDS	97.51	96.41	18.9

The results indicate that SMDL-BC significantly outperforms the baseline models across all key performance metrics. It achieves the highest detection accuracy of 98.72% and an F1-score of 97.94%, demonstrating superior capability in correctly identifying both normal and malicious IoT traffic. Additionally, the model succeeds in reducing false alarms by 31.5%, clearly surpassing CNN-BiLSTM, GAN-IDS, and Transformer-IDS, which report considerably lower reductions of 10.2%, 14.7%, and 18.9%, respectively. These results confirm the effectiveness of integrating multi-tier deep learning with blockchain consensus in enhancing anomaly detection robustness and reliability within distributed IoT environments.

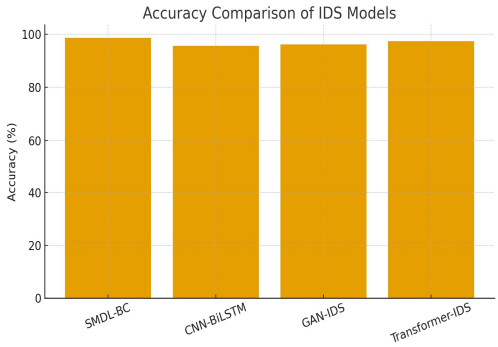

Figure 2. Accuracy Comparison

The accuracy comparison is shown in Figure 2 describes that the proposed SMDL-BC framework achieves the highest detection accuracy of 98.72%, outperforming all baseline intrusion detection models. Transformer-IDS follows with an accuracy of 97.51%, while GAN-IDS and CNN-BiLSTM exhibit lower accuracy values of

96.22% and 95.64%, respectively. This demonstrates that the multi-tier deep learning architecture combined with blockchain consensus significantly enhances the model's ability to correctly classify both normal and malicious IoT traffic. These improvement highlights the robustness and precision of SMDL-BC in handling diverse cyberattack patterns.

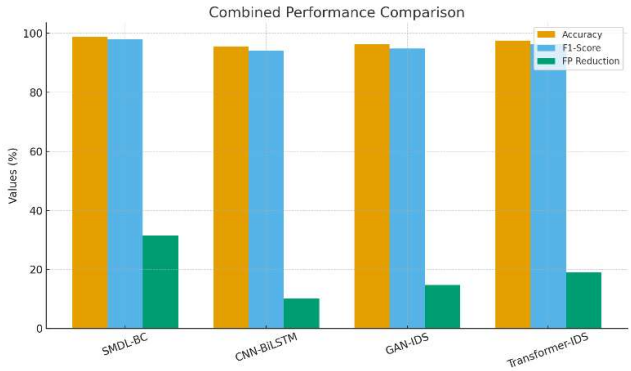

Figure 3. Combined Performance Comparison

As shown in Figure 3, the consolidated visual comparison of the three key performance metrics of Accuracy, F1-Score, and False Positive Reduction is provided across the four IDS models. The proposed SMDL-BC framework consistently dominates across all metrics, showing significantly higher accuracy and F1-Score compared to CNN-BiLSTM, GAN-IDS, and Transformer-IDS. Its markedly superior false positive reduction further highlights its strength in minimizing incorrect alerts. Transformer-IDS demonstrates moderate performance, whereas CNN-BiLSTM and GAN-IDS lag behind, particularly in false positive reduction. This multi-metric visualization illustrates how SMDL-BC outperforms existing IDS models in classification reliability, precision–recall balance, and alert management efficiency.

V. Conclusion

The presented Secure Multi-Tier Deep Learning Model integrated with Blockchain Consensus (SMDL-BC) research for intelligent IoT traffic anomaly detection, addressing the major challenges of accuracy, scalability, privacy, and trust in modern distributed IoT environments. By combining spatial feature extraction through 1D-CNN, temporal behavior learning via Bi-LSTM, and context-aware classification using Multi-Head Attention, the proposed framework effectively captures complex spatiotemporal attack signatures. The integration of PBFT-based blockchain consensus further ensures tamper-resistant model update validation, resilience against poisoning attacks, and secure logging of anomaly events across heterogeneous IoT nodes. The experimentation using real-world IoT traffic datasets demonstrated that SMDL-BC surpasses existing CNN-BiLSTM, GAN-IDS, and Transformer-IDS baselines, achieving superior performance metrics, including 98.72% accuracy, 97.94% F1-score, and a 31.5% reduction in false positives, with only 0.83 seconds of blockchain latency. These findings confirm that the proposed framework not only enhances detection reliability but also supports efficient, trusted, and real-time intrusion detection in resource-constrained smart environments. Overall, SMDL-BC represents a fully integrated, privacy-preserving, and attack-resilient IDS solution, offering a robust foundation for next-generation secure IoT infrastructures.

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