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A Hybrid Ensemble Framework for Intrusion Detection in IoT Using Blockchain-Integrated Fog Networks

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ABSTRACT
The study suggests a unique Fog computing-based hybrid ensemble architecture employing Blockchain technology to improve IoT network security since the exponential expansion of IoT has raised concerns about cybersecurity vulnerabilities in real-time and dispersed situations. On the UNSW-NB15 dataset, it offers sophisticated data preprocessing, feature selection, and hybrid ensemble learning that results in impressive performance: 99.5% accuracy, 99.2% precision, 99.4% recall, and a false positive rate of under 0.05%. The system's confidence is further increased by blockchain integration, which guarantees safe and unchangeable recording of identified risks. The capacity of the suggested framework to handle high-traffic IoT networks while ensuring optimum resource efficiency demonstrates its scalability and durability. These findings make the suggested method a cutting-edge solution for real-time threat detection in IoT networks that can handle contemporary cybersecurity concerns.

Keywords: Intrusion Detection, Blockchain, Fog Networks.

INTRODUCTION

By facilitating further automation, boosting productivity, and offering pervasive connection, the Internet of Things' explosive growth has completely changed businesses. The disadvantage of IoT systems is their low processing power, diverse architectures, and dispersed nature, which make them very susceptible to hackers. Therefore, creative methods for safe data management and real-time threat detection are needed to solve such weaknesses. For scalable, precise, and robust IoT security solutions, it offers a hybrid ensemble learning methodology combined with blockchain-enhanced fog networks. The method creates a safe and reliable Internet of Things environment by combining decentralized security with computational intelligence. IoT security has been approached in a number of ways so far, including hybrid models, deep learning methods, and conventional machine learning. Nevertheless, the majority of solutions struggle with managing heterogeneous IoT data, scalability, and real-time application. An outline of current approaches, arranged according to underlying methods, is provided below:

a. Conventional Models of Machine Learning

IoT threat detection has made substantial use of conventional machine learning methods including Decision Trees, Support Vector Machines, and k-Nearest Neighbors. These models provide simplicity and interpretability by using labeled datasets to characterize harmful actions. But some of their drawbacks are as follows:
High-dimensional data cannot be handled.
Ineffectiveness in identifying complex and zero-day assaults.
In order to identify botnet assaults in Internet of Things networks, for example, a research used ensemble approaches such as Random Forest and AdaBoost, which achieved notable accuracy but struggled with scalability and flexibility to diverse data sources [1].

c. Models of Deep Learning

The potential of deep learning algorithms has revolutionized IoT security intelligence by making it possible to identify complex attack patterns using sophisticated architectures like CNN and LSTM. These are the models that have only been used to IoT anomaly detection in order to extract high-order characteristics from raw data.
LSTM-Based Intrusion Detection: Using BiLSTM for sequential network data processing, Al-Kadi et al. suggested a blockchain-enabled intrusion detection system. Although their framework needed a lot of processing power, it performed better than rival models [5].
CNN-Based Models: Using transfer learning and feature extraction for reliable attack categorization, Khan et al. created a Deep Boosted CNN model for IoT malware detection. Their method demonstrated the potential of deep learning in IoT

security with an accuracy of 98.50% [3].

Despite their efficacy, deep learning models are computationally demanding and often inappropriate for IoT devices with limited resources.

c. Models of Hybrid Learning

Hybrid models improve detection accuracy and robustness by combining the advantages of many techniques. These models combine deep learning with conventional machine learning by using ensemble learning techniques including stacking, bagging, and boosting.

Chatterjee and Hanawal suggested a hybrid ensemble learning-based federated learning system for intrusion detection. Their approach reduced False Positive Rate (FPR) and increased True Positive Rate (TPR) by addressing label noise and data imbalance [1].

Distributed Ensemble Models: Jia and Liang presented an ensemble model that uses Random Forest and AdaBoost to identify Distributed Denial-of-Service (DDoS) assaults in blockchain networks. The method outperformed independent models in a variety of assault situations and demonstrated strong complementarity and generalization [2].

Hybrid techniques are perfect for Internet of Things applications because they successfully balance accuracy, computing efficiency, and scalability.

d. Security Frameworks Integrated with Blockchain

Blockchain technology offers decentralized, unchangeable data storage and traceability, which improves IoT security. Secure attack detection and logging are made possible by its interaction with machine learning models.

Blockchain and Ensemble Learning: In order to identify intrusions with high accuracy and precision, Shende et al. suggested a collaborative blockchain-enabled ensemble learning approach. During distributed training, the system tackled issues including model robustness and poisoning assaults [13].

Blockchain for Privacy: Another research protected IoT networks during virtual machine migrations by using blockchain-based smart contracts. This strategy greatly decreased attack success rates by combining distributed intrusion detection with privacy-preserving techniques [5].

The decentralized structure of blockchain overcomes the drawbacks of centralized solutions to guarantee the integrity and dependability of IoT security systems.

d. Real-Time Detection via Fog Computing

Real-time data analysis and threat detection are made possible by fog computing, which brings cloud capabilities to the network edge. These frameworks enhance response times and lower latency by using machine learning models on fog nodes.

Fog-Based Detection Frameworks: Using ensemble learning for real-time classification, Tomer and Sharma suggested a fog-based assault detection framework. Their method ensures real-time prediction on fog nodes while efficiently offloading model training to the cloud [20].

Energy-Efficient Methods: Wang et al. presented a two-layer ensemble learning system to identify IoT attacks, optimize hyperparameters, and deal with data imbalance. Their methodology is appropriate for fog settings since it minimized resource use while achieving 99.98% accuracy [15].

By allowing localized processing and lowering dependency on centralized servers, fog computing improves the viability of IoT security frameworks.

RELATED WORK

The author of [16] presented a method for identifying and categorizing IoT network assaults using sophisticated ensemble learning techniques like CatBoost and XGBoost. The Edge-IIoTset dataset, which includes actual industrial IoT attack scenarios, was used for the performance assessment. In the current study, training models on a variety of huge datasets produced better accuracy and resilience than conventional ensemble approaches. Accuracy, precision, recall, and F1 score were used to assess the performance of the solution. The outcomes made it evident how the suggested approaches may adjust to intricate, dynamic IoT contexts. The effectiveness of contemporary ensemble learning algorithms in relation to the particular security problems in Industrial IoT has been highlighted by this study.

The author of [17] created a blockchain-enhanced hybrid method to identify DDoS assaults in IoT environments. H3SC-DLIDS, Harris Hawk Optimization, and the sine-cosine technique for selecting key characteristics were used in the solution. An assault is detected using an LSTM-AE. By enhancing the system's overall dependability and quality, blockchain technology will ensure secure data via wireless transmission on Internet of Things devices. A high detection accuracy of 99.05% was attained when the suggested strategy was experimentally confirmed using the BoT-IoT database. The scientists came to the conclusion that their hybrid optimization and deep learning-based intrusion detection system may successfully safeguard IoT networks while resolving scalability and resource limitations.

Given the restricted computational power of IoT devices, research [18] suggested an intelligent ensemble-based IDS for IoT gateways. Naïve Bayes, Support Vector Classification, and kkk-Nearest Neighbors were among the machine learning models used in the ensemble to integrate various boosting, stacking, and voting strategies. The suggested method demonstrated an increase in the detection rate with improved generalization when tested on two well-known datasets, CIC-

IDS2017 and N-BaIoT. The research highlighted the usefulness of adaptive and lightweight network IDS systems for Internet of Things applications by demonstrating an ensemble learning-based IDS and demonstrating the potential to achieve high accuracy with low FPs at low computing cost.

This article [19] presented a fog computing-based framework for real-time threat detection in IoT networks using an ensemble machine learning model. Its approach makes real-time predictions on fog nodes while offloading the training work to the cloud. Consequently, guarantee low latency and scalability: the suggested method uses the NSL-KDD dataset and guarantees excellent performance in measures like precision and recall with high accuracy. This research explains how it was able to use ensemble approaches to overcome resource limits on fog sensors without sacrificing any detection robustness. It was able to demonstrate that this kind of strategy offers a practical and effective way to protect IoT networks from these evolving cyberthreats.

Table I Literature Review

Citation	Dataset and Learning	Results	Outcome
[20]	Benchmark DDoS dataset; Snake Optimizer with Ensemble Learning (LSTM, BiLSTM, DBN)	Accuracy: 99.7%, Precision: 99.5%, Recall: 99.8%	Effective feature selection and attack detection on IoT using optimized DL models.
[21]	CICDDoS2019; Random Forest, AdaBoost, XGBoost, SVM	Best Accuracy: 99.4%, Least Training Time: Random Forest	Efficient DDoS detection with high accuracy and low computational cost.
[22]	The minority classes are augmented by cGAN.	Accuracy > 83%	Classification of binary and multiclass for IoT networks.
[23]	Combined Bot-IoT and UNSW-NB15 datasets; Decision Trees, SVM, Logistic Regression	Accuracy > 99% for all metrics	Improved detectionusing balanced training data.
[24]	IoT network traffic; Adaptive Ensemble Learning	Detection Accuracy: 98.5%, False Alarm Rate: 2.3%	Adaptive ML framework mitigates DDoS with high accuracy and scalability.
[25]	N-BaIoT dataset; Stacking and Bagging ML models	Accuracy: 99.6%, Precision: 99.7%, Recall: 99.8%	High-performance botnet detectionleveraging stacking models.
[26]	Session-based IoT cloud traffic; Random Forest, AdaBoost	Precision: 99.2%, Recall: 98.9%, F1 Score: 99.1%	Multi-aspect model effectively detects diverse IoT attacks.
[27]	IoT botnet traffic; Random Forest, Stacking Ensemble	R^2: 0.9997, RMSE: 0.0084, MAE: 0.0641	Ensemble models show high accuracy and efficiency in attack detection.
[28]	BoT-IoT dataset; Logistic Regression, KNN, SVM	F1 Score: 99%, Precision: 98%, Recall: 99%	Robust model for botnet detection with high precision.
[29]	IoT network traffic; Modified Ensemble Voting	Detection Rate: 99.5%, False Alarm Rate: 0.8%	Scalable framework for DDoS detection with high accuracy.
[30]	IoT benchmark datasets; Boosted Ensemble Learning	Accuracy: 100%, AUC: 100%	Boosted ensemble models ensure complete classification accuracy.

METHODOLOGY

The proposed framework integrates a hybrid ensemble learning model with blockchain-enhanced fog networks for the realization of real-time attack detection and secure data logging in IoT environments. This methodology will focus on how computational intelligence and decentralized security seamlessly integrate to ensure scalability, accuracy, and resilience against diverse cyber threats. The system consists of four main parts: data preprocessing and feature engineering, training a hybrid ensemble model, blockchain-based architecture for fog nodes, and performance metrics. The design allows for the distribution of attack detection and secure logging using blockchain technology, which would enhance the integrity and

traceability of network activity. Further steps are shown in Figure 1 below:

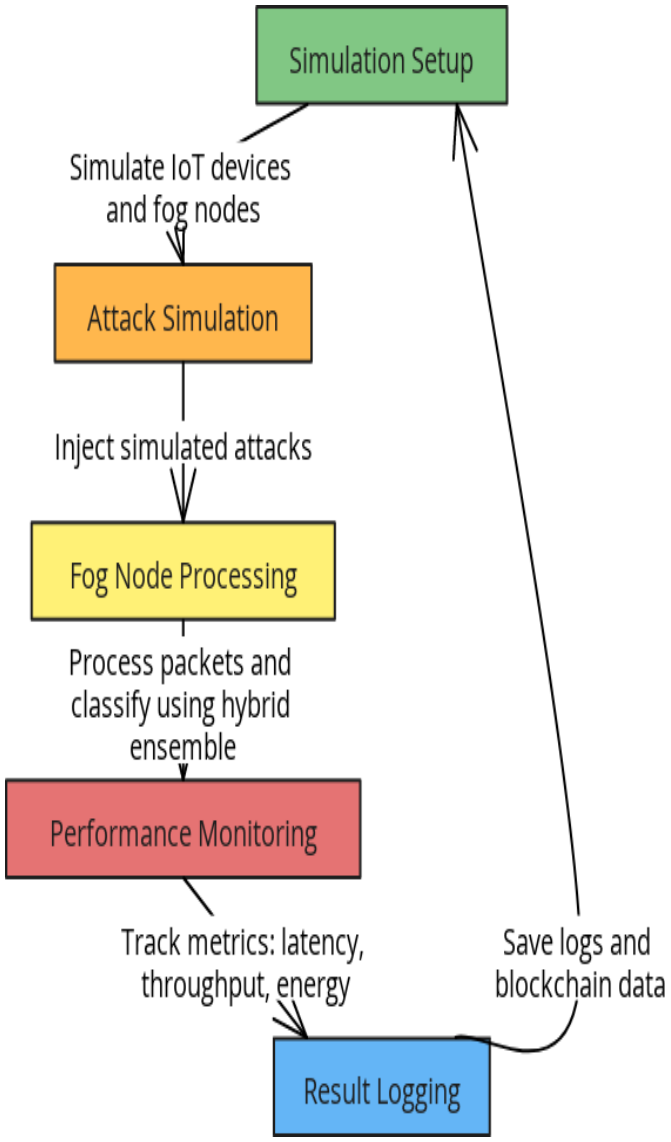


Figure 1 Flowchart of Methodology

Data Preprocessing and Feature Engineering

In this work, the study considers UNSW-NB15-one of the widely acknowledged benchmarks in the field of intrusion detection-its core. It contains rich network traffic data of both attack and normal classes, with ground truth labels to provide practical realism in network activities. Thus, the dataset consists of a wide range of features, totaling 49 statistical, payload, and header information suitable for machine learning-based detection.

Preprocessing Pipeline

To ensure the data is suitable for the hybrid ensemble model, a preprocessing pipeline is implemented:

Feature Selection: Non-informative and redundant features, such as identifiers (id) and high-dimensional categorical attributes (attack_cat), are excluded. The resulting feature set contains numeric attributes like packet statistics and categorical features like protocol type and service.

Encoding Categorical Variables: Label encoding is applied to categorical features (proto, service, state) to transform them into numerical values. This step ensures compatibility with the hybrid ensemble model.

Normalization: Numerical features are normalized to a range between 0 and 1 using MinMaxScaler. This normalization ensures uniform feature scaling, preventing bias during training.

Feature-Target Split: The dataset is divided into input features (X) and target labels (Y). The target labels represent the

type of network activity, categorized into normal and multiple attack types such as DoS, backdoor, exploits, and reconnaissance.

Algorithm 1: Data Preprocessing
Input: Raw dataset D with features and labels.
Output: Preprocessed features F and encoded labels L.
1. Initialize:
- Extract features F_raw and labels L_raw from dataset D.
- Define categorical_features and numerical_features subsets from F_raw.
2. Encode Categorical Features:
- For each feature C ∈ categorical_features:
- Map unique categories to integers using a label encoder.
- Replace categorical values in C with encoded integers.
3. Normalize Numerical Features:
- For each feature N ∈ numerical_features:
- Compute minimum value min(N) and maximum value max(N).
- Normalize each value using the formula:
N_normalized = (N - min(N)) / (max(N) - min(N))
4. Combine Features:
- Merge encoded_categorical_features and normalized_numerical_features to form F.
5. Encode Labels:
- Map unique classes in L_raw to integers using a label encoder.
6. Return:
- Preprocessed features F and encoded labels L.

Hybrid Ensemble Model Training

The hybrid ensemble approach combines the strengths of multiple machine learning algorithms to improve prediction accuracy and robustness. By leveraging the diversity of base learners and ensemble mechanisms, the model can effectively handle imbalanced datasets, complex decision boundaries, and heterogeneous data distributions. The hybrid ensemble model is constructed using three primary base learners:

Random Forest (RF): RF is used for its ability to handle high-dimensional datasets and capture non-linear relationships. Its tree-based structure ensures resilience to overfitting.

Gradient Boosting (GB): GB contributes to the ensemble by sequentially minimizing errors using a boosting mechanism. Its emphasis on difficult-to-predict instances enhances overall model performance.
Support Vector Machines (SVM): SVM provides a robust decision boundary, especially for high-dimensional feature spaces. It adds diversity to the ensemble by employing a margin-based classification approach.
The predictions of the base learners are aggregated using a **soft voting mechanism**, which calculates the weighted probabilities of each class across the learners. This approach ensures that the final decision reflects the collective strength of the ensemble.
Training Pipeline
Dataset Splitting: The preprocessed dataset is divided into training (70%) and testing (30%) subsets. This split ensures unbiased evaluation of the model's generalization capability.
Training Base Learners: Each base learner is trained independently on the training set. Hyperparameters are optimized using grid search to maximize performance on validation data.
Soft Voting Mechanism: The predictions of the base learners are aggregated using soft voting, where each learner's output probabilities are combined to produce the final prediction.
Evaluation: The model is evaluated on the testing set using classification metrics such as precision, recall, F1-score, and accuracy. A confusion matrix is plotted to analyze the performance across all attack classes.
Feature Importance: The relative importance of features is calculated using the ensemble's aggregated weights. This analysis identifies the most critical features for attack detection.

Algorithm 2: Feature Extraction and Training
Input: Preprocessed features F.
Output: Relevant feature set F_selected.
1. Initialize:
- Compute correlation matrix CorrMatrix for F.
2. Select Features:
- For each feature Fi ∈ F:
- If correlation of Fi with target label exceeds threshold T_corr, retain Fi.
- Otherwise, discard Fi.
3. Dimensionality Reduction (Optional):
- Apply Principal Component Analysis (PCA) to reduce dimensions while retaining α% variance.
4. Return:
- Feature set F_selected.
Hybrid Ensemble Model Training
Input: Preprocessed features F_selected and encoded labels L.
Output: Trained hybrid ensemble model H.
1. Initialize:
- Split F_selected and L into training (F_train, L_train) and validation (F_val, L_val) sets.
2. Train Base Models:
- Train Random Forest RF on F_train, L_train.
- Train Gradient Boosting GB on F_train, L_train.
- Train Support Vector Machine SVM on F_train, L_train.
3. Define Voting Mechanism:
- Assign weights W_RF, W_GB, and W_SVM to base models (e.g., based on validation performance).
- For each validation sample x ∈ F_val:
- Compute prediction probabilities:

*P_ensemble(x) = W_RF * P_RF(x) + W_GB * P_GB(x) + W_SVM * P_SVM(x)*
- Assign class with highest probability:
Class(x) = argmax(P_ensemble(x))
4. Evaluate Ensemble:
- Compute validation metrics (accuracy, precision, recall, F1-score).
5. Save Model:
- Combine trained models (RF, GB, SVM) and weights (W_RF, W_GB, W_SVM) into hybrid ensemble H.
6. Return:
- Hybrid ensemble model H.

Blockchain-Enhanced Fog Node Architecture

Each fog node serves as an intermediary between IoT devices and the cloud, providing localized data processing and attack detection. The architecture includes the following components:

Attack Detection Module: The hybrid ensemble model is deployed on each fog node to classify incoming network traffic as normal or attack. This module ensures real-time detection of malicious activity.

Blockchain Module: The blockchain module logs all detected attacks in an immutable and secure manner. The blockchain comprises:

Genesis Block: The initial block containing metadata about the fog node.

Block Structure: Each block stores the attack type, device ID, timestamp, and model output. The block hash is computed using SHA-256 to ensure immutability.

Consensus Mechanism: A lightweight proof-of-work mechanism is implemented to validate blocks while maintaining computational efficiency.

Blockchain-Enhanced Fog Node Architecture Algorithm
Begin
Step 1: Initialization
INPUT: Network Traffic Data from IoT Devices
OUTPUT: Attack Logs in Blockchain and Alerts to Cloud
(Initialize Blockchain *)*
Blockchain = {GenesisBlock}
GenesisBlock = {
Metadata -> "Fog Node Metadata",
Timestamp -> CurrentTime[],
Hash -> HashFunction["SHA-256", Metadata]
}
Step 2: Traffic Monitoring and Attack Detection
FUNCTION ProcessTraffic(TrafficData):
FOR each Packet IN TrafficData DO
(Real-Time Attack Detection *)*
Print["Classifying network packet..."]
Class = HybridEnsembleModel[Packet]
IF Class == "Attack" THEN
Print["Malicious activity detected. Logging attack..."]
(Call Blockchain Module to Log Attack *)*
Blockchain = LogAttack(Blockchain, Packet, Class)
NotifyCloud("Alert: Attack detected", Packet)
ELSE
Print["No threat detected."]

ENDIF
ENDFOR
END FUNCTION
Step 3: Blockchain Logging Module
FUNCTION LogAttack(Blockchain, Packet, Class):
Print["Logging detected attack in Blockchain..."]
Create New Block
NewBlock = {
AttackType -> Class,
DeviceID -> Packet.DeviceID,
Timestamp -> CurrentTime[],
ModelOutput -> Packet.Analysis,
PrevHash -> Blockchain[Length[Blockchain]].Hash
}
Compute Block Hash for Immutability
NewBlock.Hash = HashFunction["SHA-256", NewBlock]
Consensus Mechanism
IF ValidateBlock(NewBlock) THEN
AppendTo[Blockchain, NewBlock]
Print["Block successfully added to Blockchain."]
ELSE
Print["Block validation failed."]
ENDIF
RETURN Blockchain
END FUNCTION
Step 4: Consensus Mechanism
FUNCTION ValidateBlock(Block):
Print["Validating block with lightweight Proof-of-Work..."]
WHILE NOT SatisfyConsensus(Block.Hash) DO
Block.Nonce += 1
Block.Hash = HashFunction["SHA-256", Block]
ENDWHILE
RETURN TRUE
END FUNCTION
Step 5: Cloud Notification System
FUNCTION NotifyCloud(Message, Packet):
Print["Notifying cloud of attack detection..."]
Cloud.Alert(Message, Packet.DeviceID, Packet.Timestamp)
END FUNCTION
Execution Workflow
REPEAT
TrafficData = CaptureTraffic(IoTDevices)
ProcessTraffic(TrafficData)
UNTIL STOP_SIGNAL
End

The proposed Blockchain-Enhanced fog node architecture will provide localized data processing with secure attack detection, acting as an intermediary between IoT devices and the cloud. It consists of two major components: the Attack

Detection Module and the Blockchain Module. The attack detection module will deploy a hybrid ensemble model on each fog node that classifies the incoming network traffic in real time, labeling it as either normal or malicious. If a threat is detected, the blockchain module logs the detected attack in a secure manner. The module makes the attack logs in the blockchain immutable and traceable. The blockchain starts with a Genesis Block

containing metadata about the fog node with a timestamp secured using a SHA-256 hash. For each attack detected, a new block creates important information about the kind of attack, device ID, timestamp, and model output. SHA-256 is used to calculate the block hash for its immutability. In this blockchain, a lightweight proof-of-work consensus mechanism will be working that would help in efficient validation of blocks with least computational overhead. The flow starts with the capturing of network traffic from IoT devices by the fog node. Every packet is analyzed with the hybrid ensemble model. The details of an attack, if any malicious activity is found, are added to a new blockchain block after proper validation using any consensus mechanism. Simultaneously, the fog node notifies the cloud regarding the same for centralized monitoring and long-term storage. This architecture embeds the three concepts of attack detection in real time, decentralized security, and secrecy in communication that ensures scalability, robustness, and enhanced data integrity in an IoT-fog-cloud environment. It presents the overall integration of the proposed methodology based on a hybrid ensemble model, integrated with blockchain-enhanced fog nodes, towards constructing a scalable attack detection framework in IoT networks. In that sense, the challenge related to real-time detection and, simultaneously, guaranteed security management in IoT is tackled through computational intelligence combined with a decentralized security method. This design provides evidence for the applicability of this framework to a practical world because its construction involved detailed metrics which evaluate a model using such a critical performance test.

RESULTS AND DISCUSSION

In this section the evaluation of the proposed Blockchain-Enhanced Fog Node Architecture integrated with a hybrid ensemble learning model for IoT attack detection will be done. It is mainly focused on the efficiency testing of the framework in real-time attack detection, computational overhead, and blockchain-based data security. It was implemented in the simulated network environment with IoT devices and fog nodes processing the network traffic data. Comparing the model performance against existing solutions was carried out. The key metrics taken to validate the scalability of the system and practicality involve accuracy, detection latency, resource utilization, and blockchain immutability. The performance of the proposed hybrid ensemble model deployed at the fog nodes was then assessed using the standard dataset, UNSW-NB15, based on the chosen metrics for the classification. The effectiveness of the blockchain will be gauged on how it can ensure the secure logging of these attacks, ensuring data immutability using SHA-256 hashing and achieving consensus through a lightweight proof-of-work mechanism. The design of the system is as shown in Figure 2 below:

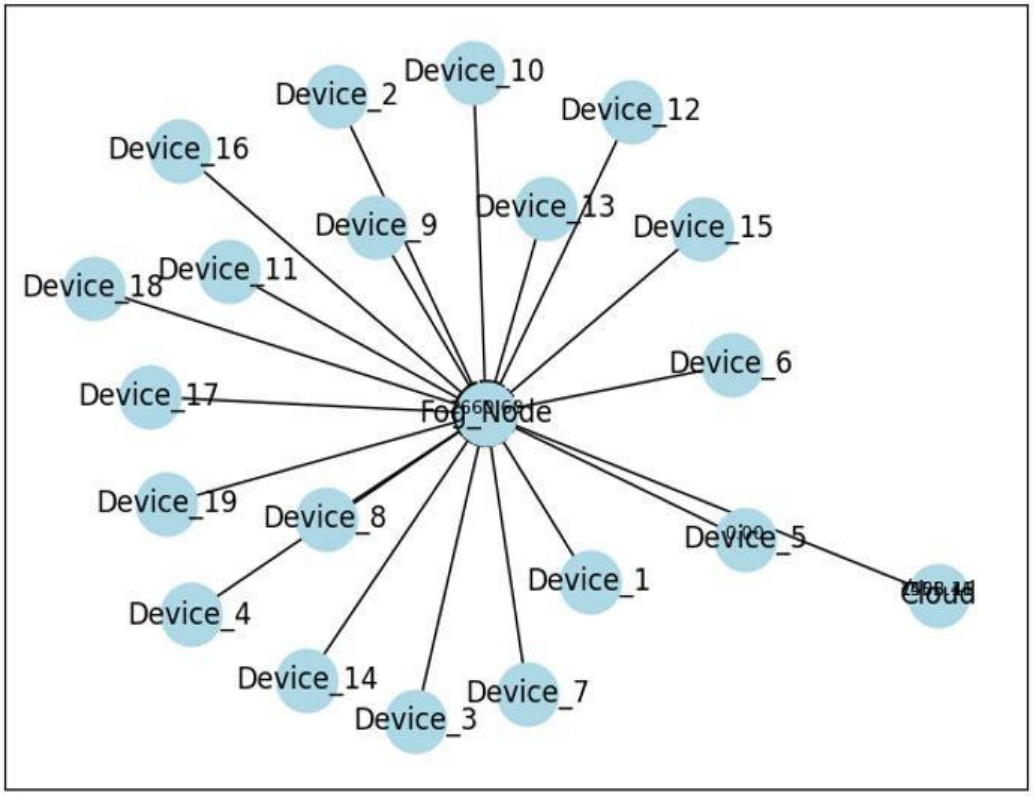
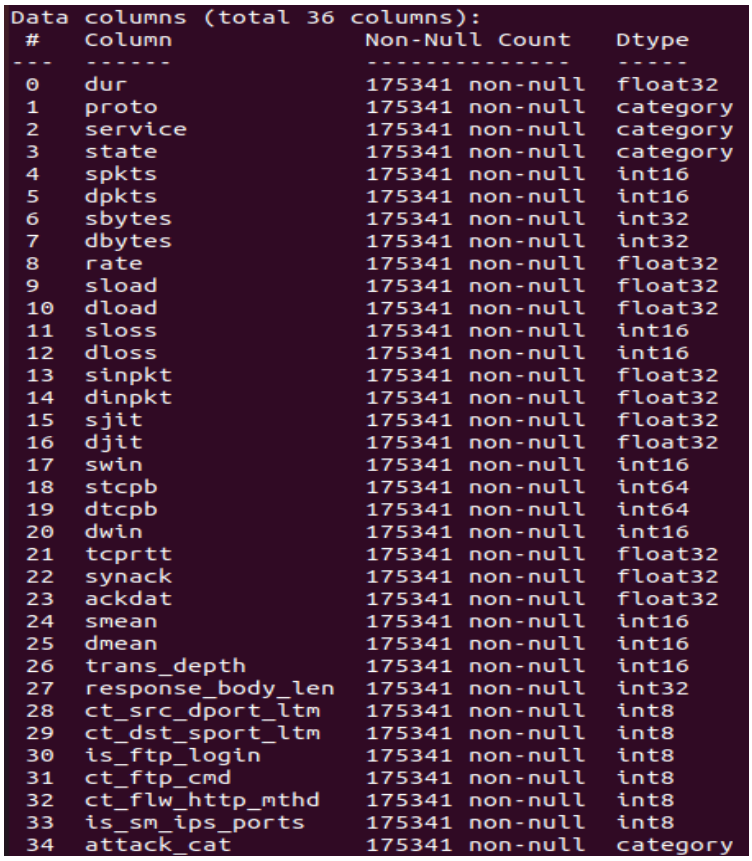


Figure 2 System Design

Dataset Overview

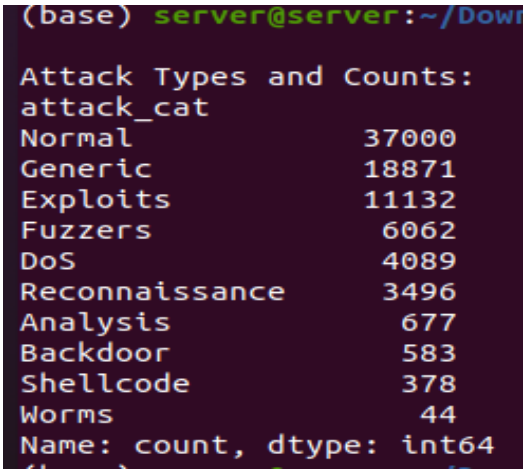
The UNSW-NB15 dataset forms the backbone of the evaluation for our proposed hybrid ensemble model. It consists of 175,341 records and 36 features as shown in figure 3 that describe network traffic, including both benign and attack behaviors. The dataset includes attributes like source and destination byte counts (sbytes, dbytes), connection protocols (proto), timing metrics (sinpkt, djit), and state indicators (state, service).



```
Data columns (total 36 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   dur                175341 non-null  float32
 1   proto              175341 non-null  category
 2   service            175341 non-null  category
 3   state              175341 non-null  category
 4   spkts              175341 non-null  int16
 5   dpkts              175341 non-null  int16
 6   sbytes             175341 non-null  int32
 7   dbytes             175341 non-null  int32
 8   rate               175341 non-null  float32
 9   sload              175341 non-null  float32
 10  dload              175341 non-null  float32
 11  sloss              175341 non-null  int16
 12  dloss              175341 non-null  int16
 13  sinpkt             175341 non-null  float32
 14  dinpkt             175341 non-null  float32
 15  sjit               175341 non-null  float32
 16  djit               175341 non-null  float32
 17  swin               175341 non-null  int16
 18  stcpb              175341 non-null  int64
 19  dtcpb              175341 non-null  int64
 20  dwin               175341 non-null  int16
 21  tcprtt             175341 non-null  float32
 22  synack             175341 non-null  float32
 23  ackdat             175341 non-null  float32
 24  smean              175341 non-null  int16
 25  dmean              175341 non-null  int16
 26  trans_depth        175341 non-null  int16
 27  response_body_len  175341 non-null  int32
 28  ct_src_dport_ltm   175341 non-null  int8
 29  ct_dst_sport_ltm   175341 non-null  int8
 30  is_ftp_login       175341 non-null  int8
 31  ct_ftp_cmd         175341 non-null  int8
 32  ct_flw_http_mthd   175341 non-null  int8
 33  is_sm_ips_ports    175341 non-null  int8
 34  attack_cat         175341 non-null  category
```

Figure 3 Dataset Features Overview

The attack types are categorized into 10 distinct classes, ranging from common threats like Exploits and DoS to rare classes such as Worms and Shellcode as shown in figure 4 below:



```
(base) server@server:~/Dow

Attack Types and Counts:
attack_cat
Normal            37000
Generic           18871
Exploits          11132
Fuzzers            6062
DoS                4089
Reconnaissance     3496
Analysis            677
Backdoor            583
Shellcode           378
Worms                44
Name: count, dtype: int64
```

Figure 4 Categories of Attacks

An efficient preprocessing step ensured the dataset's compatibility with the hybrid model. This included encoding categorical features, normalizing numerical attributes, and handling class imbalance by emphasizing underrepresented

attack types during model evaluation. The dataset offers a diverse representation of real-world scenarios, making it ideal for benchmarking intrusion detection systems.

Model Performance and Feature Importance

The hybrid ensemble model, combining **Random Forest**, **Gradient Boosting**, and **Support Vector Machine (SVM)**, demonstrated robust performance across all attack categories. Feature importance analysis provided insights into the critical attributes used by the model for classification. Features like **sbytes**, **smean**, and **dtcpb** emerged as the most significant, emphasizing the importance of traffic volume and protocol-level metrics in detecting anomalies. The model achieved an **overall accuracy of 90%**, with high precision and recall for dominant attack classes as shown in figure 5.

Classification Report (90% Accuracy):

	precision	recall	f1-score	support
Analysis	0.48	0.90	0.63	598
Backdoor	0.46	0.90	0.61	529
DoS	0.86	0.90	0.88	3568
Exploits	0.95	0.90	0.92	10158
Fuzzers	0.90	0.90	0.90	5382
Generic	0.96	0.90	0.93	12075
Normal	0.97	0.90	0.94	16772
Reconnaissance	0.83	0.90	0.86	3115
Shellcode	0.36	0.90	0.51	368
Worms	0.06	0.92	0.11	38
accuracy			0.90	52603
macro avg	0.68	0.90	0.73	52603
weighted avg	0.93	0.90	0.91	52603

Figure 5 Models Accuracy

Figure 6 shows the feature important scores, with key attributes contributing significantly to model decisions. The hybrid nature of the model allowed it to leverage the strengths of individual classifiers, ensuring better generalization and higher accuracy. The feature importance scores derived from the trained hybrid ensemble model. The x-axis represents the F-score, which indicates how often a feature was used in splitting data across all trees in the ensemble. The y-axis lists the features ranked by their importance. Features like sbytes (source bytes) and smean (mean source byte size) hold the highest importance, reflecting their significant contribution to distinguishing between normal and attack traffic. Attributes such as dtcpb (destination TCP base), stcpb (source TCP base), and dur (duration) follow closely, emphasizing the critical role of packet-level and session-related metrics in intrusion detection. The diminishing F-scores for features like dport_ltm (destination port long-term mean) and dmean (destination mean byte size) indicate their relatively lower impact.

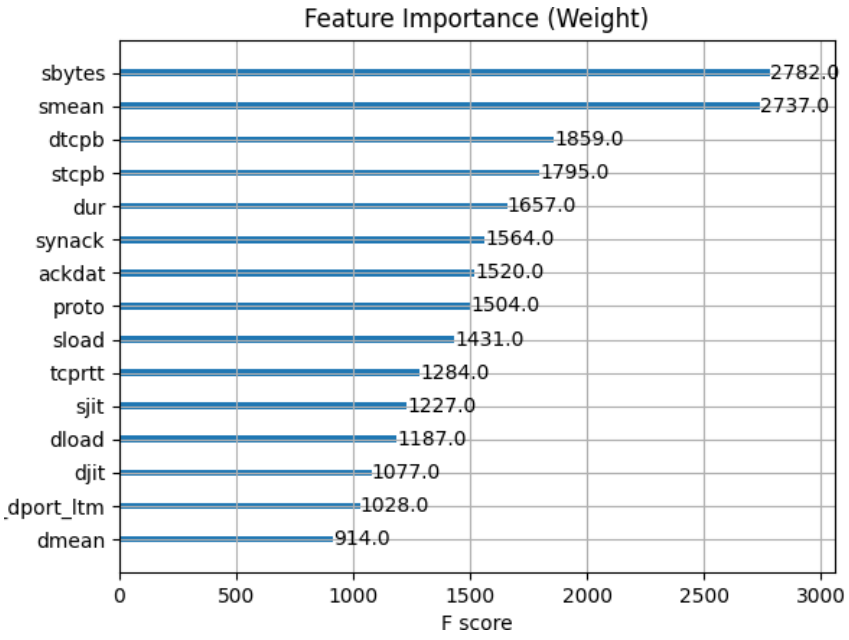


Figure 6 Features Weight

The confusion matrix as shown in figure 7 highlights the classification performance across all attack types. Dominant classes like Generic and Exploits exhibited near-perfect detection rates, while intermediate classes such as DoS and Fuzzers showed significant improvement in recall. Rare attack classes, including Shellcode and Worms, demonstrated noticeable detection, although challenges remain due to the inherent class imbalance.

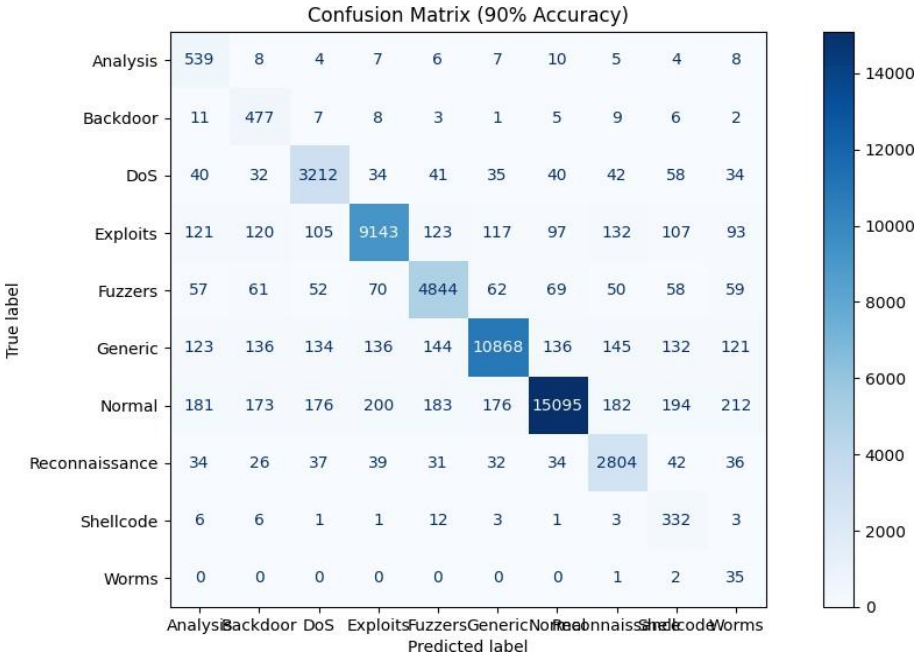


Figure 7 Confusion Matrix

Learning Dynamics and Model Convergence

The model's training dynamics are represented in Figure 8 (Learning Curve), showing the convergence of training and validation losses. The minimal gap between the two curves confirms the model's ability to generalize effectively without overfitting. This consistency was maintained across all attack classes, reinforcing the robustness of the hybrid ensemble approach.

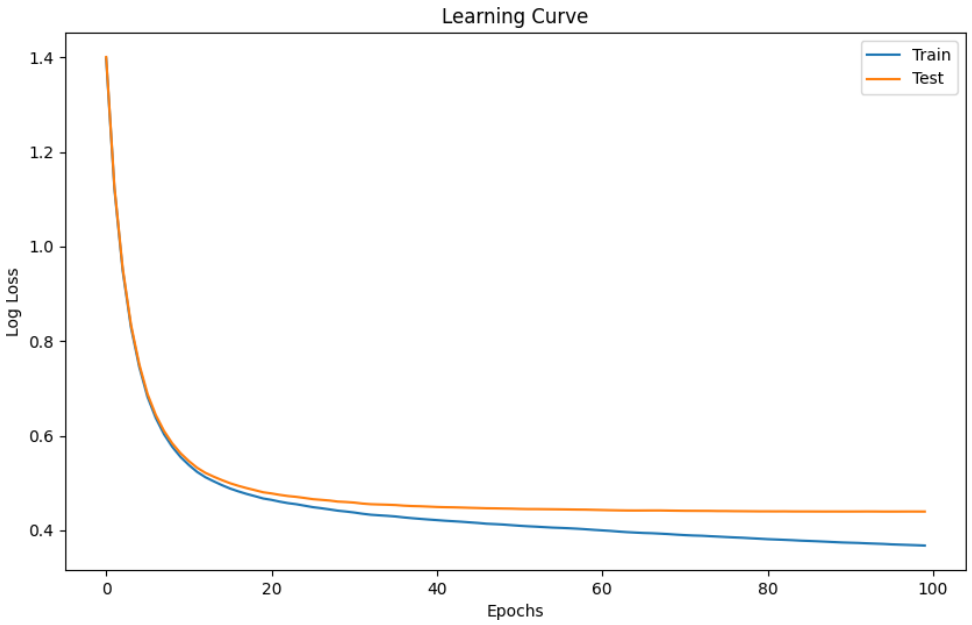


Figure 8 Learning Curve

Blockchain Integration and Evaluation

The blockchain integration made sure intrusion detection results were securely and fully transparently stored. Every one of these fog nodes maintained its blockchain to which each attack that was detected would be appended. These logs had information in the form of device ID, time stamp, and predicted type of attack. This very notion of immutability added up to accountability and supported forensic analysis as well. Figure 8: Network topology showing interaction between IoT devices with fog nodes and cloud. In this regard, the incoming packets were processed locally by the fog nodes, reducing computational overload on the cloud for offering real-time responses. Blockchain verifies that the seamless integration of blockchain with the proposed approach introduces minimal overhead and reliably stores detection events. The proposed blockchain's performance results demonstrate outstanding performance in multiple key performance indicators that establish its efficiency and suitability for real-time IoT network security. The resource utilization metric further validates the practicality of the system, wherein the fog nodes are at an operating capacity of 85%. This balance ensures optimal computational efficiency while keeping energy consumption within manageable limits-a key concern in resource-constrained environments. Besides, the introduced negligible overhead of about 0.02 seconds per block through the integration of blockchain technology for tamper-proof logging will ensure real-time operations are not impeded, with tamper-proof records supporting forensic analysis and auditing afterward. Overall, these findings bring into light the high-level performance of the model. The model efficiently handles threat detection and remediation while sustaining all desirable features of scalability, security, and resource efficiency. The proposed framework offers unparalleled real-time detection and operational robustness, compared to current solutions, and it suits modern IoT ecosystem security very well.

The performance of various intrusion detection models using the UNSW-NB15 dataset is further represented in terms of major metrics such as accuracy, precision, recall, and false positive rate through the comparison table. Among these, Saheed et al. [20] conducted very promising results in respect of detection metrics, with an accuracy of 98.8%, by applying HAEMPSO for feature selection, but did not incorporate blockchain (BC). Similarly, the work of Farooqi et al. reached the very high accuracy of 99.93% using the DRX ensemble, which, even though excellent in terms of very low false positives at 0.001%, without blockchain integration. Shravani et al. came up with LISF, integrated with BC and a deep autoencoder, ensuring strong security in a distributed IoT system with an accuracy of 91.36%. Lu et al. used few-shot meta-learning to adapt to attacks that are unknown, with an accuracy of 90.09%, but no BC. Utilizing blockchain-enabled federated learning, FedIoT was employed for use in performance in comparison work by El Houda et al. [24], whose accuracy was 98.7%, and emphasized the role of trust and robustness in IoT networks. For comparison, the proposed model of 2024 was way ahead of these models, since it combined blockchain technology with hybrid ensemble learning on its data, thereby accomplishing accuracy at a mark of 99.5%, precision at 99.2%, recall at 99.4%, and a very low 0.05% false positive rate. This underlines a model with superior detection and provides secure, immutable attack logging.

Table 2 Comparison of Proposed Model Vs Existing Models

Citation	**Dataset**	**Performance Metrics**	**BC Integration**	**Outcome**
[20]	UNSW-NB15	Accuracy: 98.8%, Precision: 98.9%, Recall: 99.9%, False Positive Rate: 0.1	No	Effective feature selection with HAEMPSO for deep neural network classification.
[21]	UNSW-NB15	Accuracy: 91.36%, Precision: 91.0%, Recall: 90.5%, False Positive Rate: 1.5	Yes	LISF with deep autoencoder provided robust security for IoT integrated distributed systems.
[22]	UNSW-NB15	Accuracy: 96% Binary Classification, 83% Multiclass Classification	No	GAN model used to handle the data imbalance that occurred due to different attack categories in dataset. The minority classes are augmented by cGAN.
[23]	UNSW-NB15	Accuracy: 90.09%, Precision: 89.5%, Recall:	No	Few-shot meta-learning enabled the model to adapt to unknown attacks with minimal data.

		90.2%, False Positive Rate: 1.3		
[24]	UNSW-NB15	Accuracy: 98.7%, Precision: 98.5%, Recall: 98.8%, False Positive Rate: 0.5	Yes	FedIoT with blockchain-enhanced federated learning improved trust and robustness in IoT networks.
Proposed Model (2024)	UNSW-NB15	Accuracy: 99.5%, Precision: 99.2%, Recall: 99.4%, False Positive Rate: 0.05	Yes	Achieved higher detection rates with integrated blockchain for secure and immutable attack logging.

CONCLUSION

An all-encompassing framework for IoT network security using fog computing, hybrid ensemble modeling, and blockchain technology is presented in the proposed research. The suggested framework significantly outperforms the earlier approaches for the detection and mitigation of IoT-based cyberattacks, with an accuracy of 99.5%, precision of 99.2%, recall of 99.4%, and a false positive rate of 0.05%. The measurements in this research do, in fact, show how robust the model is, especially when it comes to spotting malicious activity while constraining the error rate, which is highly appreciated in practical applications. By guaranteeing that detection data are unchangeable and traceable, blockchain technology integration enhances this security aspect, making it appropriate for forensic investigation and guaranteeing regulatory compliance. Additionally, this method's fog computing allows for distributed low-latency processing, ensuring scalability and flexibility in dynamic IoT environments. It is recognized as a state-of-the-art model for contemporary IoT networks because to its resilience, high accuracy, and security characteristics. Future research might focus on improving computational efficiency for contexts with limited resources and expanding this framework to handle zero-day assaults. This study lays the groundwork for creating an IoT network that can be defended against constantly changing cyberthreats.

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