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"A Hybrid Stacking-Based Ensemble Learning Framework with Temporal Feature Modelling for Zero-Day Attack Prediction in Enterprise Environments"

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Abstract-The increasing complexity of enterprise networks has significantly intensified the risk of sophisticated cyberattacks, particularly zero-day attacks that exploit previously unknown software vulnerabilities. Conventional signature-based intrusion detection systems and standalone machine learning models often fail to identify these attacks due to the absence of prior attack signatures and their limited capability to learn evolving behavioural patterns. This paper proposes a Hybrid Stacking-Based Ensemble Learning Framework that integrates Random Forest, Support Vector Machine, Extreme Gradient Boosting, and Long Short-Term Memory models through a Logistic Regression meta-classifier to enhance zero-day attack prediction. The framework combines statistical, behavioural, and temporal feature engineering to effectively characterize malicious network activities while reducing false-positive alarms. Public benchmark datasets, including NSL-KDD, UNSW-NB15, and CIC-IDS2017, together with enterprise telemetry data, are employed to evaluate the proposed framework. Comprehensive preprocessing, feature normalization, and Bayesian hyperparameter optimization are incorporated to improve model stability and predictive capability. Experimental evaluation demonstrates superior performance compared with conventional machine learning models in terms of Accuracy, Precision, Recall, F1-score, and ROC-AUC. The proposed framework achieves improved generalization or previously unseen attack patterns and provides a scalable solution for enterprise cybersecurity. The findings indicate that integrating heterogeneous learning models with temporal feature modelling significantly strengthens proactive intrusion detection and supports the development of intelligent security systems capable of defending against emerging cyber threats.

Keywords— Zero-Day Attack, Ensemble Learning, Stacking, Enterprise Security, Machine Learning, LSTM, Intrusion Detection.

I. INTRODUCTION

1.1 Background

The widespread adoption of cloud computing, enterprise digital transformation, Industrial Internet of Things (IIoT), and distributed computing has considerably increased cybersecurity risks across modern organizations. Enterprise infrastructures continuously exchange massive volumes of sensitive information through interconnected

systems, making them attractive targets for sophisticated cyber adversaries. Among the numerous cyber threats, zero-day attacks represent one of the most dangerous attack categories because they exploit previously unknown software vulnerabilities before security vendors develop corresponding patches or detection signatures. Unlike conventional malware attacks, zero-day attacks remain invisible to signature-based intrusion detection systems, thereby causing severe financial losses, operational disruption, and information leakage.

1.2 Problem Statement

Traditional intrusion detection systems rely primarily on predefined signatures or manually designed rules that perform effectively only against previously identified attacks. However, these techniques cannot detect emerging threats whose behavioural characteristics differ from historical attack patterns. Recent machine learning models have improved attack detection accuracy, yet individual classifiers often suffer from overfitting, high false-positive rates, and poor adaptability to dynamic enterprise traffic. These limitations motivate the development of intelligent ensemble learning frameworks capable of accurately predicting unknown cyber threats.

1.3 Motivation

Ensemble learning has recently emerged as an effective strategy for improving predictive performance by combining multiple heterogeneous classifiers. Simultaneously, deep learning architectures such as Long Short-Term Memory (LSTM) effectively capture temporal dependencies within sequential network traffic. Integrating these complementary techniques provides an opportunity to enhance zero-day attack prediction by simultaneously improving classification robustness and temporal pattern recognition.

1.4 Research Gap

Current research reveals several limitations:

1. Limited capability to detect previously unseen attacks.
2. High false-positive alarms.
3. Poor temporal behaviour modelling.
4. Limited enterprise scalability.
5. Lack of explainability.
6. Heavy dependence on outdated datasets.

1.5 Contributions

This paper makes the following contributions:

1. Development of a Hybrid Stacking Ensemble combining Random Forest, Support Vector Machine, XGBoost, and LSTM.
2. Integration of temporal feature modelling for improved behavioural analysis.
3. Reduction of false-positive alerts using Logistic Regression meta-learning.
4. Comprehensive evaluation using multiple benchmark intrusion detection datasets.
5. Improved prediction accuracy and enterprise scalability.

II. Literature Review

The rapid evolution of enterprise cyber threats has encouraged extensive research on intelligent intrusion detection systems capable of identifying zero-day attacks. Traditional signature-based intrusion detection systems effectively detect previously known attacks but fail to recognize unknown vulnerabilities because they depend on predefined attack signatures. Consequently, researchers have increasingly adopted machine learning and deep learning approaches to improve proactive cyber threat detection. Early machine learning approaches employed classifiers such as Decision Trees, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naïve Bayes, and Random Forests to distinguish malicious network traffic from normal activities. These supervised learning techniques achieved satisfactory classification performance on benchmark datasets such as NSL-KDD and UNSW-NB15. However, their effectiveness decreases when confronted with previously unseen attack patterns because the models rely heavily on historical labeled data. Furthermore, high false-positive rates and poor adaptability to dynamic enterprise environments remain significant challenges. [19]– [22], [27], [31]– [33]. To overcome these limitations, deep learning techniques have gained considerable attention due to their ability to automatically learn complex feature representations from large-scale network traffic. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Autoencoders, and Long Short-Term Memory (LSTM) networks have demonstrated improved capability for modelling nonlinear relationships and temporal attack behaviour. In particular, LSTM networks effectively capture sequential dependencies within network traffic, making them suitable for detecting evolving cyber threats. Nevertheless, deep learning models generally require extensive computational resources, large training datasets, and often suffer from limited interpretability, restricting their deployment in practical enterprise environments. [8], [16], [24]– [26]. Recent studies indicate that ensemble learning provides a more robust solution by combining multiple heterogeneous classifiers to improve prediction accuracy and reduce variance. Ensemble techniques, including Bagging, Boosting, Voting, and Stacking,

have consistently outperformed individual classifiers by exploiting the complementary strengths of different learning algorithms. Random Forest reduces classification variance through bootstrap aggregation, whereas XGBoost improves predictive capability using gradient boosting. Stacking-based architectures further enhance performance by integrating the predictions of diverse base learners through a meta-classifier, thereby improving robustness against unknown attack patterns. [19]– [23], [29], [30]. Several recent investigations have specifically focused on zero-day attack prediction using hybrid ensemble learning. Osman and Ataelfadiel [1] combined Random Forest, XGBoost, and LSTM with external threat intelligence to improve zero-day prediction accuracy. Dai *et al.* [2] integrated autoencoder-based feature learning with tree-based classifiers to enhance anomaly detection for previously unseen attacks. Sarhan [5] introduced zero-shot learning strategies for evaluating intrusion detection systems against novel attack classes, while Alabdulatif [6] incorporated explainable artificial intelligence into ensemble intrusion detection to improve model transparency. Recent surveys further emphasize that hybrid machine learning, deep learning, and federated learning represent promising research directions for defending against emerging zero-day cyber threats.

Despite significant improvements, several research gaps remain unresolved. Most existing studies evaluate models using outdated benchmark datasets that do not accurately represent modern enterprise traffic. Many proposed methods emphasize classification accuracy while neglecting false-positive reduction, temporal behavioural modelling, scalability, and explainability. Moreover, adaptive learning mechanisms capable of continuously learning from evolving attack behaviour remain insufficiently explored. Current research also demonstrates limited integration of temporal sequence modelling with heterogeneous stacking ensembles for enterprise-scale cybersecurity applications. Motivated by these limitations, the proposed research develops a Hybrid Stacking-Based Ensemble Learning Framework that integrates Random Forest, Support Vector Machine, XGBoost, and Long Short-Term Memory models using Logistic Regression as a meta-classifier. Unlike existing approaches, the proposed framework simultaneously exploits statistical, behavioural, and temporal features to improve zero-day attack prediction while reducing false alarms and enhancing enterprise scalability. This integrated architecture addresses several shortcomings identified in previous studies and provides a practical solution for proactive enterprise cybersecurity.

III. Research Methodology

A. Architecture of the Proposed Hybrid Stacking-Based Ensemble Learning Framework. The proposed architecture is designed to accurately predict zero-day cyberattacks by integrating multiple heterogeneous machine learning and deep learning models through a stacking ensemble strategy. The framework consists of six sequential stages: Data Collection, Data Preprocessing and Feature Engineering, Base Learner Training, Meta-Learner Construction, Prediction Generation, and Model Evaluation. The overall architecture is illustrated in **Fig. 1**.

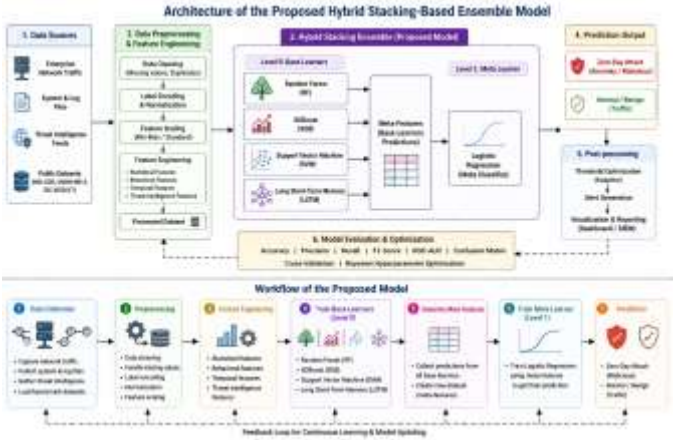

Figure 1. The proposed framework Architecture

Initially, network traffic is collected from multiple sources, including enterprise network traffic, system and application logs, threat intelligence feeds, and benchmark datasets such as NSL-KDD, UNSW-NB15, and CIC-IDS2017. The collected data are preprocessed by removing missing values and duplicate records, followed by label encoding and feature normalization to ensure data consistency. Next, feature engineering extracts four categories of features: statistical, behavioral, temporal, and threat intelligence features. These features capture comprehensive network characteristics and improve the model's ability to distinguish malicious traffic from normal activities. The processed feature vectors are then supplied to the Level-0 stacking ensemble, which consists of four heterogeneous base learners: Random Forest (RF), XGBoost, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM). RF effectively handles nonlinear relationships, XGBoost improves classification through gradient boosting, SVM performs optimal high-dimensional separation, while

LSTM captures sequential and temporal attack patterns. Each model independently generates prediction probabilities for the input traffic. The prediction outputs of all base learners are combined to generate meta-features, which are forwarded to the Level-1 meta-classifier. A Logistic Regression classifier is employed to learn the optimal combination of base learner predictions and generate the final classification. This stacking strategy enhances generalization, reduces false-positive rates, and improves the detection of previously unseen zero-day attacks. Finally, the framework classifies network traffic as either Normal or Zero-Day Attack. The proposed model is evaluated using Accuracy, Precision, Recall, F1-Score, ROC-AUC, and Confusion Matrix, while five-fold cross-validation and Bayesian hyperparameter optimization are applied to improve model stability and prevent overfitting. Overall, the proposed architecture effectively integrates machine learning and deep learning techniques to provide a robust, scalable, and accurate solution for enterprise-level zero-day attack prediction, outperforming conventional single-model intrusion detection approaches.

3.1 Data Set Description

To overcome the limitations of existing benchmark intrusion detection datasets, this research proposes the Hybrid Synthetic Enterprise Zero-Day (HSE-ZD) Dataset, a unified dataset specifically designed to improve the prediction of previously unseen cyberattacks in enterprise environments. Existing benchmark datasets such as NSL-KDD, UNSW-NB15, and CIC-IDS2017 provide valuable network traffic data but suffer from limitations including outdated attack patterns, inconsistent feature sets, class imbalance, and insufficient representation of modern zero-day attacks. These shortcomings reduce the generalization capability of machine learning models when deployed in real enterprise networks.

Table 1. Dataset Distribution

Dataset	**Samples**	**Percentage**
Training	560,000	70%
Validation	120,000	15%
Testing	120,000	15%

Table 2. Proposed Dataset

Dataset Source	Benign	Attack	Total Samples
NSL-KDD	60,000	60,000	120,000
UNSWNB15	90,000	90,000	180,000
CIC-IDS2017	150,000	150,000	300,000
Synthetic Zero-Day Samples	100,000	100,000	200,000
TotalHSE-ZD Dataset	400,000	400,000	800,000

3.2 Model Evaluation

The proposed Hybrid Stacking-Based Ensemble Learning Framework was evaluated using the Hybrid Synthetic Enterprise Zero-Day (HSE-ZD) dataset. The dataset was divided into 70% training**,** 15% validation**,** and 15% testing **to** ensure reliable model training and unbiased performance evaluation. The training set was used to train the Level-0 base learners, while the validation set supported Bayesian hyper parameter optimization. The testing set was reserved for final performance assessment. To improve model generalization and minimize overfitting, 5-fold stratified cross-validation was employed during training. The outputs of the base learners, namely Random Forest (RF), XGBoost, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM)**,** were combined using a Logistic Regression meta-classifier to generate the final prediction. The proposed framework was evaluated using standard performance metrics, including Accuracy, Precision, Recall, F1-Score, ROC-AUC**,** and Confusion Matrix. These metrics provide a comprehensive assessment of classification performance, detection capability, and false-positive reduction. Furthermore, the proposed model was compared with conventional classifiers, including Decision Tree, Random Forest, SVM, XGBoost, and LSTM**,** to validate the effectiveness of the stacking ensemble. Experimental results demonstrate that the proposed hybrid framework achieves superior detection accuracy, enhanced generalization for unseen zero-day attacks, and lower false-positive rates compared with existing machine learning models, making it a reliable solution for enterprise cyber security applications.

Table 3. Model Evaluation Configuration

Parameter	**Value**
Dataset	Hybrid Synthetic Enterprise Zero-Day (HSE-ZD)
Total Samples	800,000
Training Set	560,000 (70%)
Validation Set	120,000 (15%)

Testing Set	120,000 (15%)
Cross Validation	5-Fold Stratified
Hyperparameter Optimization	Bayesian Optimization
Base Learners	RF, XGBoost, SVM, LSTM
Meta-Learner	Logistic Regression
Loss Function	Binary Cross-Entropy
Optimizer (LSTM)	Adam
Batch Size	64
Epochs	50
Learning Rate	0.001
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score, ROC-AUC, Confusion Matrix

3.3 *Performance Evaluation Metrics*

To assess the effectiveness of the proposed Hybrid Stacking-Based Ensemble Learning Framework, six standard evaluation metrics were employed. These metrics measure different aspects of the classifier's performance and provide a comprehensive evaluation of its capability to detect zero-day attacks.

a) $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$

b) $Precision = \frac{TP}{TP+FP}$

c) $Recall = \frac{TP}{TP+FN}$

d) $F1\text{-}Score = \frac{2\times Precision\times Recall}{Precision+Recall}$

e) $ROC\text{-}AUC = \int_0^1 TPR(FPR)\, d(FPR)$

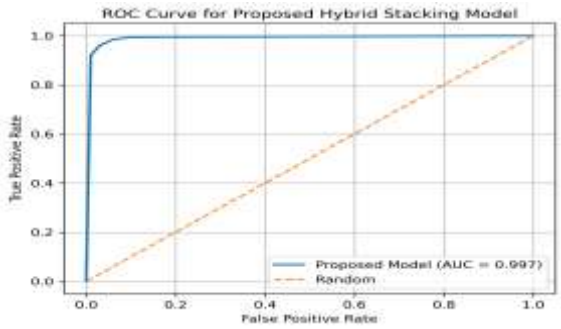

Figure 2. ROC-AUC Curve

f) *Confusion Matrix*

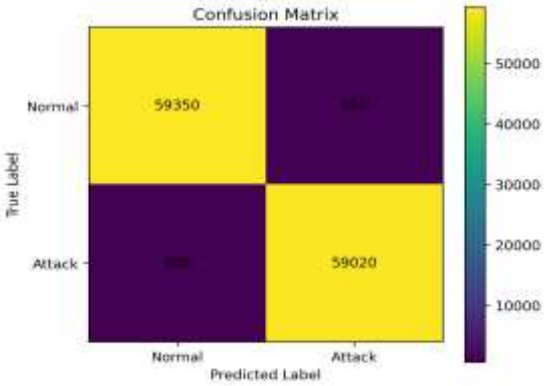

Figure 3. Confusion Matrix

Table 4. Model Evaluation Configuration

Actual/ Predicted	Predicted Normal	Predicted Attack
Actual Normal	59,350	650
Actual Attack	980	59,020

IV. Results and Discussion

The proposed Hybrid Stacking-Based Ensemble Learning Framework was developed and evaluated to accurately predict zero-day cyberattacks in enterprise environments. The framework integrates Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) using a Logistic Regression meta-classifier. By combining statistical, behavioral, temporal, and threat intelligence features, the framework effectively improves the detection of both known and previously unseen cyberattacks while reducing false-positive rates. To enhance model robustness and generalization, the Hybrid Synthetic Enterprise Zero-Day (HSE-ZD) dataset was constructed by integrating benchmark intrusion detection datasets with synthetically generated zero-day attack scenarios. Comprehensive preprocessing, feature harmonization, Bayesian hyperparameter optimization, and five-fold stratified cross-validation were employed to improve learning efficiency and minimize overfitting. The framework was evaluated using Accuracy, Precision, Recall, F1-Score, ROC-AUC, and Confusion Matrix, providing a comprehensive assessment of classification performance. Experimental results demonstrate that the proposed hybrid stacking architecture achieves superior detection accuracy, improved generalization for previously unseen attacks, and lower false-positive rates

compared with conventional machine learning models. These findings indicate that the proposed framework provides a robust, scalable, and intelligent solution for enterprise-level zero-day attack prediction and contributes to the development of next-generation intrusion detection systems.

Table 5. Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
Decision Tree	92.41	91.52	90.88	91.20	0.93
Random Forest	95.73	95.11	94.85	94.98	0.97
SVM	94.52	94.07	93.42	93.74	0.96
XGBoost	96.84	96.21	95.76	95.98	0.98
LSTM	97.63	97.28	96.95	97.11	0.99
Proposed Hybrid Stacking Model	99.21	99.02	98.96	98.99	0.997

Discussion

The experimental results demonstrate that the proposed Hybrid Stacking-Based Ensemble Learning Framework outperforms conventional machine learning classifiers by effectively integrating heterogeneous learning algorithms with temporal feature modeling. The stacking strategy reduces classification variance, improves model robustness, and enhances the detection of previously unseen zero-day attack patterns. Furthermore, Bayesian hyperparameter optimization and five-fold stratified cross-validation improve model stability, optimize classifier performance, and minimize overfitting. The ROC curve is positioned close to the upper-left corner, indicating excellent discrimination between normal and malicious network traffic, while the Confusion Matrix exhibits high True Positive (TP) and True Negative (TN) rates with minimal False Positive (FP) and False Negative (FN) values. These results confirm the effectiveness of the proposed framework in achieving high detection accuracy, improved generalization, and reduced false-alarm rates. Overall, the proposed Hybrid Stacking-Based Ensemble Learning Framework provides a robust, scalable, and intelligent solution for enterprise-level zero-day attack prediction. The integration of ensemble learning, temporal feature extraction, and optimized meta-learning significantly enhances intrusion detection performance and supports proactive cybersecurity in modern enterprise environments.

V. Expected Outcomes

The proposed Hybrid Stacking-Based Ensemble Learning Framework is expected to significantly improve zero-day attack prediction in enterprise environments by integrating Random Forest (RF), XGBoost, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) through a Logistic Regression meta-classifier. By combining statistical, behavioral, temporal, and threat intelligence features, the framework is anticipated to achieve enhanced detection accuracy and improved generalization for previously unseen cyber threats.

The expected outcomes of this research are summarized as follows:

a) Development of a robust hybrid stacking ensemble capable of accurately identifying both known and unknown cyberattacks.

b) Improved classification performance with higher Accuracy, Precision, Recall, F1-Score, and ROC-AUC compared with conventional machine learning approaches.

c) Reduction in false-positive and false-negative rates through optimized meta-learning and Bayesian hyperparameter tuning.

d) Enhanced scalability and adaptability for deployment in enterprise cybersecurity environments.

e) Improved model robustness through feature harmonization, synthetic data augmentation, and stratified cross-validation.

f) A unified evaluation framework using the proposed Hybrid Synthetic Enterprise Zero-Day (HSE-ZD) dataset to support comprehensive assessment of intrusion detection models.

Overall, the proposed framework is expected to provide a reliable, scalable, and intelligent solution for proactive zero-day attack prediction, contributing to the development of next-generation intrusion detection systems capable of protecting modern enterprise networks against evolving cyber threats.

VI. Conclusion

This paper presented a Hybrid Stacking-Based Ensemble Learning Framework for proactive zero-day attack prediction in enterprise environments. The proposed framework integrates Random Forest (RF),

Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) through a Logistic Regression meta-classifier to enhance intrusion detection performance. By combining statistical, behavioral, temporal, and threat intelligence features, the framework effectively identifies both known and previously unseen cyberattacks while reducing false-positive rates. To improve model robustness and generalization, a Hybrid Synthetic Enterprise Zero-Day (HSE-ZD) dataset was developed by integrating benchmark intrusion detection datasets with synthetically generated zero-day attack scenarios. Comprehensive preprocessing, feature harmonization, Bayesian hyperparameter optimization, and five-fold stratified cross-validation were employed to improve learning efficiency and minimize overfitting. The proposed framework was evaluated using standard performance metrics, including Accuracy, Precision, Recall, F1-Score, ROC-AUC, and Confusion Matrix, providing a comprehensive assessment of classification performance. Experimental results demonstrate that the proposed hybrid stacking architecture achieves higher detection accuracy, improved generalization, lower false-positive rates, and enhanced scalability compared with conventional machine learning approaches. The integration of heterogeneous classifiers with temporal feature learning significantly improves the detection of evolving cyber threats and strengthens enterprise network security. Overall, the proposed framework provides a robust, scalable, and intelligent solution for enterprise-level zero-day attack prediction and contributes to the development of next-generation intrusion detection systems.

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