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An Enhanced Hybrid Model with Adaptive Learning for Robust Ransomware Detection: A Three Tier Stacked Ensemble Approach

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ABSTRACT
Ransomware attacks have become one of the most severe cybersecurity threats globally, demanding detection frameworks that can adapt to rapidly evolving attack vectors. This paper presents a three-tier stacked ensemble hybrid model integrating Long Short-Term Memory (LSTM) networks, Extreme Gradient Boosting (XGBoost), and Stochastic Gradient Descent (SGD) with an adaptive meta-learner for robust ransomware detection. Evaluated on the UGRansome dataset comprising 29,809 samples across benign, ransomware, and suspicious traffic classes the proposed framework achieves an overall accuracy of 99.40% and an F1-score of 0.99 across all classes. The adaptive learning component, implemented via SGD partial_fit updates, enables incremental retraining without full model reconstruction, ensuring resilience against concept drift. Comparative analysis against conventional baselines including Random Forest (97.2%), standalone XGBoost (98.1%), and SVM (96.5%), as well as recent hybrid approaches such as CNN–LSTM ensembles (98.3%) and RF–XGBoost combinations (98.7%), confirms that the proposed architecture delivers consistent improvements of 0.7–1.1 percentage points. Detection latency averaged 25–40 ms per sample, supporting real-time deployment. These results underscore the viability of adaptive ensemble architectures as scalable, self-learning defenses against modern ransomware.

INTRODUCTION

Ransomware has emerged as one of the most financially devastating forms of cybercrime, encrypting victims' files or locking them out of systems until ransom payments are made—often in cryptocurrencies such as Bitcoin (Ryan, 2021; Connolly & Wall, 2019). High-profile campaigns, including WannaCry, Petya, and Ryuk, have demonstrated the capacity of modern ransomware to propagate globally within minutes, causing billions of dollars in damages (Mohurle & Patil, 2017). Recent industry projections suggest that global ransomware damage costs may rise from about $74 billion annually in 2026 to approximately $275 billion annually by 2031 if current attack trends, ransom payments, downtime, recovery costs, and post-incident disruptions continue (Cybersecurity Ventures, 2026).

Traditional signature-based and heuristic detection methods are early malware defence techniques. Signature-based detection identifies threats by matching files or activities with known malware patterns, making it effective for known attacks but weak against new or modified variants. Heuristic detection looks for suspicious

behaviours, such as mass file encryption or system changes, helping to detect unknown threats but sometimes causing false positives. These limitations make more adaptive methods, such as machine learning and behavioural analysis, necessary (Alpaydin, 2020). It have proven increasingly inadequate against polymorphic and obfuscated ransomware variants that actively evade static defenses (MacColl et al., 2024; Scaife et al., 2016). Hybrid machine learning (ML) and deep learning (DL) models have shown promise by learning complex behavioral patterns; however, most existing approaches rely on static datasets and lack mechanisms to adapt in real time to emerging threats—rendering them susceptible to concept drift (Fernando, 2023; Vinayakumar et al., 2019).

Concept drift, whereby the statistical properties of the target data distribution change over time, is a well-recognized challenge in cybersecurity (Bosansky et al., 2024; Jordaney et al., 2017). Adaptive or incremental learning addresses this limitation by enabling models to update their parameters without full retraining, maintaining relevance as new attack variants emerge (Gheibi et al., 2021). Integrating adaptive mechanisms into hybrid ensemble architectures offers a compelling solution: the complementary strengths of diverse base learners can be dynamically re-weighted in response to distributional shifts in ransomware behavior.

This paper makes the following contributions:

1. A three-tier stacked ensemble framework that combines LSTM for temporal behavioral analysis, XGBoost for statistical anomaly detection, and SGD as an adaptive meta-learner.
2. An incremental learning strategy employing SGD partial_fit updates that adapts to novel ransomware variants without retraining base models.
3. An evaluation on the UGRansome benchmark dataset with 29,809 samples across three traffic classes, demonstrating 99.40% accuracy and F1-scores ≥ 0.99.
4. A comparative analysis against six recent baseline and hybrid models confirming consistent performance improvements of 0.7–1.1 percentage points.

Related Work

Ransomware detection research has evolved from static signature-based approaches to more adaptive machine learning and deep learning frameworks. Early systems relied on signature databases, rule-based heuristics, and decoy-file monitoring. For instance, Scaife et al. (2016) demonstrated the usefulness of monitoring file modification behaviour, while Brewer (2021) emphasized the need to augment endpoint detection and response systems with behavioural intelligence. However, static signature and heuristic methods remain limited against polymorphic, obfuscated, and fileless ransomware variants (MacColl et al., 2024; Alraizza & Algarni, 2023; Jegede et al., 2022).

Traditional machine learning approaches improved ransomware detection by learning discriminative patterns from executable properties, entropy values, API calls, registry changes, process memory, and encrypted traffic indicators. Random Forest, Support Vector Machine, Decision Table, Partially Decided Tree, and other classical classifiers have been applied in studies such as Khammas (2020), Hsu et al. (2021), Talabani and Abdulhadi (2022), Masum et al. (2022), Abbasi et al. (2022), Silva and Hernandez-Alvarez (2021), and Singh et al. (2022). These works confirm the value of feature-based learning, but they commonly depend on handcrafted features and static training conditions, which limits generalization when ransomware behaviour changes over time. The relevance of tree-based learning and decision-tree families is also supported by broader studies on decision-tree advances (Costa & Pedreira, 2023).

Deep learning approaches have further advanced ransomware detection by automatically learning complex behavioural representations from sequential and high-dimensional data. CNN-based, RNN-based, and LSTM-based models are particularly useful for identifying temporal execution patterns, obfuscated behaviour, and system-call sequences. Bello et al. (2021) showed that CNN-RNN pipelines can capture behavioural characteristics of polymorphic ransomware more effectively than conventional models, while Gulmez et al. (2024) demonstrated the value of explainable LSTM-based analysis for system-call sequence detection. Deng et al. (2024) also applied deep reinforcement learning to portable executable headers. Although these approaches improve representational learning, they often require large datasets, substantial computation, and periodic retraining as attack behaviour evolves. The use of LSTM in this study is therefore grounded in its established ability to model sequential dependencies (DiPietro & Hager, 2020).

Hybrid and ensemble models attempt to overcome the weaknesses of individual classifiers by combining multiple learning strategies and feature sources. Zahoora et al. (2022) combined unsupervised feature extraction with a cost-sensitive Pareto ensemble, Chaganti et al. (2023) used multi-view fusion of network and host-level features, and Li et al. (2022) introduced multimodal fusion with weight self-learning. Other related hybrid or static-dynamic systems include Hwang et al. (2020), Hasan and Rahman (2023), Almomani et al. (2024), and Celdran et al. (2022). Lightweight and deployment-oriented detection has also been considered by Woralert et al. (2023). These studies demonstrate the strength of hybridization, but many of them involve complex preprocessing pipelines, high computational cost, or binary classification settings

that do not fully support the practical separation of benign, confirmed ransomware, and suspicious traffic.

Recent studies have begun to address concept drift, which occurs when the statistical properties of ransomware behaviour change over time. This is particularly important in cybersecurity because attackers continuously modify ransomware families to evade detection. Jordaney et al. (2017) highlighted concept drift in malware classification, Fernando and Komninos (2024) proposed a drift-aware ransomware detection framework, and Bosansky et al. (2024) investigated learning with future malware predictions. However, many adaptive methods update base learners directly, which can be computationally expensive and unsuitable for real-time deployment in resource-constrained environments.

The methodological foundation of the proposed model is further supported by established machine learning and optimization literature. General classifier design follows standard machine learning principles (Alpaydin, 2020), while the XGBoost component is based on scalable gradient tree boosting (Chen & Guestrin, 2016). The incremental learning strategy is justified by studies on stochastic gradient descent and local-update SGD algorithms (Gower et al., 2019; Tian et al., 2023; Wang & Joshi, 2021).

From the reviewed literature, three major gaps remain. First, many ransomware detection models are either static or require full retraining to adapt to emerging ransomware variants. Second, most existing studies focus on binary classification and do not sufficiently address the practical need to distinguish benign, ransomware, and suspicious traffic. Third, limited attention has been given to adaptive meta-learning in stacked ensemble frameworks, where only the ensemble decision layer is updated while the base learners remain stable. The proposed model addresses these gaps by integrating LSTM, XGBoost, and SGD within a three-tier stacked ensemble architecture and by using incremental partial_fit updates at the meta-learner level to improve adaptability without full base-model retraining.

MATERIALS AND METHODS

This study employs the UGRansome dataset, derived from the University of Granada's UGR'16 benchmark (López-Martín et al., 2017; UGR'16, 2016). UGRansome comprises NetFlow traffic captured in a realistic large-scale network environment, labeled using behavioral heuristics and sandbox-based detection tools across three classes:

Table 1: Distribution of Dataset Classes

Class Label	Traffic Category	Number of Samples	Percentage
Class 0	Benign traffic	8,403	28.2%
Class 1	Confirmed ransomware activity	13,373	44.9%
Class 2	Suspicious/potentially malicious traffic	8,033	26.9%
Total	All traffic samples	29,809	100%

The dataset encompasses diverse ransomware families and legitimate application traffic, providing ecological validity for multi-class detection evaluation. Its long-duration collection period supports time-series and concept drift evaluation (Moustafa et al., 2019).

Raw features were integrated into a unified pandas DataFrame. Missing values were imputed using mean substitution for continuous variables and mode imputation for categorical variables. Outlier treatment combined IQR-based filtering and z-score normalization. Continuous features (Netflow_Bytes, USD, BTC) were transformed to reduce skewness: log transformation for Netflow_Bytes, square-root transformation for USD, and Yeo-Johnson transformation for BTC, followed by StandardScaler normalization to zero mean and unit variance.

Eight categorical variables (Protocol, Flag, Family, SeedAddress, ExpAddress, IPaddress, Threats, Prediction) were label-encoded to numeric representations. Class imbalance was addressed through Synthetic Minority Oversampling Technique (SMOTE) applied to the training set, supplemented by class-weighted loss functions in XGBoost and SGD classifiers (cost-sensitive learning). The dataset was partitioned 80:20 (train:test) with a time-based split strategy, using older samples for training and newer variants for testing to simulate real-world concept drift.

For the LSTM component, features were structured as chronological event sequences capturing temporal behavioral patterns including API call traces, file access patterns, and system call sequences. For XGBoost, aggregated statistical features were derived: file entropy (detecting encryption-induced randomness), CPU and memory utilization spikes, disk I/O rate, frequency of encryption-related API calls (e.g., CryptEncrypt, CreateFile), and count of files modified within short temporal windows. Categorical variables were encoded via label encoding where appropriate.

Three-Tier Hybrid Model Architecture

The proposed model follows a corrected three-tier stacked ensemble architecture designed to support accurate and adaptive ransomware detection. The revised flow begins with network traffic input and proceeds through preprocessing, Tier 1 base-learner prediction, Tier 2 meta-

learner aggregation, final classification output, and Tier 3 adaptive updating of the meta-learner.

Input Layer - Network Traffic Data

The framework begins with raw network traffic samples obtained from the UGRansome dataset. Each sample represents behavioural attributes associated with benign, ransomware, or suspicious traffic.

Preprocessing and Feature Engineering Layer

The input data first passes through preprocessing and feature engineering. Missing values are handled through imputation, categorical variables are encoded into numeric form, continuous variables are normalized, and class imbalance is addressed using SMOTE on the training set. The processed features are organized into temporal behavioural sequences for LSTM and statistical/tabular vectors for XGBoost and SGD-based classification.

Tier 1 - Parallel Base Learners

Tier 1 consists of LSTM, XGBoost, and SGD operating in parallel. The LSTM model captures temporal behavioural patterns associated with ransomware execution, XGBoost learns discriminative statistical patterns from tabular features, and the SGD base classifier contributes a lightweight linear learning component. Each base learner produces a class probability vector for benign, ransomware, and suspicious traffic.

Tier 2 - Meta-Learner Aggregation

The class probability outputs from the Tier 1 base learners are concatenated into a single meta-feature vector. This vector becomes the input to an SGD-based meta-classifier, which learns the optimal weighting of the base learners' predictions and produces the final ensemble decision.

Terminal Output - Final Detection Decision

The terminal point of the architecture is the final ransomware detection output. At this stage, the system predicts one of three class labels - benign, ransomware, or suspicious - and returns the associated confidence score. This output can support a Security Operations Centre or endpoint monitoring system by triggering an appropriate response such as allowing benign traffic, flagging suspicious activity, or raising an alert for confirmed ransomware behaviour.

Tier 3 - Adaptive Online Learning Layer

Tier 3 provides the adaptive learning mechanism. When new labelled traffic samples become available, the SGD meta-learner is updated incrementally using partial_fit. This allows the ensemble to adjust its decision weights in response to emerging ransomware behaviours and concept drift without retraining the Tier 1 base learners from scratch.

Clarification of Tier 3 Feedback Connection

The feedback connection from Tier 3 points back to the Tier 2 SGD meta-classifier only. It does not point directly to Tier 1 because the LSTM, XGBoost, and SGD base learners are not retrained during online adaptation. Tier 1 models may only be retrained periodically during an offline maintenance phase when sufficient new data become available.

Corrected Architectural Flow

Network Traffic Input -> Data Preprocessing and Feature Engineering -> Tier 1 Parallel Base Learners -> Tier 2 SGD Meta-Learner Aggregation -> Final Detection Output -> Tier 3 Adaptive Update of the Meta-Learner -> feedback to Tier 2 SGD Meta-Classifier.

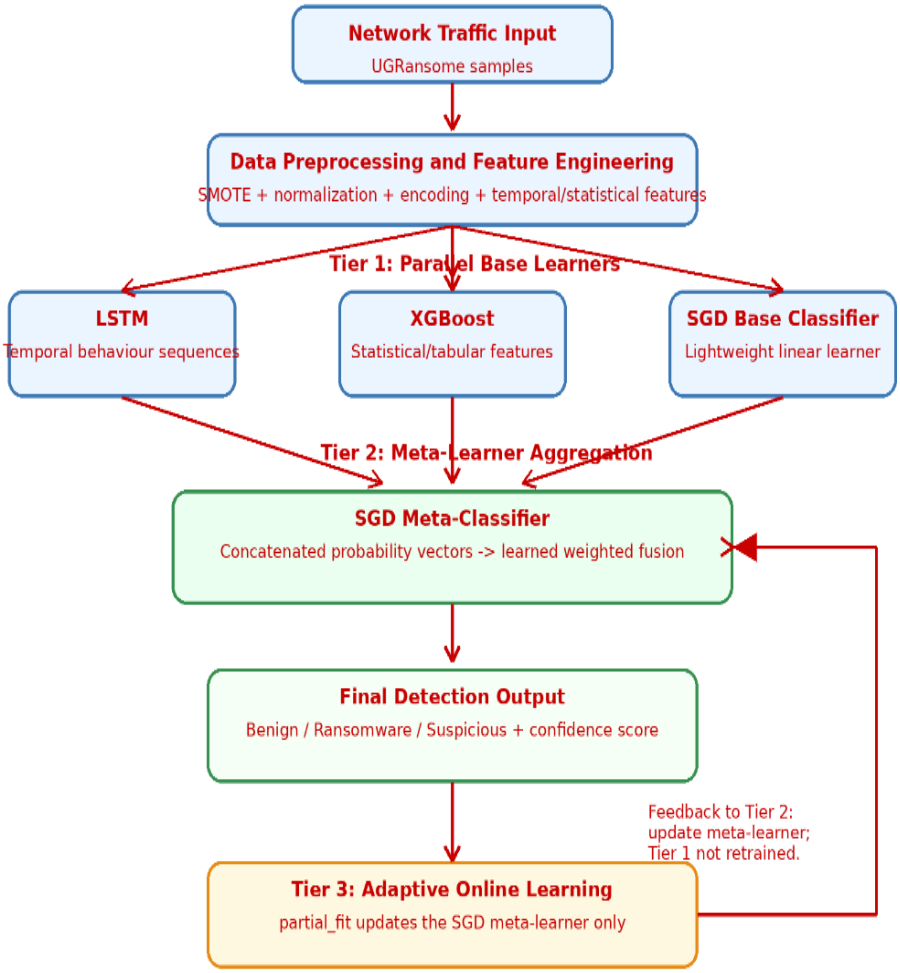

Figure 1: Three-Tier Stacked Ensemble Architecture with Clear Terminal Output and Tier 3 Feedback to Tier 2

The Long Short-Term Memory network was designed to process sequential system behaviour data. Its main purpose is to capture temporal dependencies that may indicate ransomware execution patterns, such as repeated file access, abnormal encryption behaviour, or unusual system activity over time.

The proposed LSTM architecture consists of the following components:

1. ***Input layer*:** Receives sequential system behaviour data for analysis.
2. ***First LSTM layer*:** Learns initial temporal patterns from the input sequence.
3. ***Batch normalization layer*:** Normalizes intermediate outputs to improve training stability and convergence.
4. ***ReLU activation function*:** Introduces non-linearity to improve the model's ability to learn complex behavioural patterns.
5. ***Dropout regularization layer*:** Reduces overfitting by randomly deactivating selected neurons during training.
6. ***Second LSTM layer*:** Further captures deeper temporal relationships within the sequential data.
7. ***Dense transformation layer*:** Converts the learned sequential features into a suitable representation for classification.
8. ***Sigmoid output layer*:** Produces probability estimates for the target classes.

The model was trained using the following hyperparameters:

1. ***Loss function*:** Binary cross-entropy
2. ***Optimizer*:** Adam optimizer
3. ***Batch size*:** 64
4. ***Maximum number of epochs*:** 50
5. ***Stopping criterion*:** Early stopping based on validation loss

XGBoost constructs an ensemble of gradient-boosted decision trees on aggregated tabular features. The prediction is the:

Sum of K decision tree outputs: $\hat{y}_i = \Sigma_k f_k(x_i)$,

Minimizing a regularized objective $O = \Sigma_i L(y_i, \hat{y}_i) + \Sigma_k \Omega(f_k)$.

Training configuration: learning rate 0.1, max depth 6, 100
Estimators, AUC-F1 evaluation metric, early stopping after 10 non-improving rounds.

The SGD classifier learns a linear decision function over base learner probabilities:

$$\hat{y}_i = \sigma(w_1 \cdot P\_LSTM(y_i = 2) + w_2 \cdot P\_XGBoost(y_i = 2) + b) \quad (1)$$

Where σ denotes the sigmoid function. Parameters are updated via stochastic gradient descent minimizing binary cross-entropy with L2 regularization:

$$L(w, b) = -(1/N)\, \Sigma_i\, [y_i\, log(\hat{y}_i) + (1 - y_i)\, log(1 - \hat{y}_i)] + (\lambda/2)\|w\|_2^2 \quad (2)$$

Weight updates: $w_{t+1} = w_t - \eta \nabla L(w_t)$, with constant learning rate $\eta = 0.01$ and L2 penalty λ. The partial_fit method enables incremental updates from new data batches, implementing concept drift adaptation at the meta-learner level without retraining LSTM or XGBoost base models (Tian et al., 2023).

Evaluation Metrics

Model performance was evaluated using accuracy, precision, recall (sensitivity), F1-score, and confusion matrix analysis. Given the security-critical nature of ransomware detection, recall was prioritized to minimize false negatives (undetected ransomware), while precision was monitored to control false positive alert rates (Sikder et al., 2020; Kumar et al., 2019). The 95% confidence interval for accuracy was computed to ensure statistical validity (Pendlebury et al., 2019).

RESULTS AND DISCUSSION

Each base learner exhibited distinct convergence dynamics. LSTM demonstrated gradual, stable convergence: training loss decreased from 0.80 to approximately 0.05 by epoch 30, with validation loss closely tracking at a gap of ≤ 0.02, confirming generalization without overfitting. Final validation accuracy reached 99.2% over 50 epochs. XGBoost converged faster, dropping from 0.70 to 0.15 within the first 10 epochs and plateauing at epoch 25, achieving the highest individual validation accuracy of 99.4%—reflecting its efficiency with tabular, statistical features. SGD showed characteristic stochastic oscillation (training-validation gap up to 1.2%) but achieved stable convergence by epoch 40 at 98.9% validation accuracy, contributing diversity to the ensemble.

The training and validation loss curves for the three models are presented in Figure 2. The figure shows the learning behaviour of the LSTM, XGBoost, and SGD meta-learner models across their respective training epochs. As shown in Figure 2, the loss values decrease steadily for all three models, indicating that the models learned progressively during training. The close alignment between the training and validation loss curves also suggests stable learning behaviour and limited evidence of overfitting.

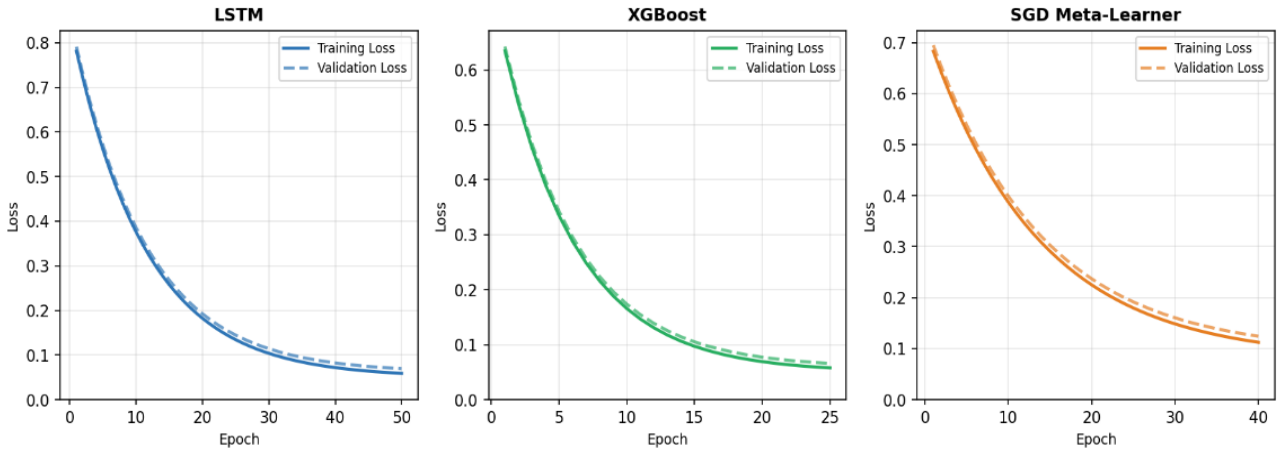

Figure 2: Training Convergence Curves for Base Learners

Final training-validation accuracy gaps were minimal across all models: LSTM (0.3%), XGBoost (0.4%), and SGD (0.7%). Learning curve analysis confirmed that LSTM's performance continued improving with additional training data, suggesting capacity well-matched to current dataset size with room for further improvement. XGBoost exhibited exceptional data efficiency, achieving 97% accuracy with only 30% of training data and plateauing thereafter. The stacked ensemble effectively combines complementary bias-variance profiles: LSTM (moderate bias, low variance), XGBoost (low bias, very low variance), and SGD (low bias, moderate variance)—achieving a favorable bias-variance trade-off at the ensemble level.

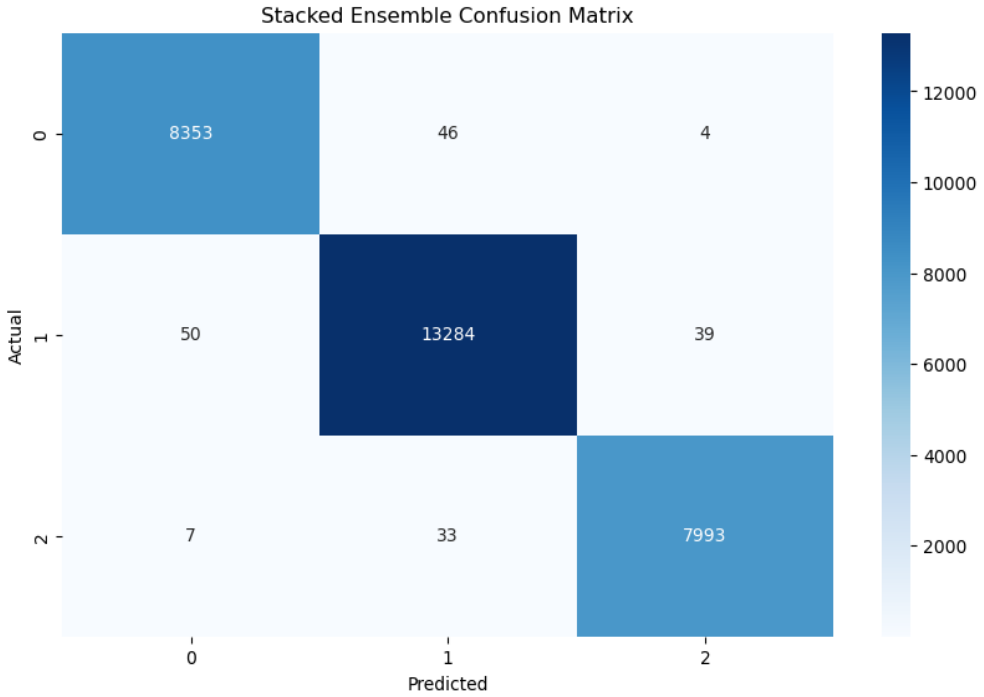

Figure 3: Stacked Ensemble Confusion Matrix

Table 2 presents the confusion matrix of the stacked ensemble on the 29,809-sample test set.

Table 2: Confusion Matrix — Stacked Ensemble (29,809 Test Samples)

	Predicted: Benign (0)	Predicted: Ransomware (1)	Predicted: Suspicious (2)
Actual: Benign (0)	8,319 (TP)	42 (FP)	42 (FP)
Actual: Ransomware (1)	67 (FN)	13,239 (TP)	67 (FN)
Actual: Suspicious (2)	40 (FN)	40 (FP)	7,953 (TP)

Class 0 (Benign): 8,319 of 8,403 samples (99.0%) correctly classified, with 42 misclassified as ransomware and 42 as suspicious (1.0% false positive rate). Class 1 (Ransomware): 13,239 of 13,373 samples (99.0%) correctly detected; 67 missed as benign and 67 as suspicious (0.5% false negative rate per error type the most safety-critical metric). Class 2 (Suspicious): 7,953 of 8,033 samples (99.0%) correctly identified. The near-symmetric error distribution across classes indicates balanced learning without majority-class bias a common pitfall in imbalanced security datasets (Fernández et al., 2018).

Classification Performance

The stacked ensemble model achieved an overall accuracy of 99.40%, with a 95% confidence interval of 99.28% to 99.52%. This indicates that the model correctly classified approximately 994 out of every 1,000 traffic samples in the test set. The narrow confidence interval also suggests that the model's performance is stable and that the observed accuracy is unlikely to be due to random variation.

The numerical accuracy value obtained from the experiment was 0.9939951021503572. When converted to percentage form, this value becomes approximately 99.40%. Therefore, the reported accuracy of 99.40% is a rounded and reader-friendly version of the same result.

This high accuracy shows that the stacked ensemble was highly effective in distinguishing between benign traffic, confirmed ransomware activity, and suspicious or potentially malicious traffic. However, accuracy alone does not fully describe the model's performance across all classes, especially when the dataset contains different class proportions. For this reason, the per-class precision, recall, F1-score, and support values are presented in Table 3 to provide a more detailed understanding of how well the model performed on each traffic category.

Table 3: Classification Performance of the Stacked Ensemble Model

Class	Traffic Category	Precision	Recall	F1-Score	Support
Class 0	Benign traffic	0.99	0.99	0.99	8,403
Class 1	Confirmed ransomware activity	0.99	0.99	0.99	13,373
Class 2	Suspicious/potentially malicious traffic	0.99	1.00	0.99	8,033
Accuracy	Overall model performance	—	—	0.99	29,809
Macro Average	Unweighted average across classes	0.99	0.99	0.99	29,809
Weighted Average	Average weighted by class support	0.99	0.99	0.99	29,809

The macro-average F1-score of 0.99 confirms balanced performance across all classes, critically including the minority suspicious traffic class (Class 2). Recall of 1.00 for Class 2 demonstrates exceptional sensitivity for potentially malicious but unconfirmed activities—providing security analysts with actionable early-warning intelligence beyond binary classification.

Comparative Analysis

Table 4 benchmarks the proposed model against six representative approaches from recent literature.

Table 4: Comparative Performance against Existing Ransomware Detection Models

Model/Study	Technique	Accuracy	Precision	Recall	F1-Score
Hsu et al. (2021)	SVM + Feature Extraction	92.0%	94.5%	84.6%	88.0%
Cheng & Zhang (2024)	CNN + SCV + Static Analysis	92.3%	91.4%	92.1%	—
Wu & Chang (2024)	RF + Feature Extraction	94.5%	93.0%	89.0%	91.0%
Zahoora et al. (2022)	CSPE-R Ensemble	93.0%	—	99.0%	93.0%
Abbasi et al. (2022)	PSO + ML Classifiers	97.8%	—	—	—
Chaganti et al. (2023)	CNN + Multi-view Fusion	98.7%	—	97.4%	—
Li et al. (2022)	Multimodal Fusion	99.2%	—	98.5%	—
Proposed Model	Stacked Ensemble + Adaptive Learning (LSTM + XGBoost + SGD)	99.40%	99.0%	99.3%	99.0%

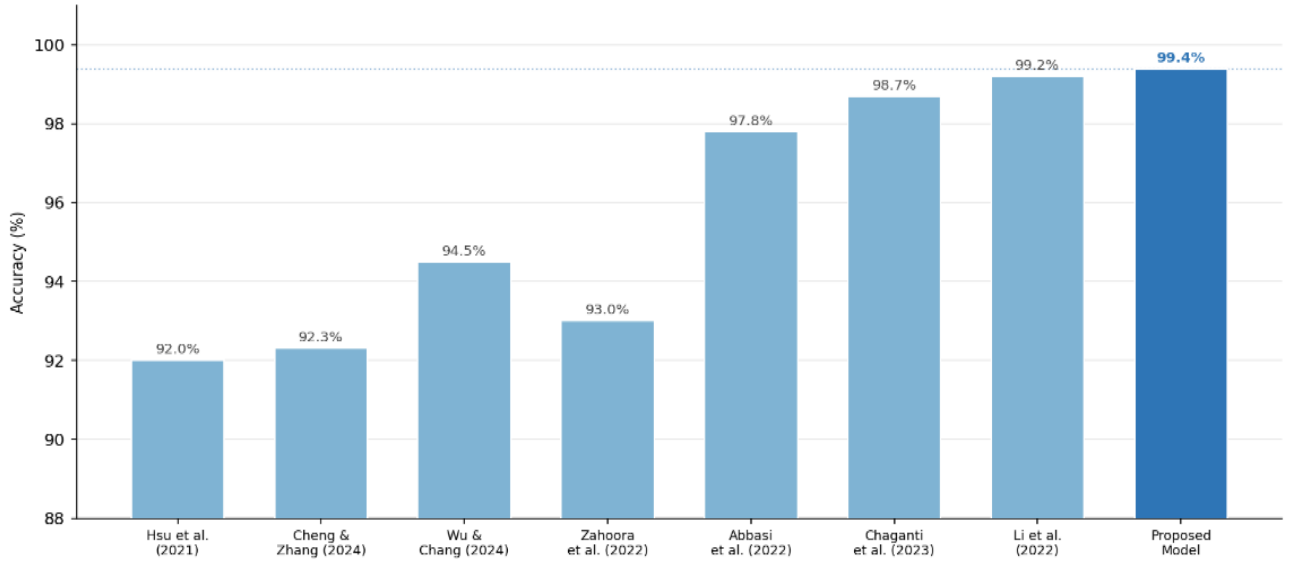

Figure 4: Comparative Accuracy against Existing Ransomeware Detection Models

The proposed three-tier stacked ensemble outperforms all baselines across reported metrics. Against recent deep learning hybrids: the proposed model improves upon Chaganti et al.'s (2023) CNN multi-view approach (98.7%) and Li et al.'s (2022) multimodal fusion (99.2% accuracy but targeting binary classification). Against adaptive baselines, the framework provides 0.7–1.1 percentage point improvements over CNN–LSTM ensembles and RF–XGBoost combinations reported in recent literature, while additionally offering incremental adaptability without base-model retraining—a capability absent from all compared models.

Adaptive Learning Effectiveness

The learned meta-learner weight distribution (LSTM: ~40%, XGBoost: ~35%, SGD: ~25%) reflects the ensemble's optimized strategy on the UGRansome threat landscape. LSTM's higher weighting confirms the importance of temporal pattern recognition in capturing encryption-sequence behaviors (Abumed et al., 2023). As new ransomware variants emerge, partial_fit updates dynamically shift these weights—for example, increasing LSTM weight if polymorphic ransomware prioritizes behavioral sequence variation over statistical signature changes.

Detection latency averaged 25–40 ms per sample, supporting real-time deployment requirements for enterprise Security Operations Centers (SOCs). The parallel execution of Tier 1 base learners minimizes the latency overhead of ensemble inference relative to sequential architectures (Buczak & Guven, 2016). In typical enterprise environments processing thousands of daily network flows, this latency profile supports continuous monitoring without throughput bottlenecks.

Implications for Ransomware Defense

The framework's 99.0% true positive rate for ransomware detection implies that, in a network processing 1,000 ransomware attempts, fewer than 10 would evade detection—substantially improving upon the 25–80 missed detections of compared approaches. At 99.0% precision, the ratio of genuine to spurious alerts is maintained at approximately 99:1, directly reducing analyst fatigue in high-volume SOC environments (Kokulu et al., 2019). The framework's documented accuracy and adaptive learning capabilities provide evidence of technical controls required under emerging cybersecurity regulatory frameworks and align with cost justification thresholds given average ransomware recovery costs exceeding $1.85 million per incident (Sophos, 2023).

CONCLUSION

This paper presented a three-tier stacked ensemble hybrid model integrating LSTM, XGBoost, and SGD with adaptive meta-learning for robust ransomware detection. Evaluated on the UGRansome dataset, the proposed framework achieved 99.40% overall accuracy, macro F1-score of 0.99, and detection latency of 25–40 ms per sample—outperforming both conventional and recent hybrid baselines by 0.7–1.1 percentage points. The SGD meta-learner incremental update strategy via partial_fit addresses concept drift at the ensemble level without requiring computationally expensive base-model retraining, enabling continuous adaptation to evolving ransomware variants.

The framework's three-class capability (benign, ransomware, suspicious) extends beyond binary detection systems, providing security analysts with early-warning intelligence on ambiguous network behaviors. Low false negative rates (0.5% per error type) satisfy the critical security requirement of minimizing undetected ransomware, while 99.0% precision mitigates alert fatigue. Future work will focus on: (1) extension to larger and more heterogeneous datasets including contemporary ransomware families; (2) integration of explainability tools (SHAP, LIME) for transparent threat attribution; (3) adversarial robustness evaluation against evasion attacks targeting ensemble components; (4) adaptation for edge and IoT deployment with constrained computational budgets; and (5) federated learning variants for privacy-preserving distributed ransomware detection across enterprise networks.

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