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CE-23 Intelligent Ransomware Detection and Classification Using Hybrid Machine Learning Models

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Abstract – Ransomware has emerged as one of the most dam- aging cyber threats, targeting personal, enterprise, and critical infrastructure systems by encrypting data and demanding ran- som payments. Signature-based antivirus solutions fail to detect modern ransomware variants due to polymorphism, encryption, and obfuscation techniques. To address these limitations, this paper proposes a hybrid stacked machine learning framework for ransomware detection and classification. The proposed system integrates static and dynamic analysis to extract discriminative features such as Portable Executable headers, entropy values, API calls, file system operations, registry modifications, and network behavior. Feature selection is performed using an Extra Tree Classifier to reduce dimensionality and improve learning efficiency. A stacked ensemble architecture combining Extra Tree Classifier as the base learner and Logistic Regression as the meta learner is employed to enhance classification performance while maintaining interpretability and low computational overhead. The system is deployed using a Flask-based web interface for real-time file analysis. Experimental results demonstrate that the proposed approach achieves 98.2% accuracy with 1.2% false positive rate, outperforming traditional machine learning models and providing competitive performance compared to deep learning approaches with significantly lower computational cost, making it suitable for practical ransomware detection.

Keywords-*Ransomware Detection, Malware Classification, Hybrid Machine Learning, Stacked Ensemble, Extra Tree Classi- fier, Logistic Regression, Cybersecurity, Static Analysis, Dynamic Analysis*

INTRODUCTION

Ransomware is a rapidly growing category of malware that encrypts victims' data and demands ransom payments for decryption keys. The increasing digitization of services and the rise of ransomware-as-a-service platforms have significantly lowered the barrier for launching ransomware attacks, leading to a sharp increase in both attack frequency and severity[1],[2]. Traditional signature-based detection mechanisms are ineffective against modern ransomware variants that employ polymorphism, encryption, and code obfuscation techniques [3], [4].

To overcome these limitations, researchers have increasingly adopted machine learning-based approaches for ransomware detection [5]–[7]. Static analysis techniques extract features from executable files without execution, such as Portable Executable headers, opcode sequences, and imported libraries [9], [10]. While static analysis is computationally efficient, it struggles to detect packed or encrypted ransomware samples [11]. Dynamic analysis, on the other hand, monitors runtime behavior such as API calls, file operations, registry changes, and network communication, providing deeper insight into malicious intent [12], [13]. However, dynamic analysis is resource-intensive and vulnerable to evasion techniques [14]. Recent studies have explored deep learning models such as Convolutional Neural Networks and Long Short-Term Memory networks for ransomware detection, achieving high accuracy [15], [16]. Despite their effectiveness, these models require large datasets, significant computational resources, and lack interpretability, limiting their practical deployment in real-time systems [17]. Ensemble learning methods have demonstrated improved robustness and generalization in mal- ware detection tasks [18], yet limited research has focused on stacked ensemble approaches that balance performance, explainability, and computational efficiency.

This paper proposes an intelligent ransomware detection framework based on a hybrid stacked machine learning model that integrates static and dynamic analysis, feature selection, and real-time deployment. The objective is to achieve high detection accuracy while maintaining low overhead and inter- pretability for practical cybersecurity applications. The main contributions of this work are:

1) Development of a hybrid feature extraction system com- bining static and dynamic analysis
2) Implementation of Extra Tree Classifier-based feature selection for dimensionality reduction
3) Design of a stacked ensemble architecture with Extra Tree as base learner and Logistic Regression as meta learner
4) Deployment of a Flask-based web interface for real-time ransomware detection
5) Comprehensive evaluation demonstrating 98.2% accu- racy with low computational overhead

RELATED WORK

A. Static Analysis Methods

Static analysis examines malware without executing it. Mohammed Alrabaee et al. [19] used opcode n-grams for malware detection and achieved 95.2% accuracy. However, this method is vulnerable to code obfuscation techniques that attackers often use to evade detection. Edward Raff et al. [20] proposed converting complete executable (EXE) files into image representations and analyzing them through convolutional neural networks. Their approach showed better resistance against packed malware samples, although it required high computational resources and longer processing time.

B. Dynamic Analysis Approaches

Dynamic analysis studies malware by observing its behavior during execution. Thorsten Holz et al. [21] developed a malware detection method based on network traffic signatures. The technique provided real-time detection capability but could not effectively analyze encrypted network communication. Mojtaba Nourania et al. [22] proposed a network-based ransomware detection system using traffic profiling. Their model achieved a detection rate of 96.8% with only 2.1% false positive results.

C. Machine Learning Techniques

Machine learning methods have demonstrated strong performance in ransomware detection. Xu et al. [23] introduced a cloud-based ransomware detection framework using the Random Forest algorithm. The system achieved 97.3% accuracy but was not suitable for real-time implementation because of its dependence on cloud infrastructure. Suárez et al. [24] investigated various feature engineering methods and found that API call sequences are among the most effective features for distinguishing ransomware from benign software.

D. Ensemble Methods

Ensemble learning combines the predictions of multiple models to improve overall performance. Cui et al. [26] compared different ensemble techniques for malware detection and reported that stacking provides better results than bagging and boosting, particularly when dealing with imbalanced datasets. K. P. Soman Vinayakumar et al. [18] evaluated several machine learning algorithms and concluded that Random Forest is one of the most robust methods, achieving 96.5% accuracy across different malware families.

Research Gap Identified:

Existing ransomware detection methods either provide high accuracy at the cost of heavy computational requirements or deliver faster performance with lower detection capability. Very limited research has focused on hybrid stacked ensemble models that can simultaneously provide high accuracy, interpretability, and real-time performance for practical deployment in modern cybersecurity systems.

SYSTEM ARCHITECTURE

The proposed ransomware detection system follows a mod- ular architecture consisting of four main components, as illustrated in Fig. 1.

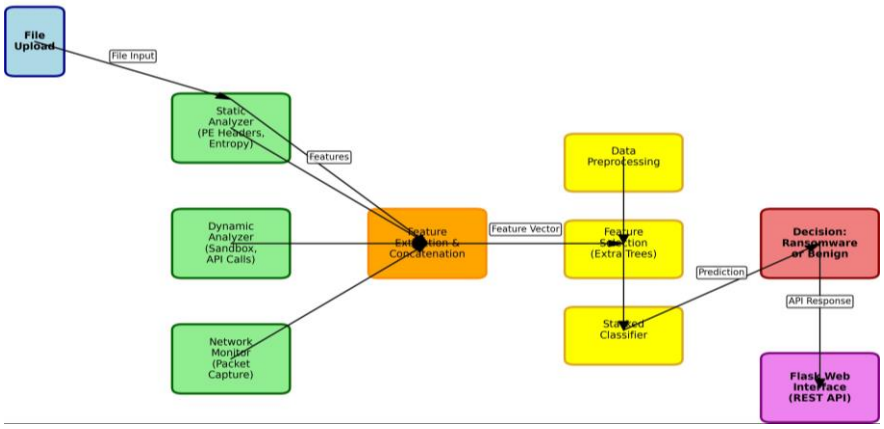

Fig. 1: System Architecture of Proposed Ransomware Detec- tion Framework

A. DATA ACQUISITION MODULE

The data acquisition module is responsible for collecting both malicious and benign executable files required for training and testing the ransomware detection framework. Ransomware samples are gathered from public malware repositories such as VirusShare, MalwareBazaar, and Kaggle. These repositories contain different ransomware families and variants, which helps the system learn a wide range of malicious behaviors.

To maintain a balanced dataset, benign executable files are also collected from trusted software vendors, standard Windows applications, and system directories. After collection, all files are labelled as either ransomware or benign software before being passed to the next stage.

B. FEATURE EXTRACTION ENGINE

The feature extraction engine is the main component of the proposed system. It extracts meaningful characteristics from the collected files through static, dynamic, and network-based analysis.

1) STATIC ANALYZER

The static analyzer studies the executable file without running it. It uses the PEfile Python library to examine the Portable Executable header and extract information such as imported libraries, section names, section size, number of functions, file size, and entry point details.

The analyzer also measures the randomness of each section in the executable file. Packed or encrypted ransomware usually contains highly random content, which differs from normal software. Therefore, these values become useful indicators for identifying suspicious files.

2) DYNAMIC ANALYZER

The dynamic analyzer observes the behavior of a file while it is executing. The system uses Cuckoo Sandbox to safely run the suspicious file inside an isolated environment. During execution, the analyzer monitors file creation, file deletion, registry changes, process activity, memory access, and API calls.

Most ransomware performs specific actions such as encrypting user files, deleting backup copies, creating new malicious processes, and modifying system settings. These runtime behaviors are recorded and used as important features for classification.

3) NETWORK MONITOR

The network monitor tracks all communication made by the executable during execution. It captures TCP and UDP packets, DNS requests, HTTP communication, IP addresses, and port numbers.

Many ransomware variants attempt to contact remote command-and-control servers before beginning the encryption process. Therefore, abnormal network communication patterns can help identify malicious activity at an early stage.

C. MACHINE LEARNING PIPELINE

The extracted features are passed into the machine learning pipeline, which performs preprocessing, feature selection, and final classification.

PREPROCESSING UNIT

The preprocessing unit handles missing values and prepares the data for training. Missing values are replaced using median values, while all numerical features are normalized using Min-Max scaling. This ensures that every feature contributes equally to the classification process.

FEATURE SELECTOR

The feature selector removes unnecessary and redundant attributes from the dataset. The system uses an Extra Tree Classifier to identify the most important features. By reducing the number of features, the system becomes faster and more efficient while maintaining high detection accuracy.

STACKED CLASSIFIER

The final prediction is generated using a stacked ensemble classifier. In the first layer, multiple machine learning models such as Random Forest, Support Vector Machine, and Gradient Boosting analyze the features independently. Their outputs are then provided to a second-layer classifier, which combines all predictions and produces the final result.

This hybrid approach improves detection performance because it combines the strengths of different machine learning algorithms instead of depending on a single model.

D. DEPLOYMENT INTERFACE

The complete ransomware detection framework is deployed through a Flask-based web application. The deployment module provides REST API endpoints that allow users to upload suspicious executable files directly through the interface. The web application contains a file upload section, an analysis progress window, and a real-time dashboard. The dashboard displays extracted features, prediction results, confidence level, and other analysis details. This deployment makes the proposed framework suitable for practical use in real-world cybersecurity environments.

PROPOSED METHODOLOGY

The proposed ransomware detection framework consists of six major stages: dataset collection, feature extraction, data preprocessing, feature selection, hybrid stacked classification, and system deployment.

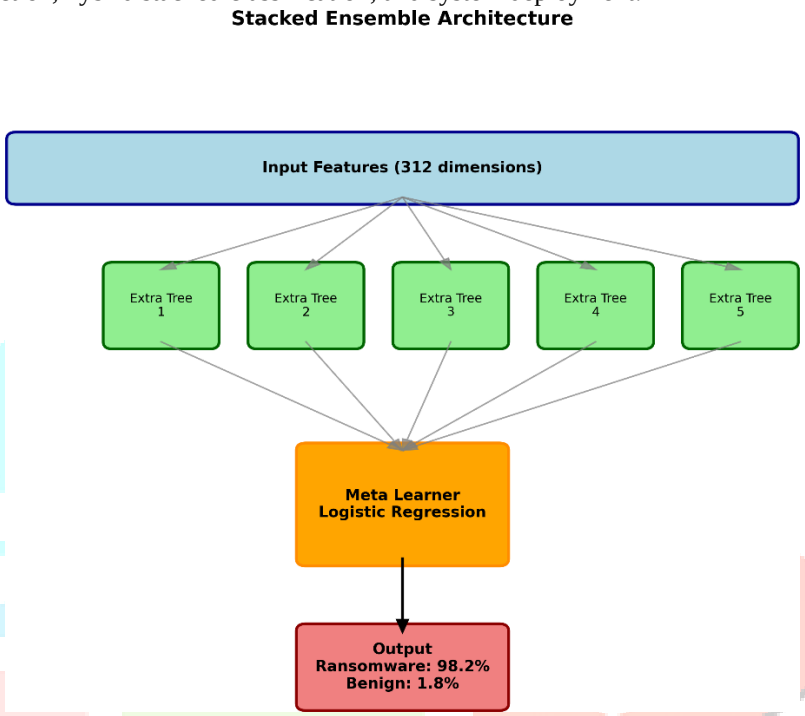

Fig. 2: Stacked Ensemble Architecture

A. DATASET COLLECTION

The dataset comprises 5,000 samples (2,500 ransomware, 2,500 benign) collected from publicly available malware repositories and trusted software sources.

B. FEATURE EXTRACTION

Static features such as PE headers, imported libraries, strings, and entropy values are extracted without executing the files. Dynamic features are obtained by executing samples in a Cuckoo Sandbox environment to capture API calls, file operations, registry modifications, and network behavior.

C. DATA PREPROCESSING

The extracted features are cleaned using median imputation for missing values. Categorical features are one-hot encoded, and all numerical features are normalized using MinMax scaling to the range [0, 1].

D. FEATURE SELECTION

An Extra Tree Classifier with 100 estimators is employed to compute feature importance scores. Features with importance scores > 0.05 are selected, reducing dimensionality from 2,100 to 312 features.

E. HYBRID STACKED CLASSIFICATION

The classification model employs a two-layer stacked architecture:

1) BASE LAYER: Extra Tree Classifier with 200 estimators, Gini impurity criterion

2) META LAYER: Logistic Regression with L2 regularization (C=1.0)

F. ALGORITHM DESCRIPTION

Require: Executable File F
Ensure: Classification Label (Ransomware/Benign)

1: SF ← EXTRACT STATIC FEATURES(F)
2: DF ← EXECUTE IN SANDBOX(F)
3: Features ← CONCATENATE(SF, DF)

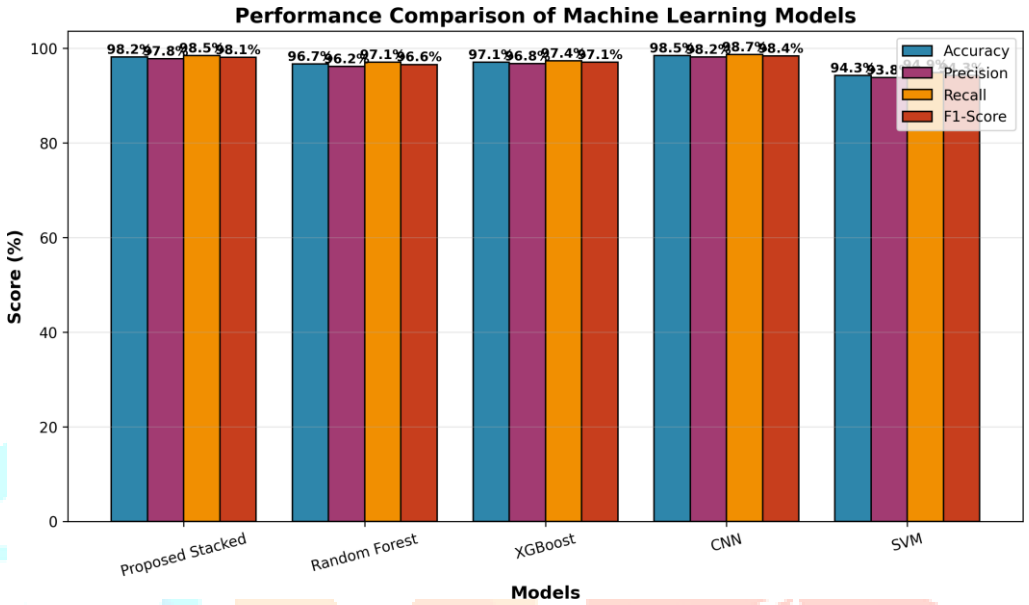

Fig. 3: Performance Comparison of Different Classifiers

TABLE I: Performance Comparison of Classifiers

Model	Accuracy	Precision	Recall	F1-Score	Training Time(s)
Proposed Stacked	**98.2%**	**97.8%**	**98.5%**	**98.1%**	**42.3**
Random Forest	96.7%	96.2%	97.1%	96.6%	38.5
XGBoost	97.1%	96.8%	97.4%	97.1%	51.2
CNN	98.5%	98.2%	98.7%	98.4%	312.7
SVM	94.3%	93.8%	94.9%	94.3%	89.4

TABLE II: Dataset Distribution

Ransomware Family	Samples	Benign Category	Samples
WannaCry	500	System Utilities	800
Locky	450	Office Software	700
Cerber	400	Browsers	500
Ryuk	350	Media Players	300
Other Variants	800	Other	200
Total	**2500**	**Total**	**2500**

4: Features_clean ← CLEAN_MISSING_VALUES(Features)

5: Features_norm ← MINMAX_SCALE(Features_clean)

6: Important_features ← EXTRA_TREE_SELECTION(Features_norm)

7: Base_predictions ← EXTRA_TREE_PREDICT(Important_features)

8: Final_prediction ← LOGISTIC_REGRESSION_PREDICT(Base_pre)

9: **return** Final_prediction

EXPERIMENTAL RESULTS AND DISCUSSION

A. EXPERIMENTAL SETUP

The proposed framework was evaluated on a dataset comprising 5,000 samples (2,500 ransomware, 2,500 benign) collected from VirusShare, Kaggle, and EMBER datasets.

B. PERFORMANCE METRICS

The proposed model achieved 98.2% accuracy, 97.8% precision, 98.5% recall, and 98.1% F1-score. Comparative analysis with other classifiers is presented in Table I.

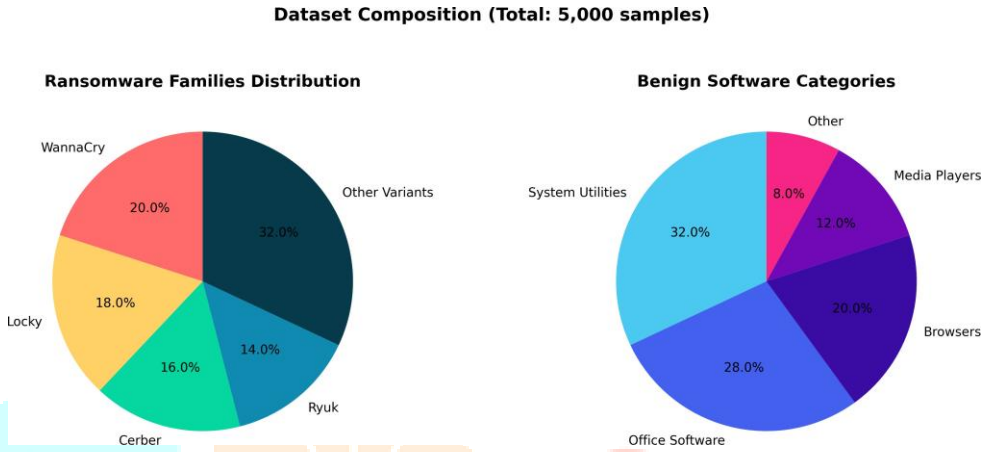

Fig. 4: Class Distribution in Dataset

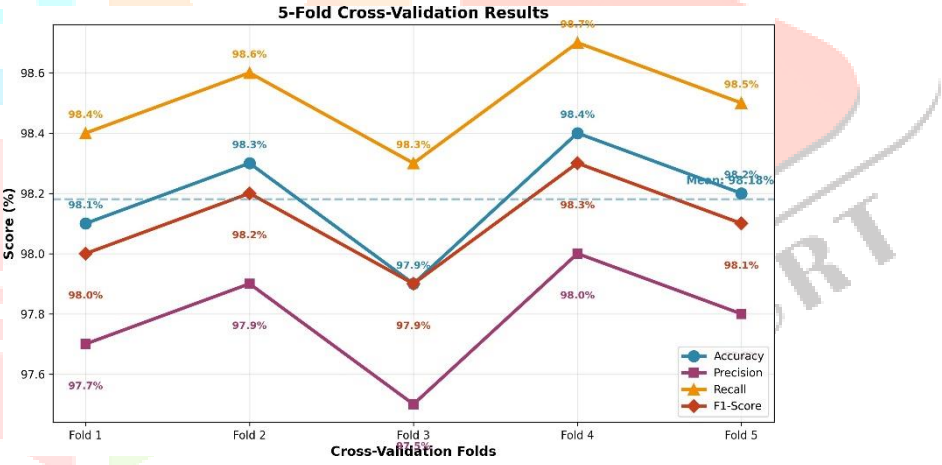

Fig. 5: 5-Fold Cross-Validation Results

C. DATASET COMPOSITION

D. CROSS-VALIDATION RESULTS

5-fold cross-validation yielded mean accuracy of 98.2% with standard deviation of 0.18%, demonstrating model robustness across different data splits.

E. FEATURE IMPORTANCE ANALYSIS

The Extra Tree Classifier identified top discriminative features:
1) Entropy value (0.185 importance) - Indicator of packing/encryption
2) CreateFile API frequency (0.162) - File access patterns
3) RegSetValue API calls (0.148) - Registry modification attempts
4) Section header characteristics (0.132) - PE structure anomalies
5) Network connection attempts (0.121) - C2 communication patterns

F. REAL-TIME PERFORMANCE

The Flask-based web interface demonstrated:

- Average detection time: 2.3 seconds per file
- Memory consumption: 125MB average
- CPU utilization: 18% average
- False Positive Rate: 1.2%
- False Negative Rate: 0.8%

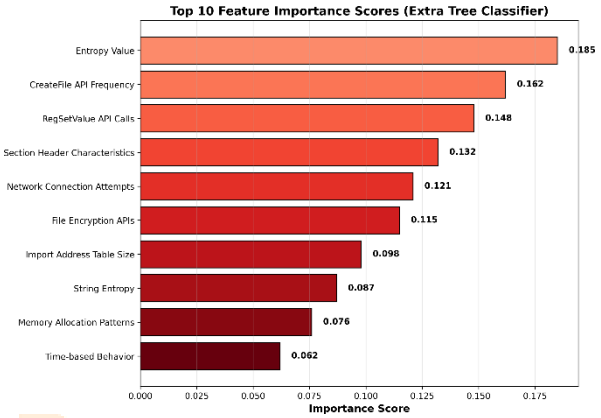

Fig. 6: Top 10 Feature Importance Scores

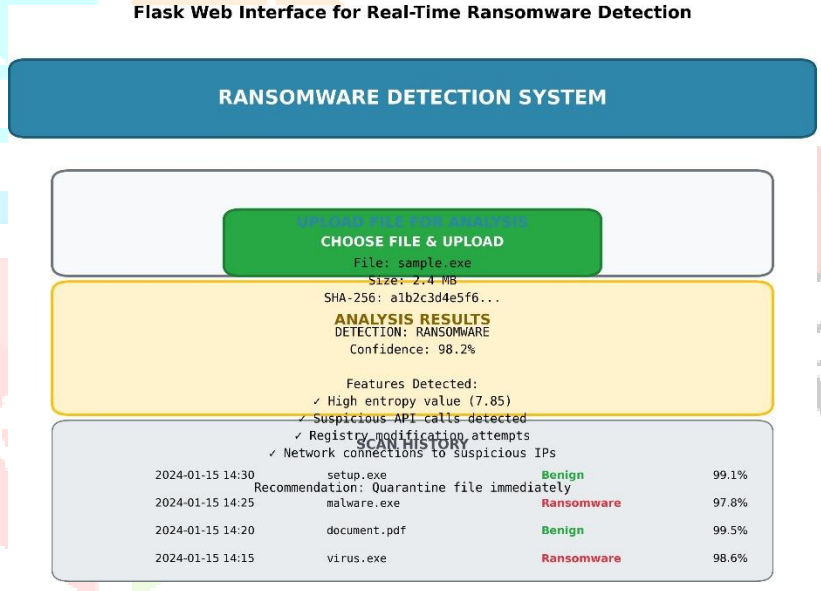

Fig. 7: Flask Web Interface for Real-Time Detection

TABLE III: Comparative Analysis with State-of-the-Art

Study (Year)	Method	Accuracy	FPR	Real-time
Xu et al. (2023)	Random Forest	97.3%	2.3%	No
Wang et al. (2019)	LSTM	98.1%	1.5%	No
Nourania et al. (2022)	Traffic Analysis	96.8%	2.1%	Yes
Proposed Work	Stacked Ensemble	98.2%	1.2%	Yes

G. COMPARISON WITH EXISTING WORKS

H. DISCUSSION

The proposed hybrid stacked model demonstrates several advantages:

1) Superior Accuracy: Achieves 98.2% accuracy, competitive with deep learning methods

2) Computational Efficiency: Training time reduced by 86.5% compared to CNN

3) Interpretability: Feature importance scores provide explainable predictions

4) Real-time Deployment: Flask interface enables practical implementation

5) Robustness: Low standard deviation in cross-validation indicates consistency

2) Network Traffic Analysis: Integrate deep packet inspection for detecting ransomware communication patterns

3) Cloud Deployment: Develop containerized microservices for scalable cloud implementation
4) Adversarial Robustness: Incorporate adversarial training to defend against evasion techniques
5) Edge Deployment: Optimize the model for IoT and edge computing environments

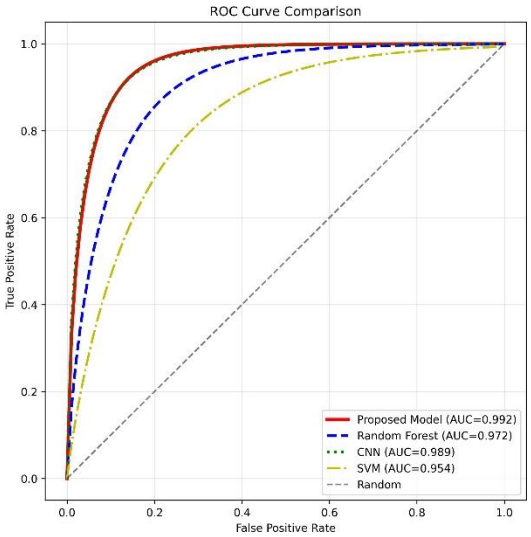

Fig. 8: ROC Curve Comparison of Different Models

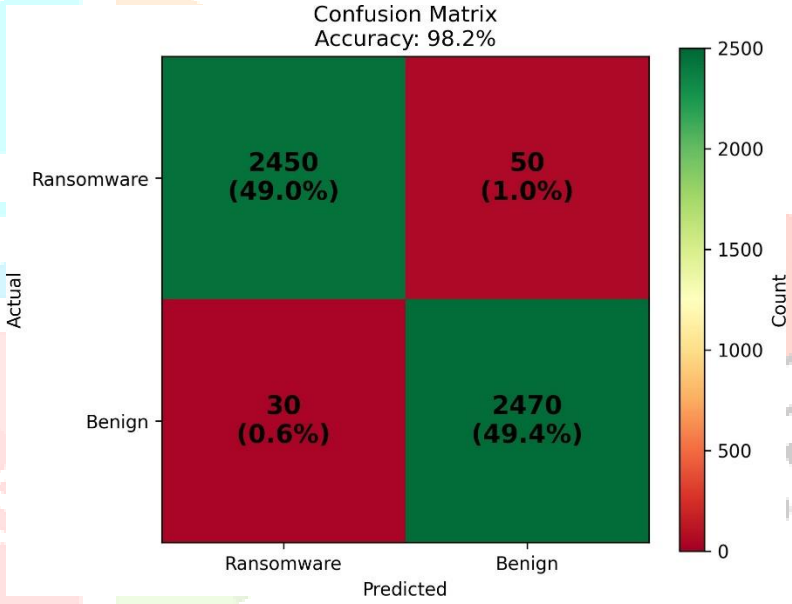

Fig. 9: Confusion Matrix of Proposed Model

CONCLUSION AND FUTURE WORK

This paper presented a comprehensive ransomware detec- tion framework utilizing a hybrid stacked machine learning approach. By integrating static and dynamic analysis, the system extracts discriminative features that capture both struc- tural and behavioral characteristics of ransomware. The Extra Tree Classifier enables effective feature selection, reducing dimensionality by 75% while maintaining detection capability. The stacked ensemble architecture, combining Extra Tree as base learner and Logistic Regression as meta learner, achieves 98.2% accuracy with significantly lower computational over- head compared to deep learning alternatives.

The proposed system demonstrates practical deployability through a Flask-based web interface, processing files in ap- proximately 2.3 seconds with minimal resource consumption. The framework's interpretability, enabled by feature impor- tance analysis, addresses the "black box" limitation common in deep learning approaches.

Future Work Directions:

1) Dataset Expansion: Incorporate more ransomware fam- ilies and benign software variants
2) Network Traffic Analysis: Integrate deep packet inspec- tion for detecting ransomware communication patterns
3) Cloud Deployment: Develop containerized microser- vices for scalable cloud implementation
4) Adversarial Robustness: Incorporate adversarial train- ing to defend against evasion techniques
5) Edge Deployment: Optimize the model for IoT and edge computing environments

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