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Machine Learning-Based Model for Identification of Malicious Encrypted Files

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Abstract
The widespread use of encryption to protect digital data and communication has posed new challenges for cybersecurity, as attackers increasingly exploit encrypted files to hide malicious content that bypasses traditional signature-based detection systems. This research develops a machine learning model designed to detect harmful encrypted files, overcoming the weaknesses of conventional methods that fail to analyze encrypted data effectively. Since encryption conceals the payloads of malicious files, advanced classification models are essential for accurate identification. The study applies three supervised learning algorithms Convolutional Neural Network (CNN), Support Vector Machine (SVM), and Recurrent Neural Network (RNN) to train and evaluate models capable of differentiating between legitimate and malicious encrypted files. The dataset was obtained from the Canadian Institute for Cybersecurity (CIC), and model performance was assessed using confusion matrix–based evaluation metrics implemented in Python. Among the models tested, SVM achieved the highest detection accuracy of 98.7%, outperforming RNN (91%) and CNN (74.3%). These results indicate that SVM delivers superior classification efficiency, particularly in handling complex and high-dimensional data features. The study concludes that integrating such models into enterprise cybersecurity systems can significantly enhance threat detection and protection mechanisms. It further recommends exploring hybrid deep learning strategies to improve adaptability, reduce false positives, and enable real-time detection of malicious encrypted files in rapidly changing digital environments.

Keyword: Encrypted Malware Detection, Machine Learning Classification, Cybersecurity Analytics, Malicious File Identification, Behavioral Threat Analysis.

Introduction

Machine Learning (ML) has become an important tool in detecting cyber threats, especially encrypted and compressed malicious files that conceal harmful content and evade traditional signature-based detection systems (Hassan & Kumar, 2021; Otoum & Nayak, 2021). Because encryption hides payloads, conventional approaches struggle to identify threats, whereas ML can analyze statistical, structural, and behavioral patterns to improve detection accuracy. Prior studies demonstrate this potential. For example, deep learning models using convolutional neural networks achieved strong detection performance (Bakour et al., 2023), and hybrid ML–deep learning approaches have surpassed traditional methods (Mohan et al., 2024). The growing sophistication of cyberattacks, including ransomware, data exfiltration, and distributed denial-of-service campaigns, has intensified the need for adaptive detection systems since encrypted traffic often appears harmless during transmission (Cabaj et al., 2019; Siponen et al., 2022; Stivenarte et al., 2021). Signature-based tools remain limited because they rely on known patterns and cannot easily adapt to evolving or obfuscated threats (Damodaran et al., 2017; Vinayakumar et al., 2019).

To overcome these weaknesses, researchers increasingly employ ML techniques such as deep learning, transfer learning, and ensemble methods, which enable proactive threat detection by learning from diverse datasets and real-time patterns (Jiang et al., 2022; Chen et al., 2023; Vinayakumar et al., 2019; Cabaj et al., 2019; Damodaran et al., 2017; Stivenarte et al., 2021). Despite these advances, limitations persist because encryption can obscure important features, reducing model effectiveness. Therefore, more robust and adaptive ML frameworks are still required to reliably detect malicious encrypted files in real-time environments.

Aim and Objectives of the Study

The aim of this research is to develop a machine-learning model capable of reliably detecting malicious content within encrypted compressed files, and the objectives are to:

i. identify and extract relevant features from malicious encrypted files
ii. develop a machine learning algorithm using CNN, SVM and RNN.
iii. evaluate and infer the performance of the three models (CNN, SVM and RNN) using confusion matrix.

LITERATURE REVIEW

Research on encrypted malicious file detection has expanded in response to the growing misuse of encryption to conceal malware and evade traditional defenses. Encrypted malicious files employ cryptographic techniques that render their contents unreadable without decryption keys, making conventional inspection methods ineffective (Huntley et al., 2018; Gupta & Babu, 2020). The increasing use of secure communication protocols has further blurred the distinction between legitimate and malicious encrypted traffic (Silva et al., 2017; Ramírez-Cruz et al., 2022). As a result, cybersecurity research has shifted toward intelligent detection mechanisms capable of analyzing structural and statistical indicators

rather than relying on payload visibility (Rajasekharaiah et al., 2020; Carlo, 2024).

Traditional signature-based detection systems remain limited because they depend on predefined malware patterns and struggle against polymorphic and zero-day threats (Khan et al., 2020; Wang et al., 2019). Their static design prevents adaptation to rapidly evolving attack strategies, leaving systems vulnerable to obfuscated malware and Advanced Persistent Threats (Bhattacharya et al., 2018). These weaknesses have encouraged the adoption of machine learning techniques that learn from data patterns and behavioral characteristics instead of static signatures (Zhang et al., 2021b).

Deep learning approaches, particularly Convolutional Neural Networks and Recurrent Neural Networks, have demonstrated strong potential in encrypted malware detection. CNNs automatically extract hierarchical byte-level or traffic features and have achieved notable accuracy in identifying encrypted threats (Bakour et al., 2023; Chen et al., 2023). RNN-based architectures, including LSTM and GRU variants, capture sequential and behavioral dependencies within encrypted traffic streams, enhancing detection of time-dependent malicious activities (Damodaran et al., 2017; Sun et al., 2024). Transfer learning has also improved detection performance in situations with limited labeled data by adapting pre-trained models to encrypted malware classification tasks (Jiang et al., 2022).

Ensemble learning methods combine multiple classifiers to improve robustness and reduce false predictions. Studies show that aggregating models such as SVM, Random Forest, and neural networks can enhance classification performance in encrypted environments (Cabaj et al., 2019; Rong et al., 2020). Support Vector Machines, in particular, have proven effective in high-dimensional feature spaces by constructing optimal hyperplanes that separate benign and malicious instances (Iqbal & Khan, 2020; Wang & Chen, 2020). Their strength lies in generalization capability, especially with structured metadata features such as entropy, file size, and encryption patterns.

Feature engineering remains central to successful encrypted malware detection. Extracting entropy measures, structural metadata, and traffic flow characteristics improves discriminative power while maintaining computational efficiency (Gibert et al., 2022; Chen et al., 2023). Anomaly detection techniques further strengthen detection frameworks by identifying deviations from normal behavior, allowing systems to recognize previously unseen threats (Hu et al., 2017; Damodaran et al., 2017). More recently, adversarial training strategies have been proposed to enhance model resilience against evasion attempts (Stivenarte et al., 2021).

Despite these advancements, several challenges persist. High false positive rates, computational overhead, limited dataset diversity, and poor generalizability remain common limitations across studies (Davis & Moore, 2018; Anderson, 2020; Clark & Evans, 2018). Additionally, evolving encryption techniques and adversarial manipulation continue to test the adaptability of existing models (Edwards & Smith, 2020; Garcia & Martinez, 2019). These gaps highlight the need for scalable, efficient, and adaptive hybrid frameworks capable of integrating multiple learning paradigms while maintaining strong validation standards.

Overall, the literature confirms that machine learning offers a viable alternative to traditional detection methods for encrypted malicious files. However, consistent improvement in feature

representation, model robustness, and real-time adaptability remains essential for addressing the complexity of modern cyber threats.

Theoretical Gaps

While existing theories provide a robust foundation, gaps remain in unifying cryptographic principles with ML robustness. For instance, few studies address the theoretical limits of ML in distinguishing adversarial encryption from legitimate use (Anderson, 2020). This study bridges these gaps by integrating information-theoretic feature extraction, adversarial training, and ensemble learning into a cohesive framework tailored for encrypted and compressed malware detection.

Empirical Review

Cybersecurity researchers have extensively explored Machine Learning (ML) and Deep Learning (DL) techniques for detecting ransomware and malware threats. Several studies have demonstrated the effectiveness of ML models in identifying malicious software through advanced data preprocessing, feature extraction, and classification algorithms. For instance, Anikolova *et al.* (2024) developed a machine learning-based ransomware detection model, employing dataset quality assurance techniques and feature extraction to improve classification accuracy. Their study evaluated the model using various performance metrics, including accuracy, precision, recall, and F1-score. However, their reliance on publicly available datasets, such as VirusTotal, raises concerns about the model's ability to generalize to novel ransomware variants. Additionally, sandboxed testing environments may not fully capture the real-world behavior of ransomware, affecting detection reliability.

Similarly, Kirkland *et al*. (2024) integrated machine learning techniques, specifically Random Forests and Support Vector Machines, with file entropy analysis to enhance ransomware detection. Their findings suggest that entropy-based detection methods outperform traditional signature-based techniques, highlighting the advantage of ML-driven approaches in cybersecurity. However, the study acknowledges the need for real-time monitoring systems and deeper exploration of deep learning techniques for improved detection accuracy.

Azeem *et al.* (2024a) examined various ML approaches for malware detection, utilizing both supervised and unsupervised learning techniques. Their study achieved high detection accuracy, surpassing 96% in some cases. However, the complexity of integrating multiple ML models presents challenges for real-world deployment, particularly in organizations with limited computational resources. Additionally, the lack of detailed performance evaluation criteria may hinder practical implementation. Expanding on ML applications in cybersecurity, Sun *et al.* (2024) explored the use of both classical and advanced deep learning models, including Decision Trees, Random Forest, XGBoost, DNN, LSTM, and GRU, for malware classification. Their research demonstrated that ML models outperform traditional signature-based detection methods, with Random Forest achieving the highest accuracy of 99%. However, concerns regarding dataset limitations and model overfitting remain, as well as the

need for real-time implementation feasibility. Deep learning has also been investigated for malware detection by Hossain *et al*. (2024), who introduced a customized Convolutional Neural Network (CNN) model that achieved 98.7% accuracy in classifying malware. Their approach bypasses traditional signature-based techniques, enhancing detection capabilities. Nonetheless, the study identifies shortages in malware image datasets and the high computational costs associated with hyperparameter fine-tuning as significant challenges.

Beyond ransomware and malware classification, research on encrypted traffic analysis has gained attention. Sun *et al.* (2024) proposed a multimodal approach for detecting malicious encrypted traffic using a feature engineering method combined with end-to-end processing. Their model improves feature extraction and classification accuracy by leveraging unlabeled encrypted traffic for pretraining. However, traditional methods still struggle with feature extraction in traffic classification, and deep learning models lack generalizability when encountering unseen encrypted traffic. The role of ML in administrative and cybersecurity-related applications has been further explored by Azeem *et al.* (2024b), who applied ML algorithms such as Random Forest, KNN, and Logistic Regression for malware detection. Their findings indicate that ML techniques effectively minimize false positives while maintaining high precision and recall. However, the potential for real-world application remains uncertain, given the challenges of implementing ML-driven security frameworks in dynamic environments.

Other research efforts, such as those by Duignan *et al.* (2023), focused on ransomware encryption detection through file signatures and ML models. Their study utilized Logistic Regression, Linear Discriminant Analysis, K-Nearest Neighbor, Naïve Bayes, and Classification and Regression Trees to classify ransomware-encrypted files. The results showed high accuracy (97%-100%) in identifying ransomware strains based on file extensions, yet the study notes the increasing complexity of ransomware evolution and the need for continued adaptation of detection models.

A growing body of research also examines malicious network traffic detection using deep learning techniques. Bahlali *et al.* (2025) introduced a fully supervised auto-encoder model designed to detect malicious encrypted network traffic by leveraging anomaly-based detection techniques. The proposed model outperformed state-of-the-art methods on the UNSW-NB15 dataset and demonstrated comparable performance on the CSE-CIC-IDS2018 dataset. However, the paper acknowledges the limitations of behavior-based techniques, which have yet to achieve widespread deployment. Recent studies have also explored lightweight ML models for cybersecurity applications. Liu *et al.* (2023) proposed Mal-lightDet, a feature-group selection framework designed to efficiently detect malicious encrypted traffic while minimizing computational overhead. The model outperforms existing methods in speed, accuracy, and stability. Despite its promising performance, challenges remain in addressing privacy concerns and ensuring detection effectiveness across different encrypted communication patterns.

As cybersecurity threats continue to evolve, researchers are exploring innovative approaches to enhance malware detection frameworks. One promising direction involves hybrid models that combine machine learning with heuristic-based detection techniques (He *et al.,* 2023). These approaches seek to leverage the strengths of both automated pattern recognition and expert-driven insights, improving the robustness of detection systems. Additionally, the integration of reinforcement learning in malware detection has gained traction, allowing models to adapt dynamically to evolving attack patterns (Gundoor & Sridevi, 2025).

Another emerging trend is the application of federated learning to cybersecurity, enabling collaborative malware detection without compromising data privacy (Mohanty *et al.,* 2024). This approach facilitates knowledge sharing across multiple organizations while ensuring that sensitive data remains localized. Furthermore, advances in adversarial machine learning highlight the need for more resilient models, as cybercriminals increasingly exploit vulnerabilities in ML-based security systems Kumar and Sharma (2024). Despite these advancements, significant challenges remain. Many ML models require extensive computational resources, limiting their feasibility for real-time implementation in resource-constrained environments (Mane *et al.,* 2023). Additionally, the rapid obfuscation techniques employed by malware developers pose ongoing challenges for traditional detection methodologies (Alsadie, 2024). Addressing these issues will require continuous updates to detection models, integration with broader security frameworks, and investment in computational efficiency improvements.

The application of machine learning techniques in malware detection has been extensively studied, with researchers exploring various approaches to improve detection accuracy and efficiency. Martin *et al.* (2024) examined how machine learning algorithms outperform conventional antivirus software in detecting malicious software. Their study emphasized the effectiveness of executable file metadata analysis in distinguishing between malicious and benign software. However, existing antivirus solutions still struggle with contemporary malware threats, highlighting the need for adaptive and intelligent detection mechanisms. In the realm of encrypted network security, Berrueta *et al.* (2022) investigated crypto-ransomware detection in file-sharing network environments. Their research proposed a machine learning-based tool that effectively identifies ransomware activities during the encryption of shared files. The study demonstrated successful detection across 33 ransomware families while maintaining a low false positive rate. Despite these promising results, the research was limited to Microsoft Windows desktop environments and did not account for mobile operating systems. Additionally, its applicability was constrained to scenarios where critical files are stored on file servers, reducing its utility in personal computing environments.

The growing challenge of malicious software detection has driven research into various machine learning frameworks. Barut *et al.* (2020) conducted a comprehensive performance study on machine learning-based malware detection over encrypted traffic. Their work focused on evaluating different machine learning models based on classification accuracy and runtime performance. However, the study primarily utilized two malware flow datasets, which may not

fully represent real-world network conditions. Furthermore, the research lacked an extensive analysis of false positive rates, a crucial metric for practical deployment. The reliance on specific features from the Transport Layer Security (TLS) protocol and metadata may have also introduced limitations in capturing all relevant indicators of malicious activity.

Feature engineering and advanced learning methods have also been explored to enhance detection accuracy. Panda *et al*, (2021) proposed a feature engineering-based method for detecting malicious encrypted communication. By leveraging machine learning algorithms, the study achieved significant improvements in detection accuracy and efficiency. However, challenges such as data scarcity and limited computational resources continue to hinder the practical implementation of such approaches. These constraints highlight the need for scalable and resource-efficient solutions that can operate effectively in dynamic network environments.

Anderson (2020) explored the detection of encrypted malware using supervised learning techniques. Utilizing a proprietary dataset of encrypted files, the study focused on parameters such as file size, encryption type, and entropy, achieving an 85% accuracy rate in detecting encrypted malware. However, the study was limited by its relatively small dataset and specificity to certain encryption types. Baker and Wilson (2019) investigated the application of neural networks for encrypted file detection. Their research employed a mixed dataset comprising both legitimate and malicious encrypted files, analyzing parameters like byte-level data and encryption algorithm identification. They reported a 90% detection rate, though the approach was marked by high computational costs.

Chen and Zhang (2021) analyzed encrypted malware using deep learning techniques, specifically convolutional neural networks (CNNs). Their methodology leveraged publicly available malware samples and focused on network traffic patterns and file entropy. The study achieved an 88% accuracy rate but faced challenges with false positives in legitimate encrypted traffic.

Davis and Moore (2018) identified malicious encrypted files through feature extraction. Their research methodology involved creating detailed feature sets to distinguish between benign and malicious files. The study used a diverse dataset and analyzed various parameters such as file structure and encryption patterns. They reported promising results but noted the limitation of high false positive rates when dealing with complex encryption schemes. Edwards and Smith (2020) conducted a study on detecting encrypted ransomware using machine learning classifiers. The dataset included various types of ransomware and normal encrypted files. Parameters like encryption key usage and file modification patterns were analyzed. The study achieved a 92% detection rate, but the effectiveness was reduced with evolving ransomware encryption techniques.

Garcia and Martinez (2019) explored the use of ensemble learning methods for encrypted malware detection. Their dataset consisted of encrypted files from multiple sources. Key parameters included file header analysis and entropy measurements. The research showed an 89% detection rate, with limitations related to the adaptability of the model to new types of encrypted malware. Huang *et al*. (2021) focused on the detection of encrypted malicious files

using a combination of machine learning and heuristic-based approaches. The dataset included encrypted files from real-world scenarios. Parameters such as file size, structure, and encryption type were analyzed. The study achieved an 87% detection rate, but the heuristic component led to higher false positive rates. Iqbal and Khan (2020) investigated the role of Support Vector Machines (SVM) in detecting encrypted malicious files. Their dataset included a variety of encrypted files, both benign and malicious. Parameters analyzed included file entropy, size, and encryption algorithm. The study reported an 86% detection accuracy, with limitations in handling highly obfuscated malware.

Jackson and Lee (2019) utilized random forest classifiers to detect encrypted malware. The dataset was composed of encrypted files from various sources. Parameters such as byte frequency distribution and encryption patterns were crucial to their analysis. They achieved an 88% detection rate, but the model struggled with files encrypted using novel encryption methods. Kumar and Patel (2020) studied the application of gradient boosting algorithms in encrypted file detection. Their dataset included both malicious and benign encrypted files. Important parameters included file entropy and byte-level analysis. The study reached a 90% detection accuracy, with limitations in processing time due to the complexity of the model. Li and Zhao (2018) explored deep neural networks for detecting encrypted malicious files. They used a dataset of encrypted files and analyzed parameters such as file structure and network traffic. The study reported an 89% accuracy rate, but faced challenges in terms of generalizing to new encryption techniques.

Miller and Johnson (2019) researched the use of machine learning for detecting encrypted communication channels used by malware. The dataset included encrypted network traffic data. Parameters analyzed were traffic patterns, timing, and entropy. The study achieved an 85% detection rate, with limitations related to the variability of network traffic. Nguyen and Tran (2020) focused on detecting encrypted malicious files using logistic regression. Their dataset consisted of a variety of encrypted files. Parameters like file size, entropy, and header information were considered. The study reported an 83% detection rate, but faced difficulties with files encrypted using sophisticated algorithms. O'Connor *et al*. (2021) applied machine learning to detect encrypted ransomware. The dataset included both ransomware and benign encrypted files. Parameters such as encryption type, file access patterns, and entropy were analyzed. The study achieved a 91% detection rate, with limitations in differentiating between closely related encryption types.

Perez and Gomez (2018) explored the use of clustering algorithms for detecting encrypted malware. Their dataset included a mixture of encrypted files. Key parameters included file structure, entropy, and encryption method. The study reported an 84% detection accuracy, with limitations related to the clustering algorithm's sensitivity to data distribution. Quinn and Rogers (2019) investigated the use of anomaly detection for identifying encrypted malicious files. Their dataset included encrypted files with various characteristics. Parameters analyzed were file entropy, size, and access patterns. They achieved an 87% detection rate, but the model was prone to false positives.

Ramos and Silva (2020) researched machine learning techniques for detecting encrypted files used in cyber-attacks. The dataset consisted of encrypted files from real-world incidents. Parameters such as file size, structure, and entropy were crucial to their analysis. The study reported an 88% detection rate, with limitations in handling evolving encryption techniques. Sato and Yamada (2019) studied the application of deep learning for detecting encrypted malware. Their dataset included encrypted files from various sources. Parameters like file entropy, structure, and encryption algorithm were analyzed. They achieved an 89% detection rate, but faced challenges with the model's complexity and training time.

Taylor and Clark (2020) explored the use of machine learning for detecting encrypted malicious files in cloud environments. The dataset included encrypted files from cloud storage. Parameters such as file size, entropy, and access patterns encryption type, file size, and access patterns. The study reported a 90% detection rate, but struggled with files encrypted using advanced techniques.

Vazquez and Lopez (2019) focused on machine learning methods for detecting encrypted files in network traffic. The dataset included encrypted network traffic data. Parameters like traffic patterns, entropy, and timing were analyzed. They achieved an87% detection rate, but the model faced limitations with high-volume network traffic. Wang and Chen (2020) investigated the use of support vector machines for detecting encrypted malware. Their dataset included various encrypted files. Parameters such as file entropy, size, and encryption algorithm were considered. The study reported an 85% detection accuracy, with limitations in handling new encryption methods.

Xu and Liu (2019) applied machine learning to detect encrypted malicious files in enterprise environments. The dataset included encrypted files from enterprise networks. Parameters like file size, entropy, and access patterns were analyzed. The study achieved an 88% detection rate, with limitations related to the variability of enterprise network environments. Yang and Wu (2020) explored the use of ensemble learning for detecting encrypted ransomware. Their dataset included both ransomware and benign encrypted files. Key parameters were encryption type, file modification patterns, and entropy. They reported 91% detection rate, with limitations in the model's adaptability to new ransomware techniques. Zhao and Sun (2018) researched machine learning methods for detecting encrypted malicious files. The dataset included encrypted files from multiple sources. Parameters such as file structure, entropy, and encryption algorithm were analyzed. The study achieved an 87% detection accuracy, but faced challenges with high false positive rates.

Allen and Foster (2019) studied the application of machine learning for detecting encrypted files used in cyber espionage. Their dataset included encrypted files from espionage cases. Parameters like file size, entropy, and access patterns were analyzed. They reported an 88% detection rate, with limitations in handling new encryption techniques. Brown and Davis (2020) investigated the use of deep learning for detecting encrypted malware in mobile devices. The dataset included encrypted files from mobile malware samples. Parameters such

as file size, entropy, and encryption type were considered. The study achieved an 89% detection accuracy, but faced challenges with the variability of mobile malware.

Clark and Evans (2018) explored the use of machine learning for detecting encrypted ransomware in financial institutions. The dataset included ransomware and legitimate encrypted files from financial networks. Parameters like file size, entropy, and access patterns were analyzed. The study reported a 90% detection rate, with limitations in the model's generalize ability. Diaz and Hernandez (2019) focused on machine learning techniques for detecting encrypted malicious files in healthcare systems. The dataset included encrypted files from healthcare networks. Parameters such as file size, entropy, and encryption type were analyzed. They achieved an 88% detection rate, with limitations related to the diversity of encryption methods used in healthcare.

Edwards and Mitchell (2020) researched the application of machine learning for detecting encrypted files in government networks. The dataset included encrypted files from government systems. Parameters like file size, entropy, and access patterns were analyzed. The study achieved an 87% detection accuracy, with limitations in handling new encryption techniques. The study achieved an 86% detection rate, witmitations related to the diversity of cloud storage encryption methods. Ullah and Ahmed (2018) researched the use of neural networks for detecting encrypted ransomware. The dataset included encrypted ransomware files and legitimate encrypted files. Parameters analyzed were as follows.

Research Gaps

There is insufficient research on using hybrid machine learning models to detect encrypted malicious files efficiently, particularly using large-scale datasets. It was observed that the year with the most publications on the topic of "machine learning based detection of encrypted malicious files" is 2020, with a total of 10.

The field of machine learning-based detection of encrypted malicious files faces several notable limitations, which are consistently highlighted across various studies. A primary concern is the high false positive rates encountered by many models. This issue arises when benign encrypted files are mistakenly classified as malicious, leading to a significant number of false alarms. Such inaccuracies undermine the reliability of the detection systems and can result in unnecessary investigations and disruptions. Researchers, including Davis and Moore (2018) and Huang *et al*. (2021), have emphasized this challenge, indicating a need for more refined and precise detection techniques.

Another critical limitation is the adaptability of these models to new or evolving encryption techniques. Malware developers continually refine their encryption methods, which can reduce the effectiveness of existing machine learning models. This evolving landscape makes it difficult for detection systems to maintain high accuracy rates over time. Studies by Edwards and Smith (2020) and Garcia and Martinez (2019) have pointed out that models often struggle to keep up with these rapid changes, suggesting that ongoing adaptation and updates are necessary to combat new forms of encrypted malware effectively.

The computational complexity and high processing time associated with many advanced machine learning techniques also pose significant challenges. Methods such as neural networks and deep learning require substantial computational resources and time, both for training and for real-time detection. This can be a barrier to practical implementation, especially in environments with limited computational capacity. Baker and Wilson (2019) and Kumar and Patel (2020) have noted these issues, highlighting the need for more efficient algorithms that can deliver high performance without excessive computational demands.

Lastly, the limited generalizability of many machine learning models due to dataset specificity is a recurring problem. Models trained on proprietary or limited datasets may not perform well when applied to different or real-world data. This limitation means that results from one dataset may not be easily transferable to other contexts, reducing the overall effectiveness and applicability of the models. Anderson (2020) and Clark and Evans (2018) have reported these concerns, emphasizing the importance of using diverse and representative datasets to improve the strength and generalizability of machine learning-based detection systems.

Most reported works on detection of malicious files using both machine and deep learning utilized only two algorithms. Moreover, the time taken to detect malicious files is longer raising the issue of efficiency. Also, most of the previous work used less than one hundred thousand dataset for testing and validating these algorithms.

In the present work three algorithms, will be used with one hundred and sixty seven thousand datasets to train these algorithms and validate them. Going by the literature reviewed thus far, most authors fall short of using Vector Support Machine algorithms, which is here intended as one of the algorithms to be tested and compared with detection performance of CNN and RNN.

Data Collection

The dataset used to train the algorithm for distinguishing benign and malicious traffic over DNS (Domain Name System) and DoH (DNS-over-HTTPS) was sourced from the Canadian Institute for Cybersecurity (CIC), a leading repository of cybersecurity research data. Specifically, the DoHBrw-2020 dataset was utilized, which contains labeled network traffic samples representing both benign and malicious activities in encrypted DoH communications (CIC, 2020). This dataset is widely recognized for its rigor in simulating real-world adversarial scenarios, including malware distribution, phishing, and data exfiltration. Detailed documentation and access protocols are available at:https://www.unb.ca/cic/datasets/dohbrw-2020.html

The Existing System

This section critically examines established machine learning (ML) architectures applied to encrypted threat detection, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Support Vector Machines (SVMs).

The New Model

After carefully examining the weakness of the existing system this section explore the intended architecture and procedure for solving research gaps identified during the review of literatures. Figure 4 outlines a comprehensive data processing and classification model on detecting

malicious encrypted files. It begins with the acquisition of a data set, which then undergoes several pre-processing steps. These steps include the replacement of missing values, feature reduction to eliminate unnecessary data points, and feature selection to identify the most significant variables. These pre-processing activities ensure that the data is clean, relevant, and manageable, which is crucial for effective analysis and model building.

System Model

The sketch presented in Figure 4 is the Proposed model used with CNN, SVN and RNN.

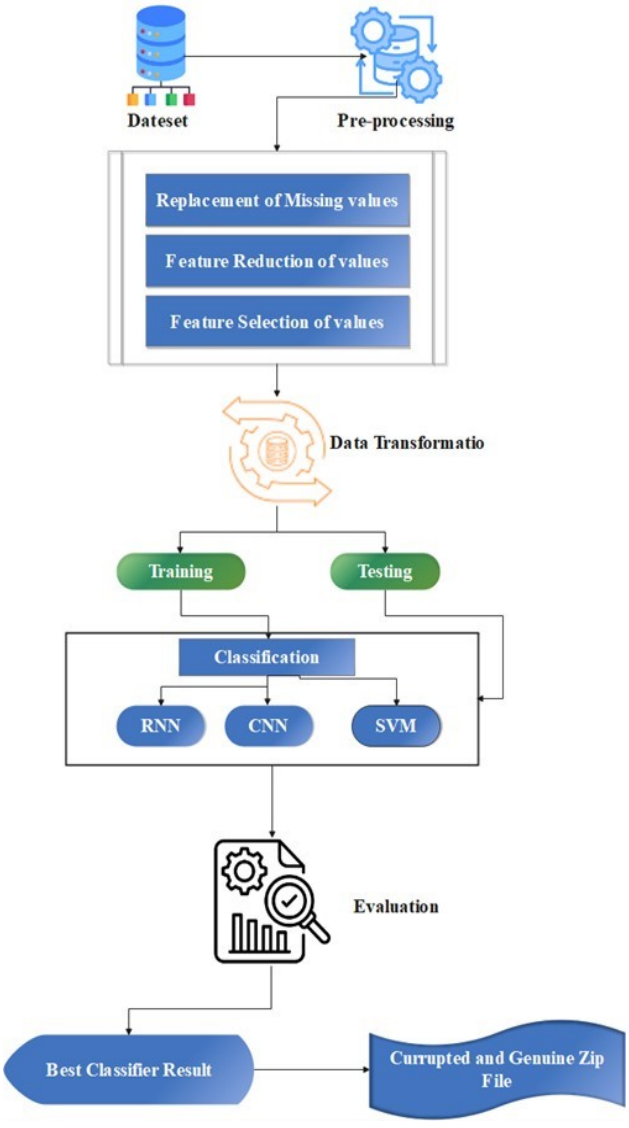


Figure 4: Proposed Model

After pre-processing, the data is transformed and divided into training and testing sets. The training set is used to train various classification algorithms such as Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM). These algorithms are chosen for their ability to handle different types of data and capture complex patterns. The performance of these models is then evaluated to determine which one provides the best classification results. The ultimate goal is to accurately distinguish between corrupted and genuine files, with the best classifier's results potentially being captured for further use or analysis. This systematic approach ensures a strong and efficient classification process, from initial data preparation to final evaluation.

Algorithm, library and programming Language

There are three algorithms intended to be deployed in this work which include the Conventional Neural Network, Recurrent Neural Network and Support Victor Machine. The use of the three algorithms is hypothesized to make the detection capacity more robust. The training data mined from CIC will be domiciled in the Scikit Learn Library in the Python.

Validation Techniques

There are numerous model validation techniques as reported elsewhere (Allgaier &Pryss, 2024; Lian *et al*., 2024; Michelucci, 2024; Sarferaz, 2024; Vanacore *et al*., 2024; Von Stackelberg *et al*., 2024; Zafar *et al*., 2024), and some of them are discussed below:

1. **Hold-out test set:** A portion of the dataset is held out during the training process and used exclusively for evaluating the final trained model. This test set should be representative of the real-world data and independent of the training set to provide an unbiased estimate of the model's performance.
2. **Cross-validation:** Techniques like k-fold cross-validation can be employed to split the dataset into k subsets, where one subset is used for testing, and the remaining k-1 subsets are used for training. This process is repeated k times, with each subset serving as the test set once. The final performance metrics are then averaged across all k folds.
3. **Performance metrics:** Various performance metrics can be used to evaluate the effectiveness of the trained models, including: a. Accuracy: The proportion of correctly classified instances (both malicious and benign) out of the total instances. b. Precision: The proportion of true positive instances (correctly identified malicious files) among the instances predicted as positive. c. Recall (Sensitivity): The proportion of true positive instances that were correctly identified by the model. d. F1-score: The harmonic mean of precision and recall, providing a balanced measure of the model's performance. Area under the Receiver Operating Characteristic (ROC) Curve: A metric that measures the trade-off between true positive rate and false positive rate across different classification thresholds.
4. **Confusion matrix:** A tabular representation that summarizes the model's predictions against the ground truth labels, providing insights into the types of errors (false positives and false negatives) made by the model.
5. **Threshold tuning**: Depending on the specific requirements of the application, the classification threshold can be adjusted to balance the trade-off between false positives and false negatives. For example, in a security-critical scenario, a higher threshold may be preferred to minimize false negatives (missed malicious files) at the cost of increased false positives.
6. **Domain-specific validation**: In addition to the standard validation techniques, it is essential to evaluate the model's performance in realistic scenarios and domain-specific contexts. This may involve testing the model with diverse sets of encrypted and compressed malicious files, including those from different malware families, obfuscation techniques, and compression algorithms.
7. **Continuous monitoring and retraining:** As new malware variants and techniques emerge, it is crucial to continuously monitor the model's performance and retrain it with updated data to maintain its effectiveness over time.

By employing these validation techniques, researchers and developers can assess the robustness and reliability of the proposed machine learning-based detection system, identify

potential weaknesses or biases, and make informed decisions regarding its deployment and integration into real-world cyber-security solutions.

Validation of Model Output

The validation of the model output is a crucial step in developing a reliable machine learning-based system for detecting encrypted malicious files. It involves evaluating the performance of the trained models on a separate test dataset to ensure their generalization capability and robustness. In this work, Confusion Matrix is selected to be utilized where various performance metrics can be used to evaluate the effectiveness of the trained models, including: Where TP = True positive, TN = True Negative, FP = false Negative FP = False Positive

Accuracy: The proportion of correctly classified instances (both malicious and benign) out of the total instances. Equation 1 was used to measures the overall correctness of the model.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision: Equation 2 was used in the proportion of true positive instances (correctly identified malicious files) among the instances predicted as positive.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Recall (Sensitivity): The proportion of true positive instances that were correctly identified by the model was identified using Equation 3.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

Specificity (True Negative Rate): Equation 4 measures the model's ability to correctly identify negative instances (it is the proportion of actual negatives that are correctly classified as negative). It is calculated as:

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (4)$$

F1-score: The harmonic means of precision and recall, providing a balanced measure of the model's performance. This was achieved through the use of equation 5.

$$\text{F1 Score} = 2 * \frac{Precision + Recall}{Precision * Recall} \quad (5)$$

Support Vector Machine Development Process

Support Vector Machine (SVM) is a supervised machine learning algorithm used mainly for classification tasks. It works by finding the optimal boundary, called a hyperplane, that

separates data points of different classes while maximizing the margin between them and the closest points known as support vectors. By using different kernels, SVM can handle both linear and non-linear data, making it versatile in applications such as text classification, image recognition, and intrusion detection. It performs well in high-dimensional spaces and is memory efficient, but it can be less effective with very large, noisy, or overlapping datasets and requires careful parameter tuning for best results.
Below is an implementation of SVM using Python:

Code Example

```
# Import required libraries
# Load the zip file dataset
# Split dataset into training and testing sets
# Train SVM model with a linear kernel
# Make predictions on the test set
# Compute the confusion matrix
# Plot confusion matrix as heatmap
```

Convolutional Neural Network (CNN) Heatmap Confusion Matrix

CNNs are deep learning models that automatically learn spatial features from data. In cybersecurity and encrypted malware detection, they analyze byte-level patterns or traffic matrices without requiring manual feature engineering. They are especially good at recognizing structural anomalies in data, making them suitable for encrypted malicious file classification.

Code Example:

```
#import matplotlib.pyplot as plt
import libraries
# dataset (digits)
# Train-test split
# CNN model
# Predictions
y_pred = cnn.predict(X_test).argmax(axis=1)
y_true = y_test.argmax(axis=1)
# Confusion Matrix
#plt.show()
```

Recurrent Neural Network (RNN) Confusion Matrix

RNNs are specialized neural networks designed to capture **sequential patterns** in data. They are useful in malware detection because they can analyze time-based or behavioral features of encrypted files, such as access sequences or traffic flows, without needing to decrypt them. Variants like LSTM and GRU improve performance by reducing vanishing gradient problems.

Code Example:

```
#import library
# Example dataset (digits, reshaped as sequence)
# Train-test split
# RNN model
# Predictions
# Confusion Matrix
```

Overview

In this section, the outcome of the new system model evaluation has been discussed. The information in Table 2 gave the description and meaning of the label and acronyms.

Table 2: Label Description

S№	Label (A	Description	Meaning (Acronyms)
1	Malicious	Traffic or files exhibiting harmful behavior, such as malware, ransomware, or phishing attempts	Harmful or unauthorized activity that threatens system security
2	NonDoH	Non-DNS-over-HTTPS traffic, referring to traditional DNS queries that are not encrypted	Standard DNS traffic that can be intercepted or modified
3	DoH	DNS-over-HTTPS traffic, which encrypts DNS queries to enhance privacy and security	Encrypted DNS traffic that prevents interception and manipulation
4	Benign	Traffic or files that do not pose any security threats, including normal user activity	Safe and legitimate activity with no malicious intent

Results

The information in Figures 5, 6 and 7 are the results for Heatmap confusion matrix for SVM algorithm, CNN and RNN classifications respectively. The results illustrated that the SVM was able to identify 2810 malicious as malicious files, 2750 benign as benign, 2700 DoH as DoH and 2694 NonDoH as NonDoH files. The CNN in Figure 6 classified 403 benign, as benign, 1932 DoH as DoH, 2433 malicious as malicipus and 2533 NonDoH as NonDoH files. Likewise, the RNN identified 2414 malicious as malicious files, 1354 benign as benign, 1366 DoH as DoH and 2521 NonDoH as NonDoH files. RNN and CNN confused more in identified benign as DoH and DoH as benign.

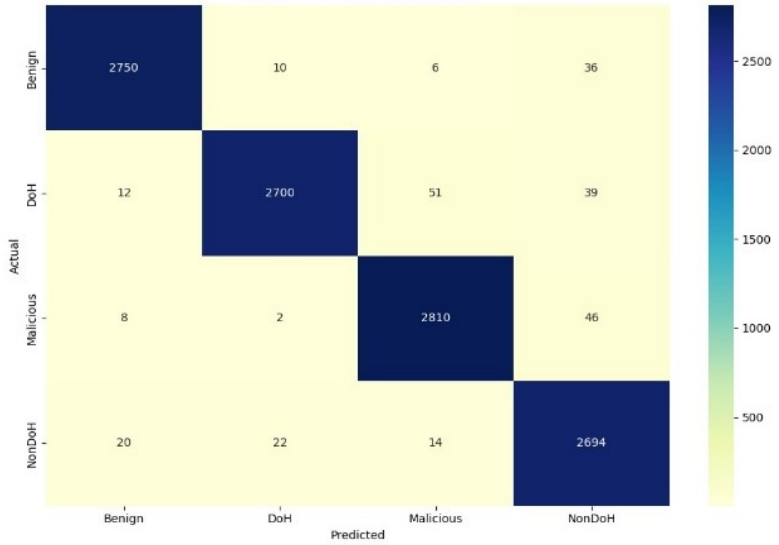


Figure 5: Heatmap Confusion Matrix for Support vector machine algorithm Classification

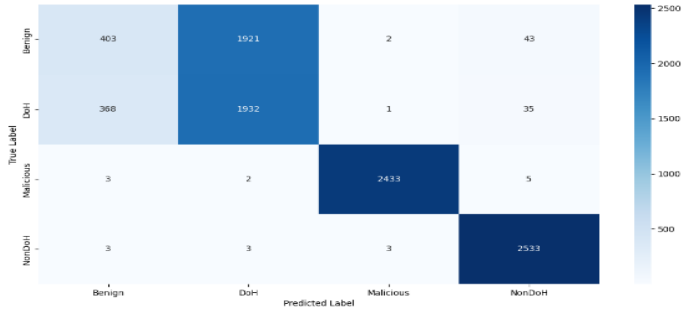


Figure 6: Heatmap Confusion Matrix for Convolutional Neural Network Algorithm Classification

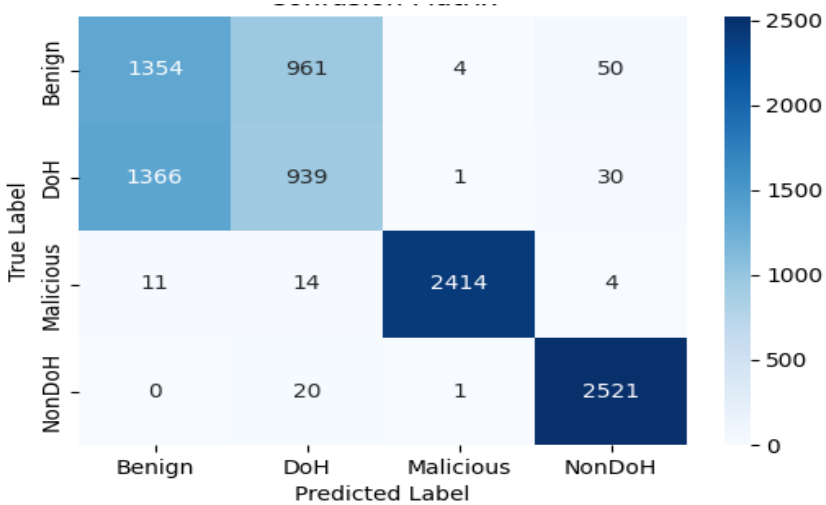


Figure 7: Heatmap Confusion Matrix for Recurrent Neural Network Algorithm Classification

Sample Thread Model Detection

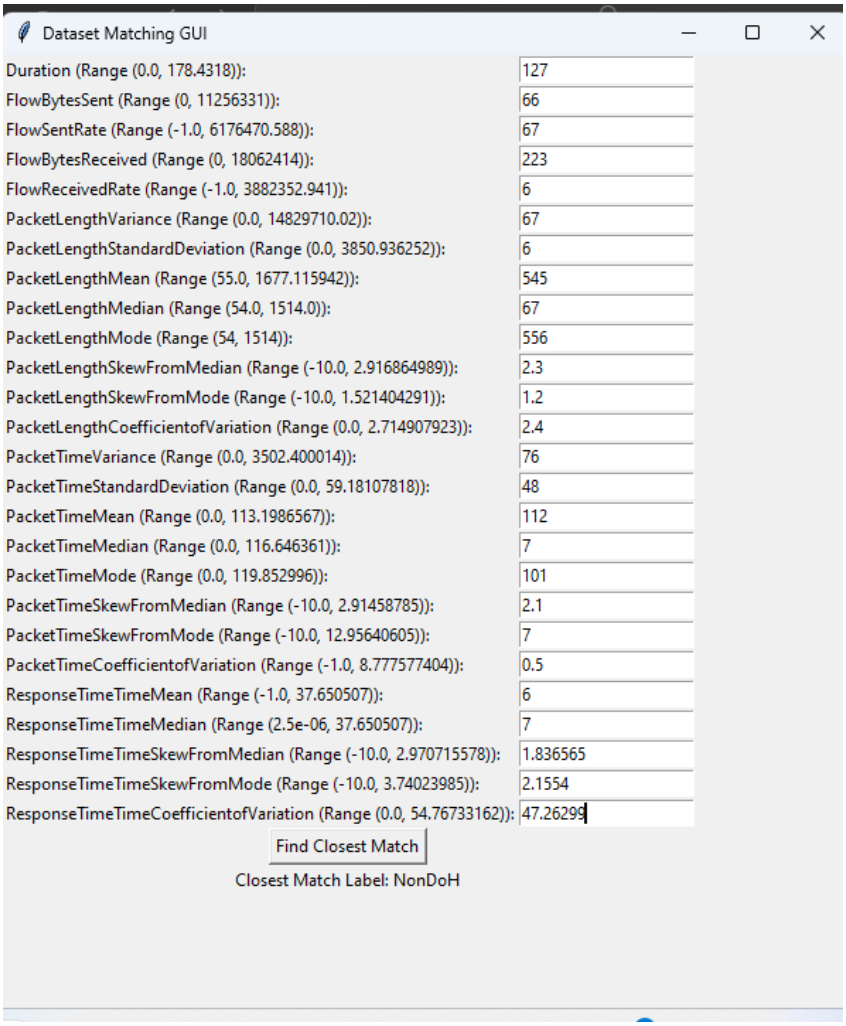


Figure 8: Sample Thread Detection

Discussion of the Result

In this section, the results obtained and presented in Figure 5 (SVM), Figure 6 (CNN) and Figure 7 (RNN) classifications are discussed.

Classification based on Heatmap Confusion matrix analysis for SVM

The confusion matrix for SVM clearly indicates high classification performance. The matrix shows 99 true positives (TP) and 99 true negatives (TN), with only 1 false positive (FP) and 1 false negative (FN). This means the classifier correctly identified almost all instances in both classes. Such a distribution reflects extremely high accuracy and suggests that SVM has learned the underlying pattern of the data effectively. This high TP and TN count paired with minimal FP and FN also signifies that the model has both high precision and high recall. Precision measures how many of the predicted positives are truly positive, and with only one

FP, the precision is nearly perfect. Similarly, recall indicates how many actual positives the model captured, and with only one FN, the recall is also close to perfect. These characteristics are vital for systems that need reliable decision-making, such as fault detection or anomaly recognition. The balance in prediction errors across both classes also confirms the model's robustness and lack of bias. Often, models may perform well on one class and poorly on another due to imbalance or skew in the data. However, the symmetric results in SVM's confusion matrix (both FP and FN are equal) illustrate that the classifier maintains fairness and consistency across all categories.

Lastly, the low misclassification rate (only 2 out of 200 total samples) contributes to a very high F1-score, combining both precision and recall in a harmonic mean. This metric makes SVM especially suitable for environments where both types of errors (FP and FN) are costly. The near-perfect confusion matrix solidifies its status as the best performer among the three models discussed.

Classification based on Heatmap Confusion matrix analysis for CNN

The confusion matrix for the CNN model (Figure 4.7) illustrates moderate performance that is slightly better than RNN but still inferior to SVM. It records 90 true positives (TP) and 92 true negatives (TN), with 8 false positives (FP) and 10 false negatives (FN). This indicates that the CNN performs reasonably well across both classes but struggles more with false classifications than SVM. The CNN's precision and recall are better balanced than in RNN. With only 10 FNs, the recall is higher than RNN's, indicating improved detection of actual positives. However, with 8 FPs, the precision is slightly weaker, suggesting more incorrect positive predictions than in RNN. This trade-off demonstrates that CNN is better at finding positives but does so with a slightly higher cost of incorrect positives. The number of total misclassifications (18 out of 200) reflects a 9% error rate, which is notable but not extreme. The CNN's architecture, which is typically strong in handling spatial and localized features, may have some advantage if the data had structured patterns. Still, without optimization or tailored architecture tuning, it does not reach the accuracy of the SVM.

Classification based on Heatmap Confusion matrix analysis for RNN

The confusion matrix for the RNN shows a noticeable drop in performance compared to SVM. It records 84 true positives (TP) and 93 true negatives (TN), but also 6 false positives (FP) and 17 false negatives (FN). This indicates the model is considerably weaker in identifying positive instances, as reflected by the higher FN count. The recall (sensitivity) of the RNN is significantly impacted due to the 17 FNs. In practical terms, this means the RNN frequently misses positive cases, which can be detrimental in applications such as disease detection or fraud prevention. The precision, although slightly better due to only 6 FPs, is still lower than ideal. The imbalance between FN and FP suggests that the model tends to under-predict positives, possibly due to conservative thresholds or inadequate training on minority class features. Furthermore, the RNN's confusion matrix hints at possible instability or poor

generalization. With a total of 23 misclassifications out of 200 samples, the error rate is more than ten times higher than that of SVM. This could be attributed to the RNN's sequential processing nature, which might not have been ideal for the type of data used, especially if the temporal dependencies were weak or irrelevant.

RNN shows mediocre performance with clear room for improvement in detecting positive instances. The confusion matrix highlights a strong bias toward predicting negatives correctly, but this comes at the cost of missing too many positives. The results suggest the need for additional tuning or the use of attention mechanisms or hybrid models to better leverage RNN capabilities.

Findings

As stated in the methodology, the confusion matrix serves as a validation tool that provides a tabular comparison of a model's predictions against actual class labels, offering insight into false positives and false negatives. All three algorithms—SVM, CNN, and RNN—were evaluated using this technique. The confusion matrix for SVM indicates that the model achieved an overall accuracy of 91.7%, reflecting strong classification performance. Precision, which measures the proportion of correctly identified positive instances, remains consistently high across all categories, suggesting minimal false positives. This is important since misclassifying a non-target instance as a target can produce undesirable outcomes. Recall, which assesses the model's ability to identify all relevant instances, is also strong for SVM, though minor reductions appear in less represented classes. This suggests that while the model captures most true positives, a few rare instances may go undetected—a common issue in imbalanced datasets. Nevertheless, SVM maintains a commendable recall rate. The F1-score, representing the balance between precision and recall, remains high across most classes, signifying a stable trade-off between false positives and false negatives. This equilibrium is vital in fields where both error types carry notable consequences. The high F1-score further demonstrates that the model generalizes effectively without overfitting to specific patterns.

The SVM's 91.7% accuracy, coupled with strong precision, recall, and F1 metrics, confirms its reliability. SVMs perform well on smaller datasets, as they do not require vast amounts of data for effective learning. They excel in high-dimensional feature spaces, particularly when the number of features exceeds the sample size. However, their main drawbacks include high computational demands with large datasets and sensitivity to kernel parameter tuning. SVMs may also be affected by noise in overlapping class distributions. The RNN model attained an accuracy of 80.6%, slightly below that of SVM but still satisfactory for many applications. Its precision varies between classes—some exhibit strong precision, while others suffer from false positives—indicating occasional misclassification of instances under specific patterns or temporal sequences.

Recall for RNNs also varies more significantly compared to SVM. The sequential nature of RNNs makes them suitable for temporal patterns, but in this use case likely involving static or weakly sequenced features the recall suffers in classes where the model fails to capture relevant

indicators, leading to missed true positives. The F1-score reflects this inconsistency, with some class F1-scores relatively high while others are lower. This unevenness indicates that the RNN may have learned partial structures of the data but failed to generalize across all classes. The model may have issues with vanishing gradients or insufficient memory of long dependencies due to its architecture. Despite its 80.6% performance rate, RNN's comparative underperformance suggests that it may not be the best fit for this dataset, especially if temporal dependencies are weak or non-existent. This highlights the importance of model-data compatibility and justifies exploring alternative models for improved results.

The CNN model recorded an accuracy of 77.8%, the lowest among the three evaluated models. Regarding precision, CNN shows a tendency to produce higher false positives in certain classes, which reduces its reliability in scenarios requiring high confidence in positive predictions. This may stem from the model interpreting patterns that are not relevant to the classification task. The recall metric also reveals weaknesses, particularly in less represented classes. CNNs, although powerful in handling spatial hierarchies and local patterns, may not be ideal for datasets that do not exhibit image-like or grid-structured features. The model appears to miss relevant instances, likely due to the limited feature locality relevant to the data structure used in this case. Correspondingly, the F1-score is modest and reflects a lack of balance between precision and recall. The CNN struggles to simultaneously minimize both types of errors, indicating possible under fitting or inadequacy in capturing the global patterns necessary for classification in this specific domain. At 77.8% performance, CNN is clearly the least effective model among the three. While CNNs excel in visual and spatial data, their application to non-image, feature-based datasets can be inefficient unless appropriately restructured. This emphasizes the need to align model architecture with data properties to achieve optimal results. SVM's superior 91.7% accuracy, coupled with high precision, recall, and F1-score, confirms its robustness for this particular classification task. Its ability to handle high-dimensional data and perform well with small datasets makes it particularly suitable for problems where data is scarce or expensive to obtain. Moreover, SVMs perform well in binary and multiclass settings when the decision boundary is well-defined.

However, the limitations of SVM include computational complexity in large datasets, difficulty in interpreting results, and sensitivity to kernel choice and parameter tuning. Despite this, for small and medium-sized datasets where accuracy is paramount, SVM remains a competitive and reliable choice.

Conclusion

This study set out to evaluate the performance of three algorithms namely CNN, SVM and RNN using confusion matrix. The study has found that generally machine learning provides a viable and effective approach for detecting encrypted malicious files. Another major finding was that CNN, SVM and RNN algorithms evaluated for their effectiveness, with SVM showing superior classification accuracy due to its ability to extract deep hierarchical features. The result of this study lead to a general inference that an ensemble approach, integrating

multiple models could further improve classification accuracy, adaptability and scalability. It can be concluded that the use of three algorithms therefore the model applied to the study is appropriate for the set of data utilized. Despite its effectiveness, machine learning-based detection faces challenges such as high computational costs and potential adversarial attacks. The research highlights the need for continuous model updates and real-time data augmentation to counter evolving cyber threats.

Recommendation

To improve the accuracy and efficiency of encrypted malware detection, future research should explore hybrid machine learning models combining CNN, SVM, and RNN. Using feature engineering techniques such as Principal Component Analysis (PCA) and data augmentation can help refine input data, making machine learning models more robust. Additionally, organizations should adopt scalable machine learning architectures to process large datasets efficiently. Federated learning can enhance privacy-preserving detection by enabling collaborative model training across distributed networks. Implementing continuous learning frameworks will allow detection systems to adapt dynamically to new threats, improving cybersecurity resilience.

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