# Machine Learning Approaches for Detecting Encrypted and Compressed Malicious Files: A Review

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***Abstract***
*The advancement of cyber threats has intensified with the rise of encrypted and compressed malicious files, posing significant challenges to traditional signature-based detection methods. Machine learning (ML) has emerged as a promising solution, capable of uncovering hidden patterns without relying on known malware signatures. This review explores recent developments in applying ML techniques such as deep learning, transfer learning, ensemble methods, and anomaly detection to identify encrypted malicious files. Studies have demonstrated that ML models can effectively analyse structural, statistical, and behavioural features, offering improved adaptability and detection accuracy. Despite these advancements, significant challenges persist, including encryption evasion, polymorphic malware, data imbalance, scalability issues, and adversarial attacks. Innovative strategies like explainable AI, federated learning, scalable architectures, and continuous learning are being investigated to enhance robustness and transparency. The dynamic evolution of cyber threats underscores the urgency of developing intelligent, adaptable, and privacy-conscious detection systems. Ultimately, this review highlights the critical role of ML in strengthening cybersecurity defences against increasingly sophisticated encrypted malicious files, emphasizing the need for continued research to address ongoing challenges and ensure resilient, scalable protection across diverse digital environments.*

***Key words:*** *Encrypted Malicious Files, Machine Learning, Cybersecurity, Anomaly Detection, Adversarial Attacks.*

## Introduction

The advancement of technology has brought along an evolution in cyber threats, particularly in the sophistication of malicious files. Among these emerging challenges are encrypted and compressed malicious files, which represent a formidable obstacle to traditional signature-based malware detection techniques. Unlike conventional malware that can be detected by identifying known patterns or signatures, encrypted and compressed files conceal their malicious intent, making them far harder to detect. Machine learning (ML) has gained attention as a powerful and adaptable tool for identifying threats that elude traditional detection systems. Recent studies have explored ML approaches to uncover patterns and behaviours indicative of malware hidden within encrypted or compressed formats. These studies illustrate the growing need for innovative security strategies, as cybercriminals increasingly use encryption and compression to bypass security defences and execute attacks undetected.

Machine learning's potential for cybersecurity applications is well-recognized, particularly in the context of detecting complex cyber threats. According to Hassan and Kumar (2021), machine learning provides robust mechanisms for identifying encrypted and compressed malicious files, leveraging behavioural and statistical patterns rather than relying solely on known malware signatures. Encrypted and compressed malicious files pose a particular challenge because they hide their payloads behind layers of obfuscation, rendering signature-based detection methods ineffective. Otoum and Nayak (2021) emphasized that traditional techniques often fail to identify these concealed threats, necessitating the use of more dynamic and intelligent methods such as ML.

Several notable studies have contributed to the evolution of this field. Bakour et al. (2023) developed a deep learning model using CNNs to detect encrypted malicious files based on byte-level pattern analysis, achieving impressive detection rates. In a complementary effort, Mohan et al. (2024) proposed a hybrid model combining machine learning and deep learning to improve detection accuracy and adaptability over standard antivirus solutions. Further contributions from Chen et al. (2023) introduced novel feature engineering techniques to enhance encrypted malware detection. By extracting structural and statistical features from compressed files, they achieved high detection rates while maintaining minimal computational overhead. Similarly, Jiang et al. (2022) leveraged transfer learning, allowing their model to generalize well even with limited training data.

The increasing reliance on encryption and compression techniques by cybercriminals, as observed by Siponen et al. (2022) and Stivenarte et al. (2021), underscores the urgency for innovative approaches in cybersecurity. These techniques enable attackers to hide data exfiltration activities, ransomware payloads, and command-and-control communications under seemingly benign traffic, making detection exponentially more difficult. As noted by Cabaj et al. (2019), traditional antivirus systems based on signature matching are fundamentally ill-equipped to handle such threats, given the obfuscation provided by encryption. Furthermore, the dynamic nature of malware development, where new variants emerge continuously, leaves conventional defences lagging behind (Damodaran et al., 2017).

Machine learning offers a dynamic and scalable alternative. By analyzing the structural, statistical, and behavioral characteristics of files, ML models can effectively identify potential threats without requiring prior knowledge of specific malware signatures. Studies by Vinayakumar et al. (2019), Bakour et al. (2023), and others have demonstrated that ML-based models offer improved adaptability and higher detection rates compared to traditional methods. This review article presents a comprehensive exploration of the application of machine learning techniques in detecting encrypted and compressed malicious files, emphasizing the potential of Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) in overcoming current cybersecurity challenges.

## Understanding the Threat of Encrypted Malicious Files

In the contemporary digital setting, the proliferation of encrypted malicious files has become a formidable challenge to cybersecurity experts globally (Rajasekharaiah et al., 2020). Encrypted files, which conceal their contents through sophisticated encryption algorithms, combined with malicious files engineered for harmful intent, pose a serious threat to the integrity and security of computer systems and networks. Over the past decade, much research in cybercrime has focused on encrypted malicious files, as cybercriminals continuously refine their methods to evade detection and exploit vulnerabilities (Carlo, 2024). This growing menace necessitates the development of robust intrusion detection systems capable of identifying encrypted malicious files. These files, which can include encrypted documents, archives, executables, or network traffic, employ cryptographic techniques that make traditional inspection and analysis methods ineffective without the corresponding decryption keys. The rapid proliferation of encryption protocols and secure communication channels has further complicated efforts to detect and manage these threats (Huntley et al., 2018; Gupta & Babu, 2020).

Cisco (2024) defines malware, or malicious software, as intrusive programs developed by hackers to steal data, damage systems, or disrupt operations. Malicious files span a broad spectrum, encompassing viruses, worms, Trojans, ransomware, spyware, and other software engineered to exploit system vulnerabilities and perpetrate cybercrimes. According to Nelms et al. (2019) and Zhou et al. (2021), these malicious files often masquerade as legitimate documents or applications, leveraging social engineering tactics to mislead users and avoid detection by conventional antivirus programmes. The convergence of encryption and malicious intent creates an especially dangerous threat landscape. Cybercriminals now employ encryption to conceal malicious payloads, allowing them to evade traditional security measures. These encrypted malicious files can be transmitted across networks, stored on compromised systems, or delivered through phishing emails, posing serious risks to individuals, corporations, and critical infrastructure (Silva et al., 2017; Ramírez-Cruz et al., 2022).

Addressing the challenges posed by encrypted malicious files demands a multifaceted strategy, incorporating innovation, threat intelligence, and proactive defence measures (Khan et al., 2020; Wang et al., 2019). Traditional signature-based detection, dependent on recognizing known malware patterns, struggles against novel or polymorphic threats. Consequently, the cybersecurity community increasingly turns to machine learning to strengthen defences and enhance detection capabilities. Machine learning algorithms can process massive datasets, uncover subtle patterns, and identify anomalies unique to encrypted malicious files. Furthermore, machine learning models, trained on comprehensive datasets of benign and malicious files, can learn to distinguish between legitimate and harmful files based on intrinsic characteristics. Such techniques offer adaptability and the ability to evolve alongside emerging threats, providing a dynamic and proactive shield against cyber adversaries (Bhattacharya et al., 2018; Zhang et al., 2021). This review highlights the application of machine learning techniques for detecting encrypted malicious files, aiming to clarify the effectiveness, challenges, and future directions of this critical cybersecurity strategy.

## Challenges Hindering the Detection of Encrypted Malicious Files

Detecting encrypted malicious files presents a range of significant challenges to cybersecurity practitioners, largely because of the advanced evasion techniques utilized by cybercriminals. Among the key technical and operational hurdles is encryption evasion, wherein encryption techniques obscure malicious payloads, rendering them invisible to traditional antivirus solutions (Souri et al., 2020; Alizadeh et al., 2021). Another critical challenge is polymorphic malware, where malicious files alter their code structures to escape signature-based detection (König et al., 2019; Mirjalili et al., 2020). Similarly, zero-day attacks exploit undiscovered vulnerabilities, allowing cybercriminals to distribute undetectable malware (Brent et al., 2018; Zhang et al., 2021). Fileless malware adds complexity by operating entirely in memory, leaving no traces on disk and complicating detection further (Zhuang et al., 2019; Gohar et al., 2020). Evasive tactics such as obfuscation, code packing, and code injection are common, which makes accurate identification difficult. Cybercriminals continually refine these methods, thereby complicating cybersecurity strategies (Guzman et al., 2020; Naseri et al., 2021). Insider threats are equally perilous, where internal malicious actors circumvent security controls to compromise systems or exfiltrate sensitive information (Köse et al., 2018; Lee et al., 2020). The scalability issue is another major concern. The enormous volume of network traffic and transmitted files necessitates highly efficient detection algorithms and distributed system architectures (Khan et al., 2021; Sarwar et al., 2022). High false positive rates, resulting from detection system inaccuracies, overwhelm security analysts and reduce overall system effectiveness (Zhang et al., 2020; Liu et al., 2021).

Data imbalance, where benign files vastly outnumber malicious ones, can bias machine learning models and diminish detection accuracy. Strategies like oversampling and synthetic data generation are crucial to address this (Chawla et al., 2019; Zhang et al., 2020). Adversarial attacks, designed to trick machine learning models through slight modifications in input data, are another pressing concern (Akhtar et al., 2018; Yuan et al., 2021). Privacy regulations present additional barriers. Data privacy laws limit information sharing, impeding the collaborative development of robust detection methods (Kandias et al., 2019; Cui et al., 2021). Balancing the need for data privacy with collective cyber defense remains a persistent challenge in the cybersecurity domain.

Resource constraints, especially on IoT and edge devices, restrict the deployment of sophisticated detection algorithms, requiring lightweight solutions (Li et al., 2020; Boubendir et al., 2022). Moreover, traditional detection systems often lack contextual understanding, resulting in frequent false alarms and missed threats in dynamic environments (Bai et al., 2019; Nadeem et al., 2021). The dynamic nature of the threat landscape demands agile detection systems capable of adapting to new malware variants and attack techniques (Nguyen et al., 2020; Hu et al., 2021). Legacy systems, operating with outdated software and inadequate security features, exacerbate these risks (Gonzalez et al., 2018; Mohammadi et al., 2021).

In summary, addressing these multifaceted challenges requires an integrated approach that leverages advanced detection technologies, strengthens threat intelligence networks, and fosters collaboration among cybersecurity stakeholders to effectively safeguard against evolving cyber threats.

### Machine Learning Techniques for Encrypted Malicious File Detection

Machine learning techniques have emerged as powerful tools in the realm of cyber-security, particularly for detecting encrypted malicious files. These files pose significant challenges to traditional signature-based detection methods due to their ability to conceal malicious content effectively. Machine learning algorithms offer the potential to analyse various features and patterns associated with encrypted malicious files, enabling the identification of potential threats without relying on static signatures. This review explores the application of machine learning techniques in detecting encrypted malicious files, highlighting advancements, challenges, and future directions in this field.

### Deep Learning for Encrypted Malware Detection

Deep learning, a subset of machine learning, has shown promise in detecting encrypted malware. By leveraging neural network architectures with multiple layers, deep learning models can extract intricate patterns and relationships from encrypted files, enabling accurate detection. For instance, Vinayakumar et al. (2019) proposed a deep learning-based approach for encrypted malware detection, achieving significant improvements in detection accuracy.

### Transfer Learning for Enhanced Detection

Transfer learning, a technique where a model trained on one task is adapted for another related task, has been applied to improve the detection of encrypted malware. Jiang et al. (2022) introduced a transfer learning-based approach that leverages pre-trained models to efficiently detect encrypted malware, even in scenarios with limited training data. By transferring knowledge from pre-trained models, this approach enhances detection performance and generalization capabilities.

### Ensemble Methods for Robust Detection

The Ensemble method combines multiple models to improve detection strength and precision. In 2019, Cabaj et al. explored the use of ensemble learning for detecting encrypted malicious files, demonstrating enhanced detection rates compared to individual models. By aggregating predictions from diverse models, ensemble methods can mitigate the impact of false positives and negatives, enhancing overall detection performance. Also, Rong et al. (2020) in their work on the application of ensemble method in the detection of encrypted malicious file supported the views put forward by Cabaj et al.

### Feature Engineering for Enhanced Discrimination

Feature engineering plays a crucial role in enhancing the discriminative power of machine learning models for detecting encrypted malicious files (Gibert et al., 2022). In a more recent published work, Chen et al. (2023) introduced a novel feature engineering technique that extracts structural and statistical features from compressed files. Findings suggest that the procedure achieves high detection precision, and at the same time minimizing computational overhead. By carefully selecting informative features, this approach improves the model's ability to discriminate between benign and malicious files.

### Anomaly Detection for Novel Threats

Anomaly detection techniques, which identify deviations from normal behaviour, offer a proactive approach to detecting novel and emerging threats. In other words, anomaly detection is one of the most important concepts of data analysis where the information object is considered as an anomaly if it significantly differs from normal data behaviour in some sphere leading to conclude that object is not like the others in a particular data array (Hu et al., 2017). Damodaran et al. (2017) investigated the use of anomaly detection algorithms for identifying encrypted malware based on behavioural anomalies. By modelling normal file behaviour and detecting deviations, anomaly detection techniques can detect previously unseen threats with high accuracy.

### Adversarial Machine Learning for Resilient Detection

Stivenarte et al. (2021) explored the application of adversarial training to improve the robustness of machine learning models for detecting encrypted malicious files. By generating adversarial examples during training, these models learn to withstand adversarial manipulations, enhancing overall detection performance. Thus, adversarial machine learning techniques always aim to enhance the resilience of detection models against adversarial attacks.

### Explainable AI for Transparent Decision-Making

Explainable AI techniques is intended to provide insights into the decision-making process of machine learning models, thereby improving their transparency and interpretability. Bakour et al. (2023) studied and proposed a deep learning model for encrypted file detection that incorporates explainable AI techniques to provide insights into the features driving classification decisions. This enable security analysts to understand model decisions, explainable AI enhances trust and confidence in detection systems.

### Scalable Machine Learning Architectures

According Rahman et al. (2020), scalability is a critical consideration in deploying machine learning-based detection systems for large-scale environments. Jiang et al. (2022) proposed scalable machine learning architectures capable of processing massive volumes of data efficiently. By leveraging distributed computing frameworks and parallel processing, these architectures enable real-time detection of encrypted malicious files at scale.

## Federated Learning for Privacy-Preserving Detection

Federated learning enables collaborative model training across distributed edge devices while preserving data privacy (Hacks, 2024). In an extensive work, Wang et al. (2019) studied the application of federated learning for detecting encrypted malware in IoT networks. By training models locally on edge devices and aggregating updates centrally, federated learning enables effective detection while minimizing data exposure and privacy risks.

## Continuous Learning for Adaptive Detection

Rahman (2024) pointed out that continuous learning techniques allows machine learning models to adapt and develop over time in response to changing threat landscapes. Khan et al. (2020) examined the use of continuous learning for detecting encrypted malicious files, demonstrating the model's ability to incorporate new information and adapt its detection capabilities dynamically.

## Conclusion

Machine learning techniques offer a promising approach to detecting encrypted malicious files, providing enhanced detection accuracy, adaptability, and scalability compared to traditional methods. By leveraging deep learning, transfer learning, ensemble methods, and other advanced techniques, cyber-security practitioners can improve their ability to identify and mitigate emerging cyber threats effectively. However, challenges such as data imbalance, privacy concerns, and adversarial attacks remain significant hurdles that require further research and innovation. As the cyber threat landscape continues to evolve, continued advancements in machine learning-based detection will be essential to stay ahead of adversaries and protect against sophisticated cyber-attacks.

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