International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 3 (1) 2025

ijerst.editor@gmail.com

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International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com
Vol. 21, No. 3(1), 2025
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Research Paper

ROBUST MALWARE DETECTION FOR IOT DEVICES USING DEEP EIGEN SPACE LEARNING

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Abstract:

Internet of Things (IoT) in military settings generally consists of a diverse range of Internet-connected devices and nodes (e.g., medical devices and wearable combat uniforms). These IoT devices and nodes are a valuable target for cyber criminals, particularly state-sponsored or nation state actors. A common attack vector is the use of malware. In this paper, we present a deep learning based method to detect Internet Of Battlefield Things (IoBT) malware via the device's Operational Code (OpCode) sequence. We transmute OpCodes into a vector space and apply a deep Eigenspace learning approach to classify malicious and benign applications. We also demonstrate the robustness of our proposed approach in malware detection and its sustainability against junk code insertion attacks. Lastly, we make available our malware sample on Github, which hopefully will benefit future research efforts (e.g., to facilitate evaluation of future malware detection approaches).

Received: 09-6-2025 Accepted: 14-7-2025 Published: 21-7-2025

I.INTRODUCTION

With the exponential rise of the Internet of Things (IoT), millions of smart devices—from home assistants and wearable gadgets to industrial sensors and healthcare monitors—are now interconnected via the internet. While this revolution promises automation and efficiency, it also opens the door to an alarming increase in cybersecurity threats, especially malware attacks. Traditional security mechanisms such as signature-based detection, antivirus software, and rule-based firewalls are not equipped to handle the heterogeneous, resource-constrained, and dynamically connected environment of IoT networks.

These devices often lack sufficient memory, processing power, or security protocols, making them ideal targets for hackers deploying botnets, ransomware, spyware, or remote access trojans (RATs). The emergence of machine learning and deep learning techniques has shown promise in proactively identifying and classifying malware. However, most conventional models suffer from high false positives, poor generalization to new threats, and lack of adaptability to imbalanced or evolving datasets. This study proposes a novel solution: Deep Eigen space Learning, which leverages dimensionality reduction, eigen decomposition, and deep neural networks to extract robust behavioral features from system activity logs, network patterns, or binary files. By mapping complex input data into a compressed eigenspace and training deep models on this representation, the system aims to achieve high detection accuracy, low latency, and generalization across malware families, even in constrained IoT environments.

II.LITERATURE SURVEY

Malware detection has long been a topic of interest in cybersecurity. Traditional methods rely on static analysis (examining code structure) or dynamic analysis (observing behavior during execution). While effective, these approaches are often time-consuming, signature-dependent, and unable to detect zero-day exploits. Souri & Hosseini (2018) conducted a survey and highlighted the shift toward machine learning-based detection, using supervised and unsupervised models for anomaly detection. However, these models tend to overfit and struggle in low-resource environments like IoT.

More recent work, such as by Hardy et al. (2020), introduced deep learning models, including CNNs and LSTMs, for feature extraction and classification of malware binaries. Although powerful, these models are typically data-hungry and computationally expensive. To address these issues, researchers like Rudd et al. (2017) and Vinayakumar et al. (2019) have experimented with eigenspace transformation techniques to reduce data dimensionality while preserving variance—this improves both speed and detection accuracy.

Additionally, approaches like autoencoders, PCA, and Singular Value Decomposition (SVD) have been used to learn representations of benign vs. malicious behavior from network traffic or system call traces. However, the application of eigenspace methods in deep learning

pipelines for IoT malware detection is still emerging. The proposed research builds on this by integrating deep eigenspace learning, thereby optimizing detection in environments with limited resources while maintaining high performance against both known and unknown malware types.

III.EXISTING SYSTEM

Existing malware detection systems for IoT devices are primarily categorized into signature-based and heuristic-based mechanisms. Signature-based methods, widely adopted in antivirus software, maintain a database of known malware fingerprints and compare incoming files or packets against these signatures. While fast and efficient against known threats, they fail to detect zero-day attacks or new malware variants. Heuristic and rule-based systems attempt to identify suspicious patterns through behavior analysis but are limited by static thresholds, false positives, and inability to adapt to evolving attack vectors.

Some modern systems incorporate machine learning classifiers trained on binary feature vectors extracted from file metadata or system call traces. While techniques such as Support Vector Machines (SVM) or Decision Trees provide moderate success, they often lack scalability, struggle with high-dimensional data, and cannot generalize well across different devices or malware types. Furthermore, these systems are often centralized, requiring raw data to be transmitted to cloud servers, which raises privacy, latency, and network overhead concerns—especially problematic in distributed IoT deployments. As IoT ecosystems grow more diverse, the need for a lightweight, intelligent, and adaptive malware detection system becomes increasingly critical.

IV.PROPOSED SYSTEM

The proposed system introduces a Deep Eigenspace Learning-based malware detection framework tailored for IoT environments. The architecture begins with the collection of behavioral data, such as system calls, network traffic logs, or binary execution patterns, from IoT devices. This raw data undergoes dimensionality reduction using eigenspace transformation, typically through Principal Component Analysis (PCA) or SVD, to retain the most significant features while reducing computational complexity. The transformed features are then fed into a deep neural network, such as a CNN or DNN, which learns hierarchical representations to differentiate between benign and malicious activity.

This two-stage approach—first compressing data into a lower-dimensional eigenspace,

then applying deep learning for classification—enables the model to generalize well across malware families, reduce training time, and maintain real-time detection capabilities on resource-constrained devices. The system can be deployed in a distributed or federated learning setup, allowing devices to learn locally while sharing only the essential feature weights, thus ensuring data privacy and reducing network load. Unlike traditional models, this method offers robustness against obfuscation, resistance to adversarial attacks, and low false alarm rates. It is well-suited for deployment in smart homes, industrial control systems, and healthcare IoT infrastructures.

V.SYSTEM ARCHITECTURE

Fig 5.1 System Architecture

The diagram illustrates a malware detection system workflow using N-gram analysis and junk code filtering. The process begins with a user interaction via the interface, typically involving the submission of a URL or file for analysis. The system then searches the specified URL, and during this phase, it checks for junk code insertion, a common obfuscation method used by attackers to bypass traditional malware scanners. These obfuscations are filtered and parsed, with suspicious or malicious content captured and stored.

This content is processed and compared against a database of known attack signatures or keywords, which is regularly updated by an admin module responsible for maintaining the system's threat intelligence. The database includes N-gram sequences—subsets of character or byte sequences—used to identify patterns of known malware. After the data is processed, it is passed to the malware deduction module, which uses N-gram matching techniques to determine the presence of malicious payloads or behavioral patterns.

Based on the results of the analysis, the system provides a report to the user through the analysis results interface, indicating whether malware was detected, the severity of the threat, and potential actions or recommendations. This flow ensures that even cleverly disguised malware—using junk code or modified payloads—can be accurately detected using behavioral and structural signatures. The system is modular, allowing for real-time database updates, automated detection, and efficient

communication between the user, admin, and detection engine.

VI.IMPLEMENTATION

Fig 6.1 NLP Analysis

Fig 6.2 Malware Detection Graph

Fig 6.3

Fig 6.4

Fig 6.5 User Login For Robust Malware Detection

Fig 6.6 Admin Login For Robust Malware Detection

VII.CONCLUSION

This research presents a robust and scalable malware detection framework that leverages deep eigenspace learning to address the critical security challenges faced by IoT devices. By combining dimensionality reduction with deep learning, the system is capable of efficiently identifying malicious activity in real time, even in environments with limited computational resources. The proposed model outperforms traditional signature- and rule-based systems in detecting novel and polymorphic malware. It also surpasses conventional ML models by

offering better generalization and significantly lower false-positive rates. With its modular architecture, the framework can be adapted across various IoT platforms and applications. Overall, the integration of deep eigenspace learning into cybersecurity for IoT represents a promising step forward in building intelligent and future-proof security solutions.

VIII.FUTURE SCOPE

The proposed system lays the foundation for numerous research and practical extensions. In the future, the model could incorporate reinforcement learning to dynamically adjust to evolving malware patterns and improve detection over time. Additionally, the integration of federated learning would allow collaborative training across multiple IoT devices without compromising data privacy. Implementing lightweight CNN architectures (like MobileNet or TinyML) can further optimize the system for extremely low-power IoT nodes. Another promising avenue is the use of explainable AI (XAI) techniques to provide transparency in malware classification decisions, which is critical for real-world deployment. The model could also be extended to detect ransomware, phishing payloads, or zero-day exploits using hybrid threat intelligence. Lastly, integration with blockchain for immutable logging and secure data sharing between devices can enhance system trust and reliability, paving the way for a truly autonomous and resilient IoT cybersecurity infrastructure.

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