MALWARE DETECTION BASED ON DEEP LEARNING AND BEHAVIOR GRAPHS

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Abstract

Malware is one of the most frequent cyberattacks, with its prevalence growing daily across the network. Malware traffic is always asymmetrical compared to benign traffic, which is always symmetrical. Fortunately, a variety of artificial intelligence approaches are available for identifying malware and differentiating it from everyday operations. The goal of this paper is to develop a reliable and effective malware detection system for computer networks. Traditional signature-based malware detection techniques are not sufficient to detect the increasingly sophisticated and polymorphic malware threats. The proposed deep learning-based behavior graph approach aims to address this problem by analyzing malware's behavioral patterns rather than relying on specific signatures. The paper uses graph neural networks to model the behavior of malware. The model learns the characteristics of malware by analyzing the behavior graphs of legitimate and malicious software. The behavior graphs represent the system calls and API functions used by the software, which the model uses to detect malicious activities.

Keywords: Deep Learning, Malware detection, Behavioral graphs, Malware, Benign.

1. Introduction

One of the biggest security risks on the Internet right now is malware. In fact, most Internet problems such as spam e-mails and denial of service attacks have malware as their underlying cause. The aim is to develop a system where the data-driven deep learning process involves CNNs looking at and learning from the raw bytes of Windows Portable Executable (PE) files. PE files are used for executables (.EXE,
.SCR) and dynamic link libraries (.DLL) in Windows-based systems.

The purpose of malware analysis is usually to provide the information you need to respond to a network intrusion. Your goals will typically be to determine exactly what happened, and to ensure that you've located all infected machines and files. There are two types of analysis for malware detection: dynamic analysis and static analysis, both of which have the primary goal of detecting malware in the system.For effective and efficient detection, the uses of feature extraction are recommended for malware detection.

A large number of malware variants have been automatically generated per day. Recent Symantec report shows that new pieces of malware grew by 36 percent from the year before in 2015 with total samples exceeding 430 million. Exponential growth of malware caused a considerable threat in our daily life.

Traditional computers bring a lot of attacks in IoT environment. Malware attacks computers and uses the infected computers to attack other connected devices in IoT environment. For example, Trojan.Mirai.1 which is the variant of Mirai can infect windows hosts and utilize these hosts to infect other devices. The infected windows can steal confidential information and transform the influenced devices into a botnet to launch a new Distributed Denial of Service (DDoS) attack. Many current traditional computers' malware attacks may also extend to other IoT devices. Unfortunately, there are no ideal solutions to avoid Mirai and other IoT threats. One approach aims to weaken these threats by protecting the security of traditional computers in IoT environment.

The fast-growing samples bring a large number of demands for malware detection in IoT environment . With so many sophisticated malware samples, plenty of researches havebeen concentrated on proposing miscellaneous malware detection methods to mitigate the rapid growth of malware. Malware detection can be divided into two main methods: static malware detection and dynamic malware detection . Static malware detection also refers to signature-based malware detection which examines the content of malicious binary without actually executing malware samples. Signature-based malware detection is able to obtain full execution path. However, it can be easily evaded by obfuscation techniques. In addition, signature-based malwaredetection requires prior knowledge of malware samples.

In response to the limitation of signature-based malware detection, various dynamic malware detection methods have been put forward . Dynamic malware detection analyzes the sample behaviors during execution and generally called behavior-based malware detection. Behavior-based malware detection methods include virtual machine and function call monitoring, information flow tracking, and dynamic binary instrumentation. Windows Application Programming Interface (API) call graph-based method has been considered as a good prospect in behavior-based malware detection for a long time .

Machine learning algorithms such as Decision Tree (DT), K-Nearest Neighbor (KNN), Naïve Bayes (NB), and Support Vector Machine (SVM) are commonly used in malware detection . The traditional machine learning algorithms can potentially learn the behavior features from the malware. Unfortunately, most machine learning algorithms' performance depends on the accuracy of the extracted features. In addition, it is often difficult to extract meaningful behavior features for improving malware detection performance. Moreover, feature processing requires expertise. Therefore, traditional machine learning algorithms are still somewhat unsatisfying for malware detection.

Deep learning is a branch of machine learning that attempts to learn high-level features directly from the original data. In short, deep learning advocates the end-to-end solutiondirectly. It completely eliminates the whole process of large and challenging project phase. Deep learning is efficient to study high-level features of samples by means of multilayer deep architecture, and it has been widely used in image processing, visual recognition, object detection, etc. .

This paper introduces a method to protect IoT devices from being attacked by local computers. In this paper, we build a behavior-based deep learning framework (BDLF) which takes full advantage of Stacked AutoEncoders (SAEs) and traditional machine learning algorithms for malware detection. SAEs is one of the deep learning models that consists of multiple layers of sparse AutoEncoders. We use SAEs model extracts high-level features from behavior graphs and then do classification by the added classifiers (i.e., DT, KNN, NB, and SVM). DT, KNN, NB, and SVM combine with the SAEs model, called SAE-DT, SAE-KNN, SAE-NB, and SAE-SVM, respectively. The proposed BDLF is implemented in cloud platform.

In short, the main contributes are as follows:

(1) In this paper, we construct a novel behavior-based deep learning framework called BDLF by combing SAEs model with behavior graphs of API calls for malware detection. The proposed BDLF aims to obtain deeper semantics in behavior graphs rather than previous API call sequences (e.g., n-gram).

(2) In the proposed BDLF, we investigate a deep learning model of SAEs to automatically acquire high-level representations of malware behaviors. Our experiment results demonstrate that our method can extract more meaningful abstract features and help to improve the average precision in malware detection.

The remainder of this paper is organized as follows. Section 2 introduces related work. Section 3 describes the proposed behavior-based deep learning framework. The evaluation and experiment results are presented in Section 4, which is followed by the conclusion and future work in Section.

2. Literature Survey

With more and more malware attacks and smart devices' connection in IoT environment, security is not a separate event . It is necessary to detect local computers' attacks for weakening the threats to other smart devices in IoT environment.
Malware detection proves an effective way for preventing IoT threats. Jiawei et al. present a method for detecting malware in IoT environment . They first convert the extracted binaries into images and then use the convolutionalNeural Network (CNN) to detect malware. The experiment demonstrated that their method obtains a good performance in malware detection.

Pa et al. analyze the IoT devices and identify four malware families in IoT environment. They propose an IoT honeypot and sandbox for analyzing attacks.

Malware samples usually achieve their intentions by performing malicious actions on operating system resources. In, the proposed behavior model captures the interactions between malware and operating system resources which consist of file, registry, process, and network.

Sanjeev et al. observe the actions that are correlated with file system, process, network, and memory.

Behavior-based malware detection has witnessed a shift towards API calls . The pattern of API calls provides an excellent expression which helps to "understand malware samples better." API calls provide efficient information about the runtime activities of a malware sample. Wu et al. transform API calls into regular expressions and then use these rules to detect malware when a similar regular expression appeared.

Taejin et al. convert API calls into the formatted codes and group the API data using an n-gram. Pratiksha et al. recognize malware by using API calls and their frequencies.

Sanjeev et al. propose a frequency-centricmodel for feature construction by employing API calls and OS resources of malware and benign samples.

Remarkably, deep learning is being applied for malware feature extraction and detection in recent years.

Wenyi et al. propose a deep learning architecture with the input rests on a sequence of API call events and null-terminated objects.

Bojan et al. use the Convolutional and Recurrent Network to analyze API call sequences in malware classification. Razvan et al.

Explore a few variants of Echo State Networks (ESNs) and Recurrent Neural Networks (RNNs) to predict next API call. Omid E. et al. extract unigrams (1-gram) API call and create an invariant compact representation of the malware behavior by using a Deep Belief Network (DBN).

Wookhyunet al. present a deep Recurrent Neural Network (RNN) to deal with the sequence of API calls. William et al. design a deep learning architecture using SAEs model. The proposed architecture is based on the API calls extracted from the Portable Executable (PE) files.

Previous works have shown that different strategies can be used to build the patterns of API calls. However, the methods using API calls and their frequencies or API call fragments are limited. Ammar Ahmed E. et al. demonstrate that combined API calls and their parameters raise the malware detection accuracy rather than considered API calls separately.

In their study, each malware is represented as an API call graph by integrating API calls and operating system resources. They first extract API calls and their parameters through preprocessing and then use the proposed API call construction algorithm to build integrating API call graph. Atlast, they calculate the similarity between different graphs to identify the input sample.

Different from the previous works, the proposed BDLF is a combined approach using behavior graphs of API calls and SAEs model. Our approach aims to capture the high-level malicious behaviors for improving malware detection in IoT environment.

Existing Systems:

Malware detection is a critical aspect of cybersecurity, and deep learning techniques have shown promising results in this field. Several existing systems utilize deep learning for malware detection, each with its unique approach and methodology.

One notable system is DeepMalware, which combines convolutional neural networks (CNNs) and recurrent neural networks (RNNs). DeepMalware extracts features from binary files and leverages the power of CNNs to capture spatial relationships in the data. RNNs are then employed to model the temporal dependencies, enabling the system to detect malware with high accuracy. DeepMalware's ability to analyze both static and dynamic aspects of malware samples contributes to its effectiveness in detecting known and unknown threats.

Another system, MalConv, takes a different approach by directly operating on raw binary data. It utilizes a convolutional neural network to learn patterns from the byte- level representation of malware samples. This eliminates the need for manual feature engineering and enables MalConv todetect malware efficiently. The system has demonstrated promising results in detecting both known and unknown malware, showcasing its effectiveness in handling new and emerging threats.

For the detection of Android malware, DroidDet offers a specialized solution. DroidDet employs recurrent neural networks (RNNs) to analyze sequences of system call API invocations in Android applications. By learning the patternsand behaviors of malicious code, DroidDet achieves high accuracy in detecting Android-specific malware. Its focus onthe unique characteristics of Android applications makes it avaluable tool in protecting mobile devices.

System log files can also provide valuable information for malware detection. DeepLogAnalyzer is a deep learning-based system designed to analyze system log sequences. By utilizing recurrent neural networks (RNNs), DeepLogAnalyzer captures the temporal dependencies in log data and identifies patterns associated with malicious activities. This system proves effective in detecting previously unseen or zero-day attacks by detecting anomalous behavior within the log sequences.

DeepDetector takes a comprehensive approach by combining static and dynamic analysis techniques. It employs both convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to analyze the static features of binary filesand the dynamic behavior of malware samples. By considering multiple aspects of malware, DeepDetector achieves high detection rates while maintaining low false positive rates.

These existing systems represent a range of approaches to malware detection using deep learning. Each system has demonstrated its effectiveness in different scenarios and contributes to the growing body of research in this field.

Researchers continue to explore and develop novel techniques, making deep learning an exciting area for furtheradvancements in malware detection.

2.1 Proposed System:

Here's a proposed system for malware detection using deep learning:

Data Collection: Collect a large dataset of malware samples and benign programs. The dataset should be diverse and representative of the types of malware that are commonlyencountered in the wild.

Feature Extraction: Extract features from the malware samples and benign programs. Features caninclude opcode sequences, API calls, file header information, and other static and dynamic features.

Preprocessing: Preprocess the features to normalize the data and remove anynoise or irrelevant information.

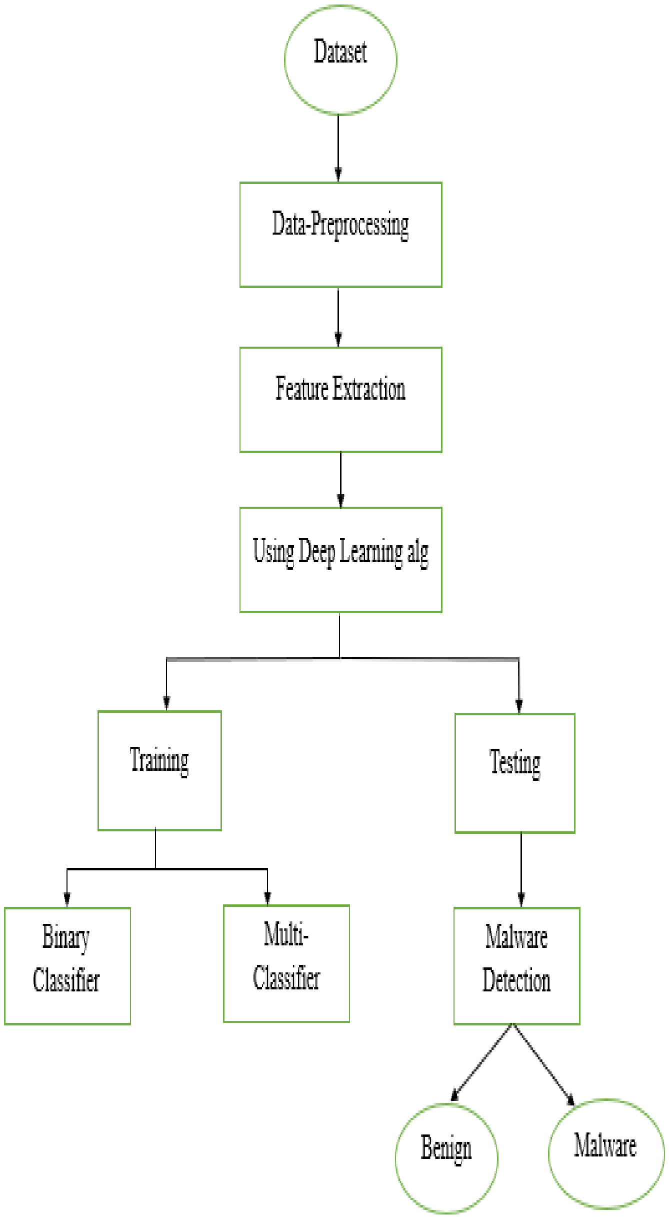
Model Selection: Select a deeplearning model architecture that is suitable for the task of malware detection. Examples of suitable architectures includeconvolutional neural networks (CNNs), long short-term memory (LSTM) networks, and autoencoders.

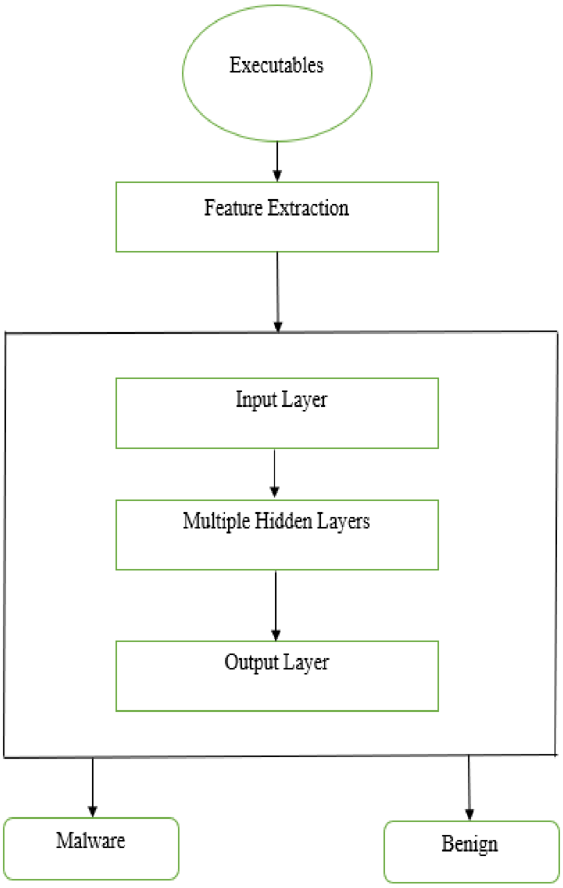
Model Training: Train the selected deep learning model using the preprocessed data. The model should be trained on both malware and benign samples to prevent overfitting and improve its ability to generalize to new, previously unseen malware samples.

Model Evaluation: Evaluate the performance of the trained model on a validation dataset. Performance metrics can include accuracy, precision, recall, and F1 score.

Deployment: Deploy the trained model in a production environment to detect malware in realtime. The model can be integrated into existing security systems or usedas a standalone malware detection system.

Continuous Improvement: Continuously monitor the performance of the deployed model and update it as new malware samples are encountered. This can involve retraining the model on new data or fine-tuning the model's parameters to improve its performance.





There are a number of measures that are frequently used to gauge the efficiency of malware detection systems. The following list of vital malware detection performance indicators:

The percentage of genuine malware samples that the detection system successfully identifies is measured by the metric known as the detection rate (also known as the true positive rate or recall). It shows how effectively the system can identify harmful files or code. A high detection rate indicates that more malware is being found on average.

False Positive Rate: This indicator calculates the percentage of legitimate files that the detection system mistakenly classifies as malicious. False positives can interfere with routine operations and trigger pointless actions like blocking genuine files or sending pointless notifications. To prevent false alarms, the false positive rate must be kept to a minimum.

Accuracy: Accuracy is a measure of how well the detecting system is working overall. It calculates what percentage of all samples (malware and benign) were successfully classified. Although accuracy is a crucial statistic, it can be affected by datasets that are unbalanced and have a disproportionately large number of benign samples compared to malicious samples. As a result, it is crucial to take into account additional parameters in addition to accuracy.

Precision measures the percentage of malware samples that were accurately recognized out of all samples that were considered to be malware. It shows how careful the system is to not mistakenly label safe files as malicious. Low false positive rates are indicative of great precision.

F1 Score: The harmonic mean of precision and recall (detection rate) is known as the F1 score. It offers a fair assessment that considers both false positives and false negatives. When there is an imbalance between malicious and benign samples in the collection, the F1 score is helpful.

Receiver Operating Characteristic (ROC) Curve: At various threshold values, the ROC curve shows the true positive rate (detection rate) versus the false positive rate. It enables the choice of an acceptable threshold based on the desired balance between the two and aids in visualising the trade-off between genuine positives and false positives.

Area Under the Curve (AUC): The AUC provides a single value that sums up the detection system's entire performance. It sums up the ROC curve, with better performance being indicated by a higher AUC. AUC can be used to compare different detection methods or gauge how well a system performs at various thresholds.

To fully comprehend the success of a malware detection system, it is crucial to take all performance parameters into account collectively. Some metrics may be more important than others, depending on the requirements and goals of the system.

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In conclusion, a deep learning-based system for malware detection can be highly effective at detecting both known and previously unseen malware threats. By leveraging the power of deep learning techniques, this system can improve the accuracy and speed of malware detection, hence enhancing the security ofcomputer systems and networks.

3. Results and Discussions:

Collect the dataset of files to be analyzed, including both benign and malicious files. This dataset should be properly labeled, with the malicious files identified as such. The dataset may also need to be preprocessed to extract features that can be used by the deep learning model. Next Extract meaningful features from the datasetthat can be used by the deep learning model. This may include static features such as file size and entropy, or dynamic features such as system calls and APIcalls.Train the deep learning model using the preprocessed dataset of labeled files. This involves feeding the model input data and adjusting its parametersto minimize the difference between the model's output and the actual labels.Evaluate the performance of the deep learning model using various metrics such as accuracy, precision, recall, and F1 score. The model may need to be finetuned or optimized based on the evaluation results.

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[Text(0, 0, 'Benign'), Text(1, 0, 'Malware')]
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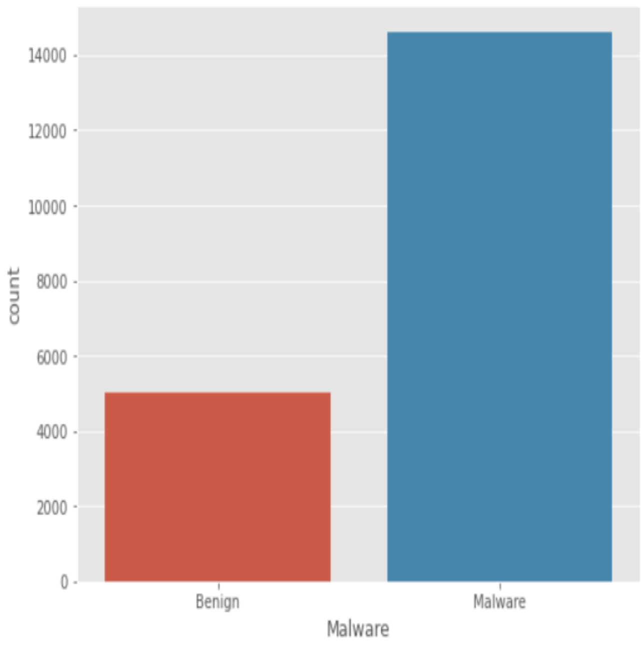

Figure-1

Figure 1 shows amount of malware and benign in our files. Scan with antivirus software,Use reputable antivirus software to scan the file or software in question. Antivirus programs employ signature-based detection and heuristic analysis to identify known malware or suspicious behavior. If the antivirus flags the file as malware, it is likely malicious.

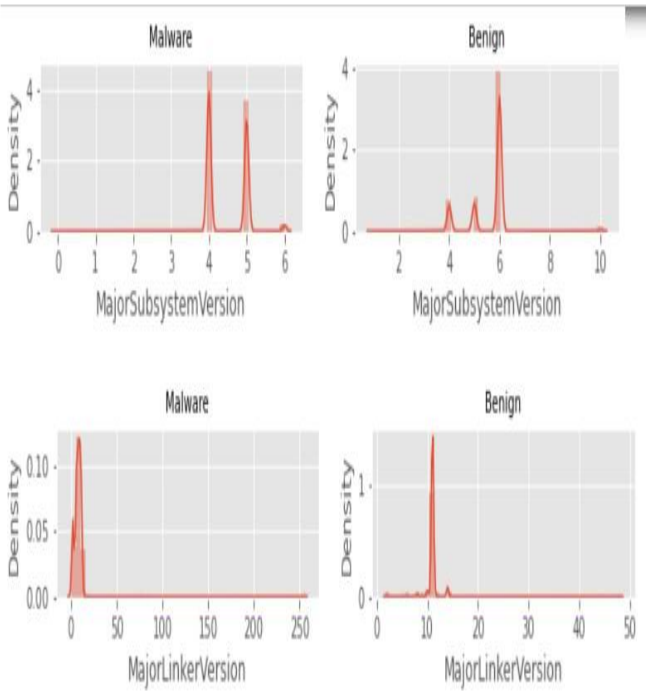

Figure-2

The Figure-2 shows the major subsystem version which means it tells the system version and over come the overfitting phenomena occur in between two layer and reduces the presence of the noise data.

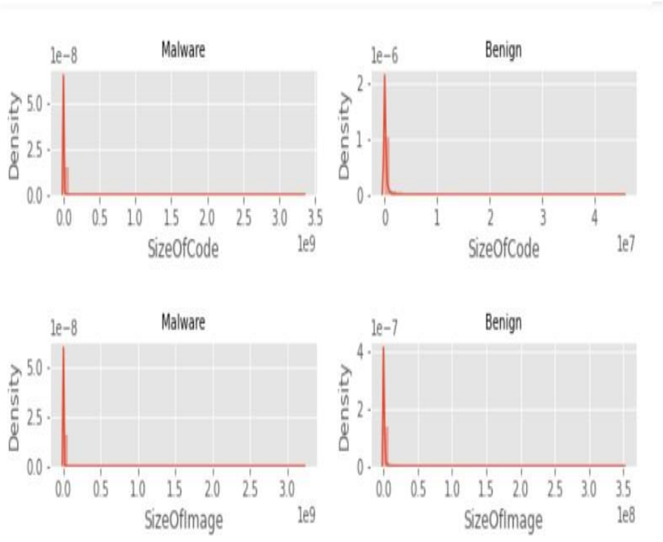

Figure-3

In the Figure-3 the shows the size of the image of the lower graph and the upper two graph shows the size of the code which on the x-axis and the y-axis shows the density of the model. It over the overfitting between the data and gives theproper results.

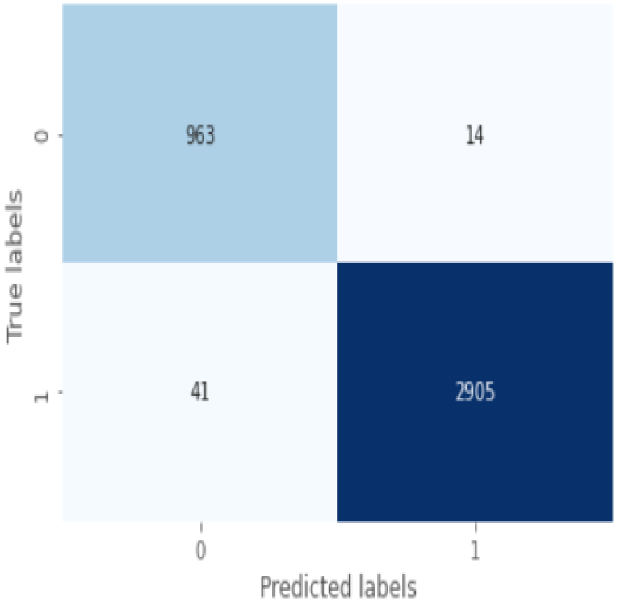

Figure-4

The Figure-4 shows the heat map detection can also be used toprovide insights into the areas of the image that the model maybe struggling with, enabling users to fine-tune the model and improve its accuracy even further.

4. Conclusion

In conclusion, malware detection using deep learning has emerged as a promising approach in the field of cybersecurity. The existing systems discussed in this context demonstrate the potential of deep learning techniques in effectively detecting malware and mitigating security risks.

Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have proven to be powerful tools for analyzing binary files, system call API invocations, and log sequences. These models can capture intricate patterns and dependencies within malware samples, enabling accurate and timely detection.

The systems reviewed, such as DeepMalware, MalConv, DroidDet, DeepLogAnalyzer, and DeepDetector, showcase different strategies and methodologies for malware detection. Some systems focus on the static features of binary files, while others leverage dynamic behavior analysis.

Each system addresses specific challenges, such as detecting unknown threats, analyzing Android malware, or identifying anomalousbehavior.

By combining deep learning techniques with advanced feature extraction and modeling, these systems have achieved significant improvements over traditional signature-based approaches. They provide more robust defenses against known and emerging malware threats, reducing the risk of cyberattacks and protecting systems and data.

It is significant to remember that deep learning-based malware detection is an area that is constantly changing. The performance and effectiveness of these systems are being improved by ongoing research, which also aims to address new problems including adversarial attacks and widespread malware campaigns.

Overall, the evaluated existing systems show the promise of deep learning for malware detection. They lay the groundwork for future developments in the industry and provide insightful information on the use of deep learning methods to enhance cybersecurity. Deep learning-based malware detection technologies are positioned to play a crucial role in protecting digital environments from unwanted activity as the threat landscape continues to change.

One area of focus is the development of more robust andresilient models that can handle adversarial attacks. Adversarial attacks involve intentionally manipulating malware samples to evade detection by deep learning models. Research efforts should aim to develop models thatcan effectively detect and defend against such attacks, ensuring the reliability and integrity of malware detection systems.

Another important avenue for future work is the exploration of multi-modal deep learning approaches. This involves incorporating multiple sources of information, such as file attributes, network traffic, and system logs, into a unified deep learning framework. By leveraging the complementary strengths of various data modalities, multi-modal models have the potential to enhance detection accuracy and providea more comprehensive understanding of malware behavior.

Additionally, there is a need for continuous research and development in addressing the challenge of detecting unknown or zero-day malware. Deep learning models that can effectively generalize and detect previously unseen malware samples are essential to stay ahead of rapidly evolving threats. Techniques such as transfer learning, unsupervised learning, and anomaly detection can be explored to improve the detection capabilities of deep learning-based malware detection systems.

The scalability and efficiency of deep learning models for large-scale malware detection is another area for future exploration. As the volume of malware samples continues to increase, there is a need for models that can handle big data efficiently without compromising on detection accuracy. Techniques such as model compression, distributed learning, and hardware acceleration can be investigated to address these scalability challenges.

Furthermore, the interpretability and explainability of deep learning models in the context of malware detection are crucial for building trust and understanding in their decision-making process. Future research should focus on developing methodologies and tools to interpret the decisions of deep learning models, enabling security analysts to understand the rationale behind malware detection outcomes and facilitating further investigation and response.

Lastly, collaboration and data sharing within the research community are vital for future advancements in malware detection using deep learning. Establishing standardized datasets, benchmarks, and evaluation metrics will allow researchers to compare and benchmark their models effectively, fostering innovation and facilitating the development of more robust and accurate malware detection systems.

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