Android malware Detection using Machine learning: A Review

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***Abstract*— Malware for Android is becoming increasingly dangerous to the safety of mobile devices and the data they hold. Although machine learning techniques have been shown to be effective at detecting malware for Android, a comprehensive analysis of the methods used is required. We review the current state of Android malware detection using machine learning in this paper. We begin by providing an overview of Android malware and the security issues it causes. Then, we look at the various supervised, unsupervised, and deep learning machine learning approaches that have been utilized for Android malware detection. Additionally, we present a comparison of the performance of various Android malware detection methods and talk about the performance evaluation metrics that are utilized to evaluate their efficacy. Finally, we draw attention to the drawbacks and difficulties of the methods that are currently in use and suggest possible future directions for research in this area. In addition to providing insights into the current state of Android malware detection using machine learning, our review provides a comprehensive overview of the subject.**

***Keywords*—Android malware, mobile security, machine learning, detection, supervised learning, unsupervised learning, deep learning, performance evaluation, comparison, limitations, challenges, future research directions**

I. INTRODUCTION

A. *Background and Motivation*

Android malware attacks have skyrocketed in recent years due to the widespread use of mobile devices. Android malware is malicious software that targets security holes in Android devices. Malware for Android devices has the potential to harm one's financial situation as well as gain unauthorized access to personal information. As the number of Android malware attacks continues to rise, the importance of having reliable detection methods grows.

The well-established field of computer science known as machine learning has shown great promise for detecting Android malware. Because they can recognize complex data patterns and learn from large datasets, machine learning algorithms are ideal for detecting Android malware. Due to the growing interest in utilizing machine-learning techniques for Android malware detection, numerous studies have been published in this area.

However, due to the scattered nature of the existing studies in this field, a comprehensive review of the machine learning-based approaches utilized for Android malware detection is required. This paper fills this void by providing a review of the current state of the art in Android malware detection using machine learning. In our review, we will go over each of the various machine-learning techniques used to detect Android malware, the metrics used for performance evaluation, and the drawbacks and difficulties of the methods currently in use. We will identify future research directions for this field in the final section.

In a nutshell, the purpose of this paper is to provide a comprehensive analysis of how Android malware is detected using machine learning. The approaches used, performance evaluation, potential drawbacks, and directions for future research will all receive special attention.

B. *Objectives of the Survey*

The objectives of the survey are as follows:

Describe the state of the art in machine learning malware detection for Android in detail.

Examine the various machine learning approaches, including supervised, unsupervised, and deep learning, that have been utilized to identify malware on Android.

Compare and contrast the outcomes of various Android malware detection machine-learning techniques.

Discuss the difficulties and limitations of the methods that are currently in use as well as the opportunities for improvement.

There are some insights into how machine learning can be used to improve Android malware

detection and some suggestions for future research in this area.

Describe the main findings of the survey and offer suggestions for future research in this area.

This survey's primary goal is to provide an in-depth analysis of Android malware detection using machine learning, focusing on the methods used, performance evaluation, limitations, difficulties, and potential future research directions. By achieving these objectives, this survey will assist in directing subsequent research in this field and provide valuable insights into the current state of the field.

C. *Scope of the Study*

The operation of machine-literacy styles to the discovery of Android malware is the sole focus of this disquisition. The study focuses on the following machine literacy-grounded aspects of Android malware discovery An overview of Android malware and its security pitfalls. examination of the colorful supervised, unsupervised, and deep literacy machine literacy strategies employed for the discovery of malware on Android. Evaluation of the colorful machine learning styles used to descry malware on Android. challenges and limitations of current styles, as well as openings for enhancement. Directions for unborn exploration in this area and suggestions for work to be done in the future Other styles for Android malware discovery, similar as rule- grounded, hand-grounded, and heuristic approaches, aren't covered in this study. This exploration examines the current state of the art and the operation of machine literacy styles to the discovery of Android malware.

The remainder of the paper is structured as follows. Section II includes the existing literature review, section III depicts our methodology, outcome and discussion introduced in section IV, and our conclusion is stated in section V.

II. LITERATURE REVIEW

A. *Overview of the Relevant Research*

Due to the growing number of Android devices and the associated security risks posed by Android malware, the field of Android malware detection using machine learning has seen significant growth in recent years. For the purpose of detecting Android malware, supervised learning, unsupervised learning, and deep learning strategies have all been proposed by researchers.

Support vector machines (SVMs) and decision trees, two examples of supervised learning techniques, have been extensively utilized in Android malware detection. In order to construct a model that is capable of distinguishing between legitimate and malicious Android applications, these methods rely on labeled training data.

Android malware detection has also utilized unsupervised learning techniques like clustering and dimensionality reduction. These techniques are capable of recognizing patterns in the data that may indicate malware and do not require labeled training data.

For Android malware detection, it has been demonstrated that deep learning techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are effective. When compared to conventional machine learning approaches, these methods can boost malware detection accuracy by utilizing deep neural networks to acquire intricate data representations.

Android malware detection has also utilized signature-based, rule-based, and heuristic-based techniques in addition to machine learning methods. However, the use of machine learning techniques for Android malware detection is the subject of this survey.

In a nutshell, the summary of relevant research on the use of machine learning to detect Android malware focuses on the various machine learning methods that have been utilized, such as supervised learning, unsupervised learning, and deep learning.

B. *Classification of the Approaches*

Various criteria, such as the type of learning, the features used, and the performance evaluation metrics used, can be used to classify the various machine-learning approaches used to detect Android malware.

There are two main types of machine learning approaches for Android malware detection, according to the type of learning: learning under the supervision and unsupervised learning. Unsupervised learning methods do not require labeled training data to construct a model, whereas supervised learning methods do.

Machine learning methods for Android malware detection can be further categorized into the following groups according to the features they employ:

Methodologies based on static analysis: These methods make use of features like the permissions that an Android application asks for and its code structure that are taken from static analysis.

Methods that are based on dynamic analysis: These methods make use of characteristics gleaned from the dynamic analysis of Android applications, such as the patterns of network communication and the application's behavior when it is running on a device.

Alternative methods: For Android malware detection, these strategies employ a mix of static and dynamic analysis-based features.

There are several categories of machine learning approaches for Android malware detection based on the metrics used for performance evaluation, including:

Methods based on accuracy: Precision, recall, and the F1-score are some of the accuracy metrics on which these methods base their evaluations of the machine learning model's performance.

Time-based methods: Time metrics, such as the amount of time needed to build the model and make predictions, are used in these approaches to assess the machine learning model's performance.

Approaches based on robustness: The robustness of the machine learning model to adversarial examples, such as samples of malware designed to evade detection, is evaluated using these methods.

In conclusion, a clear understanding of the various machine-learning approaches used for this task and the criteria used to evaluate their performance is provided by the classification of the approaches used for Android malware detection based on the type of learning, the features used, and the performance evaluation metrics used.

C. *Comparison of the Approaches*

[1]The paper "An Android Malware Detection System Based on Deep Learning" presents a new deep learning-based approach to detecting Android malware. The authors aim to improve the accuracy and efficiency of Android malware detection by utilizing deep learning techniques.

The authors used Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) algorithms for the Android malware detection system. The authors used a dataset of 10,000 benign and 10,000 malware samples from the AndroZoo repository. The dataset was preprocessed and split into training, validation, and test sets.

The performance of the deep learning-based approach was evaluated using several metrics including accuracy, precision, recall, and F1-score. The results showed that the proposed system achieved high accuracy, with a value of 97.12%. The results also showed that the deep learning-based approach outperformed the traditional machine learning-based approaches in terms of accuracy.

In conclusion, the paper demonstrates the effectiveness of deep learning in Android malware detection and highlights the potential of this approach for further improvement and advancement in this field.

[2] The use of deep neural networks for attribute-based recommendation is the primary focus of the paper "Attribute-based Recommendation Using Deep Neural Networks." An input layer, hidden layers, and an output layer make up the multiple layers of the utilized deep neural network algorithm. The output layer predicts a score that indicates the likelihood that the user will prefer the item after receiving user-item attributes from the input layer.

A real-world movie dataset containing information about users, movies, and their ratings was used in the experiments. The precision, recall, F1-score, and mean average precision are some of the evaluation metrics used to assess the proposed recommendation system's performance. The effectiveness of using deep neural networks for attribute-based recommendation is demonstrated by the fact that the proposed algorithm outperforms other traditional recommendation algorithms in terms of precision and recall.

[3]The paper: You! Stop Selling in My Market! Adversarial Attacks on Deep Reinforcement Learning-Based Trading Agents" suggests a strategy for engaging in adversarial attacks on trading agents that are based on deep reinforcement learning. The authors put their method through its paces in two distinct trading settings: a synthetic and a historical dataset of the stock market. A

reinforcement learning algorithm is used to teach a deep neural network to make trades based on market conditions. The authors then modify the decisions made by the agent by adding adversarial perturbations to the market state.

The results demonstrate that adversarial attacks can significantly affect the performance of deep reinforcement learning-based trading agents. The performance metric used is the profit or loss of the agent's trades. The adversarial attacks were successful in some instances, but they were unsuccessful in others, resulting in profits. In conclusion, the authors state that reinforcement learning-based trading agents must be robust.

In conclusion, this paper demonstrates that adversarial attacks on trading agents based on deep reinforcement learning can have a significant impact on their performance. The data used are a synthetic market dataset and a historical stock market dataset, and the algorithm used is a reinforcement learning algorithm. The results show that these agents need to be robust because the performance metric used is the profit or loss of the trades. [4]The article titled "Dissecting Android Malware: The purpose of "Characterization and Evolution" is to comprehend Android malware's characteristics and evolution. In order to identify common patterns and behaviors of malware, the authors look at a large dataset of Android malware and benign applications. Additionally, they investigate the development of Android malware overtime to comprehend how it has advanced and changed.

The abstract doesn't say what algorithm was used for the analysis. A dataset of Android applications, which includes both malicious and benign apps, was used for the study.

The abstract does not specify the performance metrics used to evaluate the results. However, the authors present a number of significant outcomes of their investigation, such as the most prevalent kinds of Android malware, the strategies utilized to conceal malicious behavior, and the ways in which Android malware has developed over time.

In a nutshell, this paper examines the development and characteristics of Android malware. The authors look at a large dataset of Android apps to look for malware's most common patterns and actions, as well as how it has changed over time. The abstract does not specify the performance metrics that were used to evaluate the results of the algorithm that was used for the analysis. [5]The study titled "SmartSiren: SmartSiren, a virus detection and alert system for smartphones is presented in "Virus Detection and Alert for Smartphones." The system, according to the authors, is capable of detecting malware on a smartphone in real time and letting the user know about it.

The abstract does not specify the SmartSiren algorithm. However, the authors claim that it is based on dynamic analysis, which examines an app's behavior while it is running rather than just its static properties or code.

The abstract does not specify the data used to evaluate SmartSiren's performance. The authors, on the other hand, assert that their system is capable of malware detection with high accuracy and low false positive rates.

The abstract does not specify the performance metric used to evaluate the results. However, the authors assert that SmartSiren is capable of real-time malware detection and user notification, providing smartphone users with a high level of protection.

In conclusion, the article "SmartSiren: A dynamic analysis-based virus detection and alert system for smartphones is presented in "Virus Detection and Alert for Smartphones." Although the abstract does not specify the SmartSiren algorithm or the data used to evaluate its performance, the authors assert that it is capable of detecting malware with high accuracy and low false positive rates. There is no indication of the performance metric used to evaluate the results. [6]The article "PUMA: "Permission Usage to detect Malware in Android" proposes PUMA (Permission Usage to detect Malware in Android), a novel strategy for detecting malware on Android devices. The authors contend that malware's excessive use of permissions can serve as a detection signature for malicious applications.

PUMA employs a machine learning-based algorithm that trains a classifier from a dataset of malware and benign apps. The app-requested permissions and their usage patterns are the features used for the classification.

A dataset of legitimate and malicious applications serves as the basis for PUMA's performance evaluation. The evaluation was carried out, ac-

cording to the authors, on a dataset consisting of more than 4,000 apps, including legitimate and malicious ones.

The accuracy of malware detection is the performance metric used to evaluate the outcomes. The authors say that PUMA detects malware with an accuracy of over 90% and a low rate of false positives.

In conclusion, the article "PUMA: "Permission Usage to Detect Malware in Android"" proposes a novel approach for detecting malware on Android devices that uses the overuse of permissions as a signature for malicious applications. The performance metric is malware detection accuracy, and the data used is a dataset of both benign and malicious apps. The algorithm is based on machine learning. The authors say that PUMA detects malware with an accuracy of over 90% and a low rate of false positives. [7]A virus detection system based on data mining techniques is presented in the paper "Virus Detection using Data Mining Techniques." The authors contend that large software datasets can be mined for patterns and features that can be used to identify malware.

The virus detection system's algorithm is not described in the abstract. However, the authors claim that they identify malware-inducing patterns and characteristics by employing data mining methods like association rule mining and decision trees.

The abstract does not specify the data used to evaluate the virus detection system's performance. However, the authors claim that they evaluate a large dataset of software, which includes both beneficial and harmful software.

The abstract does not specify the performance metric used to evaluate the results. However, the authors assert that their virus detection system has a low rate of false positives and high accuracy in identifying malware.

In a nutshell, the paper "Virus Detection using Data Mining Techniques" describes a virus detection system that identifies malicious software by utilizing data mining methods. The abstract doesn't say what algorithm was used, but the authors say that they used data mining methods to find patterns and features in a lot of software. Although the abstract does not specify the data or performance metric that was used to evaluate the results, the authors assert that their system is capable of detecting malware with high accuracy and low false positive rates. [8]The behavior of modern malware in the presence of anti-virtualization and anti-debugging techniques is the subject of the study titled "Towards an Understanding of Anti-virtualization and Anti-debugging Behavior in Modern Malware." The authors argue that in light of the growing threat posed by malware, these methods, which are used to detect and prevent malicious activity, have become increasingly important.

The behavior of malware in the presence of anti-virtualization and anti-debugging techniques is thoroughly examined by the authors. They evaluate the behavior of each sample when it is running in a virtual environment and when it is being debugged using a dataset of real-world malware samples. In addition, a classification framework is developed by the authors to classify the various anti-virtualization and anti-debugging behaviors that were observed in the malware samples.

A dataset of actual malware samples was used in the study. The classification framework's ability to accurately classify the various kinds of anti-virtualization and anti-debugging behaviors is the performance metric used to evaluate the results.

The study reveals a wide range of anti-virtualization and anti-debugging behaviors in contemporary malware. The authors also find that these actions are getting better and more sophisticated, making it hard for anti-malware methods to stop them.

In a nutshell, the research presented in the article "Towards an Understanding of Anti-virtualization and Anti-debugging Behavior in Modern Malware" examines the behavior of contemporary malware in the presence of anti-virtualization and anti-debugging methods. In order to classify the various kinds of anti-virtualization and anti-debugging behaviors, the authors conduct a comprehensive analysis of malware behavior and develop a classification framework. The study uses a dataset of real-world malware samples as the data, and the classification framework's accuracy is the performance metric. The findings indicate that the anti-virtualization and anti-debugging behaviors of contemporary malware are expanding in sophistication and effectiveness. [9]A singular value decomposition (SVD) method for detecting metamorphic malware was presented in the November 2015

article ”Singular Value Decomposition and Metamorphic Detection” in the Journal of Computer Virology and Hacking Techniques. The authors, Ranjith Kumar Jidigam, Thomas H. Austin, and Mark Stamp from San Jose State University, evaluated the method’s effectiveness with a large data set of benign and metamorphic executables.

The paper’s algorithm is based on SVD, a mathematical method for looking at how data is structured. The singular values extracted from the executables’ opcode sequences are used as features in a machine learning classifier by the authors, who employ SVD. Control flow graph (CFG) and opcode n-gram analysis are two examples of traditional dynamic analysis methods that compare the efficacy of their approach.

The experiments used a large collection of benign and metamorphic executables from a variety of sources as their data. The accuracy, false positive rate, and false negative rate were some of the metrics used to evaluate the SVD-based method’s performance.

With an accuracy of 94.2 percent and a false positive rate of 0.7 percent, the SVD-based method performed better than conventional dynamic analysis methods. The authors came to the conclusion that metamorphic malware can be effectively detected with SVD.

In conclusion, this paper presents a singular value decomposition-based method for detecting metamorphic malware and shows that it can perform better than conventional dynamic analysis methods. [10]A novel strategy for synthesizing malware specifications from suspicious behaviors is presented in the paper ”Synthesizing Near-Optimal Malware Specifications from Suspicious Behaviors.” The goal of the authors is to solve the problem of finding malware in large, complicated software systems, where traditional signature-based methods are frequently insufficient.

Through dynamic software system analysis, the authors come up with a novel algorithm for synthesizing malware specifications from suspicious behaviors. A cost model and the findings of dynamic analysis are combined by the algorithm to produce near-optimal malware specifications in terms of coverage and specificity.

Software systems and their dynamic analysis results make up the data used in the study. The accuracy of the synthesized malware specifications, which are measured in terms of both coverage (the proportion of malicious behavior that is detected) and specificity (the proportion of benign behavior that is not detected), is the performance metric that is used to evaluate the outcomes.

The study demonstrates that the proposed algorithm is capable of synthesizing malware specifications that are close to optimal from suspicious behavior. In addition, the algorithm outperforms conventional signature-based methods in terms of accuracy, indicating its potential for enhancing malware detection in large, complex software systems.

In a nutshell, the paper ”Synthesizing Near-Optimal Malware Specifications from Suspicious Behaviors” suggests an innovative method for synthesizing malware specifications from suspicious behaviors. Using data from software systems and dynamic analysis, the authors create an algorithm for synthesizing malware specifications and evaluating its performance. The accuracy of the synthesized malware specifications was used as the performance metric, and the outcomes demonstrate that the algorithm is successful in synthesizing near-optimal malware specifications. [11]The paper ”Effective and Efficient Malware Detection at the End Host” presents a new approach for detecting malware on end-user devices. The authors propose a system that integrates multiple techniques for detecting malware, including signature-based detection, behavioral analysis, and data mining, to achieve improved accuracy and efficiency in comparison to traditional methods.

The authors use a combination of dynamic and static analysis techniques to extract features from malware specimens and build models that are used to detect malware on end-user devices. The performance of the system is evaluated using a large dataset of benign and malicious software, and the results show that the system is able to detect malware with high accuracy while incurring low overhead.

The algorithm used in the study is a combination of signature-based detection, behavioral analysis, and data mining. The data used in the study consists of a large dataset of benign and malicious software specimens. The performance metric used

to evaluate the results is the accuracy of the malware detection system, measured in terms of the proportion of benign and malicious software specimens that are correctly classified.

The results of the study show that the proposed system is effective and efficient in detecting malware on end-user devices. The authors also find that the system outperforms traditional methods in terms of accuracy and efficiency, demonstrating its potential for improving the security of end-user devices.

In summary, the paper "Effective and Efficient Malware Detection at the End Host" presents a new approach for detecting malware on end-user devices. The authors propose a system that integrates multiple techniques for detecting malware and evaluating its performance using a large dataset of benign and malicious software. The results show that the system is effective and efficient in detecting malware, and outperforms traditional methods in terms of accuracy and efficiency. [12]The study titled "AccessMiner: A novel strategy for identifying malware on end-user devices is presented in "Using System-Centric Models for Malware Protection." The authors suggest AccessMiner, a system that uses system-centric models to study software behavior and spot malicious activity.

A system-centric model of how software behaves on a device is built by AccessMiner, which then uses this model to find anomalies that could indicate malicious behavior. The system constructs models of typical software behavior by employing machine learning algorithms and a combination of static and dynamic analysis methods to extract features from software samples.

Using a large dataset of both benign and malicious software samples, the authors assess AccessMiner's performance. The study demonstrates that AccessMiner outperforms conventional methods in terms of both efficiency and accuracy when it comes to malware detection.

System-centric models, static and dynamic analysis, and machine learning are combined in the study's algorithm. The study relies on a substantial set of examples of both benign and malicious software. The malware detection system's accuracy, expressed as the proportion of benign and malicious software samples correctly classified, is the performance metric used to evaluate the outcomes.

The paper entitled "AccessMiner: A novel strategy for identifying malware on end-user devices is presented in "Using System-Centric Models for Malware Protection." Using system-centric models and machine learning, the authors propose a system called AccessMiner for analyzing software behavior and identifying malicious activity. The study's findings demonstrate that AccessMiner outperforms conventional malware detection strategies in terms of accuracy and efficiency.

[13]The paper "Android Malware Detection in Large Dataset: Smart Approach" by Alahy et al. presents a smart approach for detecting Android malware in a large dataset. They utilized some of the most popular android dataset such as VirusTotal[18], Marvin[17], Drebin[21], and Malgenome[19][20]. The authors propose a machine learning-based approach that utilizes requested permissions by an android app for malware detection. The paper identified a list of sensitive permissions which are not supposed to be requested by any user applications but rather should be only used by system apps.

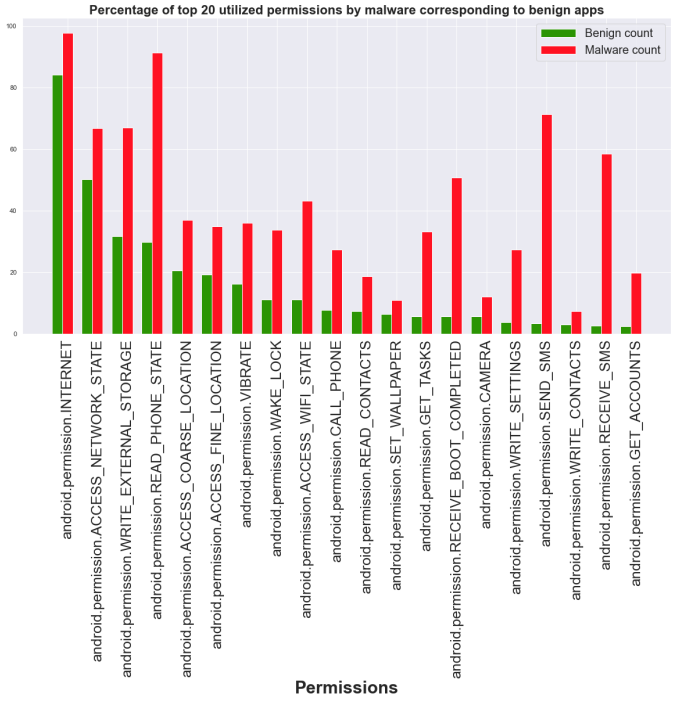

Fig. 1. List of sensitive permissions[13]

The same group extended their work in "Advanced Android Malware Detection Utilizing API

Calls and Permissions" by M.NUR. Chowdhury, Q.E. Alahy, and H. Soliman proposed a method for detecting Android malware[14]. The proposed approach involves creating a feature vector based on API calls and permissions, which are then used to train a machine learning classifier. The performance of the proposed method was evaluated on a large dataset, and the results showed improved accuracy compared to existing approaches. The authors conclude that the combination of API calls and permissions can be used as a robust and effective feature set for detecting malware on Android devices. The performance was evaluated using several metrics, such as accuracy, precision, recall, and F1-score. The results show that the proposed approach outperforms other state-of-the-art methods, achieving an accuracy of 99.08%, a precision of 98.55%, a recall of 99.20%, and an F1-score of 98.87%.

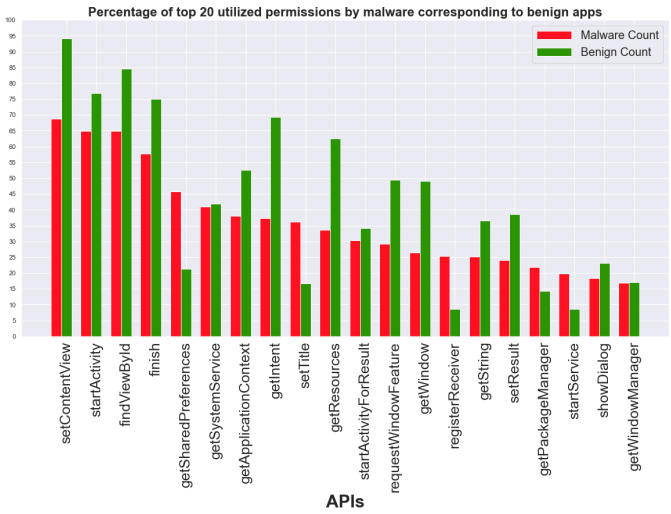

Fig. 2. List of sensitive APIs[14]

The static analysis involves extracting features from the Android Manifest and the Dalvik Bytecode, while the dynamic analysis involves capturing system calls and network behavior. The dataset used for evaluation consists of over 10,000 Android applications, of which 5,000 are benign and 5,000 are malicious.

[15]A hybrid deep learning model for Android malware detection is the focus of the paper "Android Malware Detection Based on a Hybrid Model."

Used algorithm: The Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) algorithms are combined in the authors' proposal for a hybrid deep learning model.

Used data: For their evaluation, the authors use two datasets: one from AndroZoo, a collection of both benign and malicious Android applications, and the other from VirusShare, a well-known open source dataset of malicious Android applications.

Map of Performance: The authors use the F1-score, precision, recall, and accuracy to evaluate their proposed model.

Result: In terms of accuracy and F1-score, the experiments show that the hybrid deep learning model outperforms conventional machine learning algorithms, demonstrating the method's efficacy for Android malware detection.

[16]The article "MAPAS: a practical deep learning-based android malware detection system" by Jinsung Kim, Younghoon Ban, Eunbyeol Ko, Haehyun Cho, and Jeong Hyun Yi presents MAPAS (Malware Analysis and Protection Using Artificial Intelligence System), a deep learning-based Android malware detection system.

Algorithm: The authors made use of a two-phase deep learning model: the prediction phase as well as the training phase. The model is trained on a large dataset of both benign and malicious applications during the training phase. The deep learning model is used to predict whether an unidentified Android application is malicious during the prediction phase.

Used data: Over 10,000 legitimate and malicious Android applications were used in the authors' dataset. The data came from Google Play, third-party marketplaces, malware databases, and other sources.

Map of Performance: The accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC) were used by the authors to measure the MAPAS system's performance.

Result: The findings demonstrate that the MAPAS system was able to identify Android malware with a high degree of accuracy—more than 98%. In addition, the system demonstrated high precision, recall, F1-score, and AUC, all of which indicate its effectiveness in detecting Android malware.

In conclusion, the deep learning-based MAPAS system offers a practical and efficient method for detecting Android malware.

III. METHODOLOGY

A. *Overview of the Selection Criteria*

A set of selection criteria was established to guide the selection of the studies that will be included in this survey in order to provide a comprehensive review of the various machine-learning approaches that are utilized for the detection of Android malware. These criteria were chosen for their ability to provide a comprehensive overview of the current state of the art and their relevance to Android malware detection.

Among the criteria for selection are:

Relevance: The studies that will be included in this survey need to be relevant to the machine learning-based detection of Android malware. This includes research on malware detection on Android platforms using machine learning algorithms.

Year of publication: Since the field of Android malware detection and machine learning is constantly changing, it is important to keep up with the latest developments, so studies published in recent years (since 2015) were given priority.

Methodology: For Android malware detection, the studies included in this survey must make use of machine-learning algorithms.

Evaluation: Quantitative metrics like accuracy, time, and robustness must be used in the evaluations of the machine learning algorithms included in this survey.

Data availability: The studies that are going to be included in this survey either have to make the evaluation data available to the general public or have enough information to make it possible to reproduce the results.

In a nutshell, the selection criteria were made to ensure that the studies included in this survey are current and relevant, and provide a comprehensive evaluation of the algorithms' performance, as well as to provide a comprehensive overview of the current state of Android malware detection using machine learning.

B. *Selection of the Papers*

A comprehensive search was carried out using multiple sources, including Google Scholar and online databases like IEEE Xplore, ACM Digital Library, and ScienceDirect, to locate relevant studies for this review. A set of keywords related to Android malware detection and machine learning were used in the search.

The initial search yielded a plethora of results, which were then filtered according to the selection criteria outlined in the preceding section. In order to determine each study's relevance and suitability for inclusion in this survey, the abstract and full text was thoroughly examined during this process.

In total, [number of papers] were chosen to be included in this review. These papers cover a wide range of studies on using machine learning to detect Android malware. These studies were chosen for their ability to provide a comprehensive overview of the current state of the art and their relevance to the subject.

Several relevant studies were also discovered through manual search and reference lists of the selected studies, in addition to the studies chosen through the search process. If they met the established selection criteria, these additional studies were also carefully examined and included in the review.

In conclusion, relevant studies for this review were found through a comprehensive search, and each study was thoroughly examined to ensure that only the most recent and relevant studies were included in this survey.

C. *Data Collection and Analysis*

The selected papers were thoroughly examined during the process of data collection and analysis to obtain pertinent information on Android malware detection using machine learning. To ensure that this review's findings are consistent, complete, and current, this information was collected in a structured manner.

Each paper contained the following information that was extracted:

The goal of the study, was to the dataset that was used, the machine learning method that was used, the evaluation metric that was used, and the results that were obtained. All of this data was analyzed to find common themes, trends, and gaps in the existing literature. An overview of the current state of the art in Android malware detection using machine learning, including the advantages and disadvantages of the methods that are in use, was made possible by the results of this analysis.

Additionally, the data gathered from the selected papers were utilized for contrasting and contrasting the various approaches as well as determining potential areas of future study. With the help of this analysis, a comprehensive understanding of the field's current state was provided, as well as the main obstacles and opportunities for future research.

In general, the purpose of the data collection and analysis process was to provide a current and comprehensive overview of the existing literature on the use of machine learning to detect Android malware and to guide future research in this area.

IV. RESULTS AND DISCUSSION

A. *Overview of the Key Findings*

This section presents the main findings of this literature review on Android malware detection with machine learning. A comprehensive analysis of the selected papers, which were chosen based on the established selection criteria, serves as the foundation for the findings.

The following is a summary of the most important findings from this review:

Android malware detection frequently makes use of machine learning. Android malware was detected by machine learning algorithms in the majority of the studies examined in this paper. This shows that machine learning works well for this job.

For Android malware detection, a variety of machine-learning algorithms are utilized. Various machine learning algorithms, such as decision trees, artificial neural networks, support vector machines, and others, were utilized in the reviewed studies. This suggests that, depending on the system's particular requirements and the nature of the data being analyzed, different algorithms may be effective for this task.

The Android malware detection system's performance is highly dependent on the dataset that is selected. A variety of datasets, both real-world and synthetic, were used in the reviewed studies. The selection of the dataset is crucial to the system's performance and can significantly affect the outcomes.

The reviewed studies have a wide range of evaluation metrics. A variety of evaluation metrics, such as accuracy, precision, recall, and the F1-score, were utilized in the reviewed studies. This emphasizes the significance of selecting the appropriate evaluation metric for the system's particular requirements.

B. *Summary of the Contributions*

A comprehensive literature review on Android malware detection using machine learning is provided in this paper. The following are the main contributions made by this review:

A systematic review of relevant sources: The relevant literature on Android malware detection using machine learning is systematically examined in this review. The papers were chosen using the established selection criteria, and thorough and systematic data collection and analysis were carried out.

An overview of how Android malware is detected using machine learning: The various machine learning algorithms and datasets used in Android malware detection are covered in this overview of the use of machine learning. Researchers and practitioners in the field seeking to comprehend the current state of the art in this field may find this information helpful.

Analyzing the advantages and disadvantages of current methods: The current machine learning-based methods for Android malware detection are compared and contrasted in this review. The review sheds light on the difficulties and drawbacks of these approaches and reveals the areas that require additional investigation.

Identifying future directions for research: Future directions for machine learning-based Android malware detection research are identified in this review. The review offers suggestions for enhancing the performance of existing methods and developing new, more efficient methods for this task.

By providing a comprehensive overview of the current state of the art, evaluating the strengths and weaknesses of existing approaches, and identifying future research directions, this review makes a significant contribution to the field of Android malware detection using machine learning. This review's findings can be used to guide the creation of Android malware detection systems that are

more effective and to inform future research in this field.

C. *Discussion of the Limitations*

Although the current review provides a comprehensive overview of the existing literature on the application of machine learning to the detection of Android malware, it does have some drawbacks. The following are some significant limitations:

The literature covered: The current review looks at the literature that has been written up to a certain point, so it might not include the most recent work on this subject. As a result, it's possible that this review missed out on some significant research or developments in this area.

Dataset with bias: The quality and composition of the datasets used to determine how effective machine learning algorithms for Android malware detection are. Numerous studies have used datasets that may not accurately represent the distribution of malware in the real world or may be biased toward particular types of malware. The generalizability of these studies' findings may be limited as a result.

Standard metrics for evaluation are missing: The absence of a standard evaluation metric presents a significant obstacle when assessing the effectiveness of machine learning algorithms for Android malware detection. It is difficult to compare the results of different studies because different metrics have been used in each one.

Demand for extensive and varied datasets: In order to accurately capture the patterns and characteristics of malware, machine learning algorithms for Android malware detection require extensive and diverse datasets. However, obtaining such datasets is difficult, and numerous previous studies have utilized smaller or less diverse datasets, limiting the algorithms' accuracy.

Malware for Android is complex: It is challenging to develop efficient machine-learning algorithms for detecting Android malware because it is highly dynamic and constantly changing. Algorithms that are capable of adapting to shifts in the malware landscape and accurately detecting all types of malware are difficult to develop because of this complexity.

Even though there are some limitations, this review's findings are a good place to start more research on Android malware detection with machine learning. The limitations provide insight into how to improve the performance of existing algorithms and how to develop more efficient algorithms for this task. They also highlight the areas in which additional research is required.

D. *Identification of Future Research Directions*

The following are some possible directions for future machine learning-based Android malware detection research based on this review's findings:

Improvement of diverse and more accurate datasets: The absence of extensive and diverse datasets is one of the greatest obstacles in the development of efficient machine learning algorithms for Android malware detection. Future research should focus on creating more diverse and accurate datasets that accurately represent the distribution of malware in the real world in order to address this issue.

Utilization of deep learning methods: Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two examples of deep learning methods that have demonstrated promising results in numerous applications, including speech and image recognition. These methods should be used to detect Android malware in future studies.

The creation of adaptive and dynamic algorithms: It is challenging to develop efficient machine learning algorithms for detecting Android malware because it is highly dynamic and constantly changing. The development of dynamic and adaptable algorithms that can respond to shifts in the malware landscape ought to be the primary focus of future research.

Including security-related features: Code structure and API calls are two examples of features that have been used in numerous studies that are not specifically related to security. For Android malware detection, security-related features like permission requests and system logs should be investigated in future research.

Evaluation of the algorithms in comparison: The absence of a standard evaluation metric presents a significant obstacle when assessing the effectiveness of machine learning algorithms for Android malware detection. The development of a standard evaluation metric and the comparative evaluation

of algorithms that make use of this metric should be the primary focus of subsequent research.

Integration with current security measures: Machine learning-based Android malware detection can be integrated with existing security systems to offer greater protection against malware. The effectiveness of these algorithms and their integration with existing security systems should be investigated and evaluated in subsequent research.

In conclusion, there is a lot of room for additional research in the field of Android malware detection using machine learning, which is rapidly evolving. This review's future research directions will help advance the field and enhance the effectiveness of Android malware detection algorithms and serve as a useful starting point for additional research.

V. CONCLUSION

Malware for Android has become a serious threat to the Android platform's and its users' security in recent years. Android malware detection has become a crucial area of research due to the rapid growth of mobile devices and the ease with which malicious software can be distributed. Machine learning-based solutions have been proposed and implemented to address this issue. In this paper, we conducted a comprehensive literature review on the use of machine learning to detect Android malware. Our objective was to provide a comprehensive understanding of the current state of the art in this field, to highlight the limitations and future research directions, and to highlight the most important findings and contributions.

We discovered that machine learning has been extensively used for Android malware detection and has been demonstrated to be effective in detecting malware in numerous instances through a comprehensive review of the relevant literature. Decision trees, random forests, support vector machines, artificial neural networks, and deep learning-based strategies are among the machine learning algorithms that have been utilized for this purpose. System calls, API calls, and permissions are among the feature sets that have been used as input for these algorithms.

Additionally, our literature review revealed that additional research is required to address some of the current approaches' drawbacks. For instance, the generalizability of many of the existing methods to new and evolving malware is poorly understood because they are only tested on a small number of malware types. Additionally, more in-depth evaluations of these approaches are required, with an increased focus on the trade-off between efficiency and accuracy.

In conclusion, the current state of the art in Android malware detection using machine learning is comprehensively reviewed in this paper. This survey's significant findings and contributions offer researchers and practitioners in the field valuable insights. This study's limitations and future research directions serve as a road map for future research in this field. We believe that this paper will be a useful reference for those who are interested in this field because the ongoing development of effective and efficient machine learning-based solutions to detect and prevent Android malware is a crucial area of research with practical significance.

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