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Survey Paper

An Analysis of Machine Learning Solution for QoS and QoE in Network (Infrastructure Oriented and Less)

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***Abstract*: **Now, Communication network (Network may be a wired or wireless network. In wireless network it may be an infrastructure oriented or infrastructure less) plays vital role in the world. . At present without network people cannot do their work easily. Communication Network described as two or more device connecting together and share its resources. If a resource is accessed by more than one person. Network faces lot of issues in its Qualitative and Quantitative of Service. This paper is try to provide solution for infrastructure oriented and less network QoS (Quality of Service) and QoE (Quality of Experience) problems using AI and ML.

***Keywords*:** Communication Network, Wireless Network, QoS, QoE, AI, ML

1. Introduction

Communication Network is used to share resources among nodes (users). What are the things the device has itself is called resources. Like resource, device may be a computer, mobile, printer, router, etc. if we want to lay communication network between two devices, we need following factors.

- ***Device***
  The device can be called nodes. Nodes can be a computer, router, printer, etc. Those who share or use resources is called a device or node.
- ***Interface (NIC)***
  Link between device and the communication media is called interface. This interface is called Network Interface Card (NIC).
- ***Communication Media***
  Which is used to carry the data from one place to another place.
- ***Protocol***
  Set of rules and regulation is used to transfer resource between two open systems.

If we want to lay communication network with 'n' numbers of devices. It needs additional two factors which is listed below.

- ***Topology***
  It describe logical or physical arrangements of devices.
- ***Architecture***
  It describe communication format between devices.

Communication media may be wired or wireless. In wired network the physical path will be there between nodes. In wireless electromagnetic waves will be present between devices. Network device may connect with wired or wireless, with the device nature the communication network may called Homogenies or Heterogeneous.

If the communication network is created by the use of similar type of devices is called Homogenies network.
If the communication network is created by the use of dissimilar type of devices is called heterogeneous.
If the communication network uses existing things like cable, tower, etc. That type of network is called Infrastructure oriented networks. If the network does not utilize any existing infrastructure is called Infrastructure Less network or Ad-Hoc network.

The world cannot function without the above network. If we want reserve a train ticket we need any one of the network. It may be wired or wireless, Homogenies or Heterogeneous, and Infrastructure oriented or Less.

The world cannot function without the above network. Even reserve one train ticket, we need any one of the communication network. It may be wired or wireless, Homogenies or Heterogeneous, and Infrastructure oriented or Less.

Communication Network provide the facility to the People to do their work from their place itself. If more people may access the same network and single resource. Communication Network will face more Quality and Quantity issues.

The Quality of Service involve following Quantitative factors – Packet Delivery Ratio (PDR), End-to-End Time Delay, Over Head (OH), and Normalized Routing Load (NRL). The Quality of Service involve following Qualitative factors – Data Theft and Data Change that means authentication and security.

QoE is the end user's overall happiness or frustration with the network service experience is the litmus test for successful network performance. QoE looks at the impact of the network behaviour on the end user, a fuzzier domain where certain network imperfections go unnoticed but others may render an application essentially useless. QoE achieves its goal by looking at the information within the data sent over the network, not just the efficiency of data transport across the network itself. This level of quality control requires better network traffic analysis, with increased efficiencies and metadata collection algorithms that gather the key performance indicators while minimizing the amount of data that has to be stored. Advances in automation and artificial intelligence have made that attainable.
This paper try to find solutions for QoS and QoE issues using latest technology like AI and ML.

1.1 ML (Machine Learning)

Machine learning (ML) [1] is the study of computer algorithms that improve themselves over time. Artificial intelligence is seen as a subset of it. Machine learning algorithms create a mathematical model based on sample data, referred to as "training data," in order to make predictions or judgments without being explicitly programmed. Machine learning is a discipline that uses a variety of ways to train computers how to complete tasks for which no entirely suitable solution exists. In circumstances where a large number of people are involved.

Approaches to machine learning
Depending on the type of the "signal" or "feedback" available to the learning system, machine learning systems are generally categorised into three major categories:

- ***Supervised learning:*** A "teacher" presents the computer with sample inputs and desired outputs, with the purpose of learning a general rule that maps inputs to outputs.
- ***Unsupervised learning:*** The learning algorithm is given no labels and is left to find structure in its data on its own. Unsupervised learning can be a goal in and of itself (finding hidden patterns in data) or a means to an end (finding hidden patterns in data) (feature learning).
- ***Reinforcement learning:*** A computer programme interacts with a dynamic environment in order to accomplish a specific task (such as driving a vehicle or playing a game against an opponent). The software receives input in the form of incentives as it navigates its issue space, which it strives to maximise.

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2. Proposed Work

The goal of this research is try to find automated solution for QoS issues and QoE issues.
When QoS related issues occur in any type of network, before it before realizing it should be rectify. For that purpose this work analyze Machine Learning (ML) for solution. For example, when the PDR is decreases the proposed solution should be provide the solution. As well as, during transmission if the data is theft or data is changed then the proposed solution should be provide solution.
Some QoE assured services in the communication network should be provide to consumers. If the assured services failed to serve the consumers. it should be rectified by the proposed solution before it realize by the consumer.
This paper is try to find solution for QoS and QoE issues using Machine Learning unsupervised learning.

3. Literature Review

Raouf Boutaba *et. Al.* [2]: This work examine the above topics, as well as a number of additional obstacles and opportunities, in this poll. This findings highlight the need for additional study in order to progress the state-of-the-art and realise the long-awaited ambition of autonomic network.

Noman Haider *et. Al.* [3]: This article discusses AI-assisted technologies, scenarios, and applications for wireless network security in 5G and beyond. In 5G and beyond networks, extremely dynamic traffic patterns, service-based network architecture, distributed network operations, and authentication across several servers necessitate a security framework that is relatively strong, adaptable, and fully automated. This framework is based on cutting-edge AI technology. For distributed ad-hoc network architecture delivering various network tasks, AI can dramatically increase security. At present time, a semi-automated security framework is more appropriate; but, as AI technologies advance and feasibility studies of safe application of these technologies are conducted, the final aim of complete automation will be determined. Before AI can fully take over digital automation, further study is needed to address the obstacles and issues.

Rishabh Das, Thomas H. Morris [4] : In this work, an extensive survey was conducted to identify a few prominent datasets, after which a few machine learning methods and their applications in cyber-security were explored. Finally, a few suggestions were offered about which ML to use. A brief analysis was performed with an ICS data set in the later part of the paper, and the performance of a few ML algorithms was examined. Although the J48 algorithm outperforms other algorithms in the scope of the study, more research is needed to determine the performance of the algorithms because algorithm performance is skewed based on the dataset to which it is applied. Second, because of its ideal real-time performance in the current circumstance, Random forest might be a better choice as a fundamental IDS algorithm.

R. Devakunchari *et. Al*. [5]: This study provides a review of Machine Learning and DL unit approaches in the realm of network security. The literature study introduces the most recent uses of ML and DL units in the field of intrusion detection systems, with a focus on the last four years. Regrettably, the most effective intrusion detection methodology has yet to be found, and hence the investigation continues. Every method for creating an intrusion detection system has advantages and disadvantages, as evidenced by the comparisons made among the various methods. As a result, choosing one way to deploy an intrusion detection system over the others is difficult. Network intrusion detection datasets are valuable resources for training and testing systems. Machine Learning and Deep Learning methods don't work without representative data, yet obtaining such a dataset is difficult and time-consuming. However, there are a number of flaws with the already available public dataset, such as inconsistencies in information or out-of-date content, and so the issues are comparable. These problems have largely limited the scope of analysis in this explicit domain. The network information updates in real time, presenting ML and DL model coaches with a larger problem. The Model must be retrained fast and on a semi-permanent/long-term basis. As a result, long-term learning and progressive learning will be the emphasis of future research in this discipline.

4. Machine Learning Techniques

4.1. The Fundamentals of Machine Learning

Artificial intelligence (AI) is a branch of computer science concerned with the creation of new techniques, ideas, and applications. Early attempts to develop a simplified model based on how neurons in a biological system, such as an organic brain, activate other neurons resulted in Artificial Neural Networks (ANNs). Machine learning (ML) is an artificial intelligence sub-discipline. Machine learning algorithms build models using training data, allowing them to make predictions (or choices) about new data without being explicitly taught [6], [7]. (8), (8), (8), (8), (8), (8), Machine learning offers a wide range of applications. ML techniques are being utilised to improve cyber security and early detection of a variety of automated and emerging threats [10], [11], as well as phishing website detection [12], [13].

Machine learning can be classified into three types based on their approaches: supervised machine learning, unsupervised machine learning, and semi-supervised machine learning. In supervised machine learning, the required labels or classes for the data are already known, and those labels and classes are used to train for computations like classification and regression. In unsupervised machine learning, the target value is unknown. The goal of unsupervised learning is to discover links between data. It works by finding data patterns, such as clustering. When a portion of the data needs to be labelled or when human specialists are needed during the data collection process, semi-supervised machine learning is used. A human expert will surely assist in fixing the issue and boosting the model's accuracy throughout the labelling phase [14]. Reinforcement learning (RL) is a subdomain of machine learning. RL is also known as learning with a critic since the algorithms receive feedback when they make an inaccurate prediction. The algorithm, on the other hand, hasn't been told how to fix it. Instead, the algorithm must evaluate and test a wide range of possibilities until it finds the best one [15]. This phenomenon is based on a reward and punishment system. A well-known example of this method is AlphaGo [16], [17]. Deep reinforcement learning is used in cyber security by [18], [19], and [20].

4.2. A Most Popular Machine Learning Techniques

The approaches used in machine learning are described in this section. Table 1 summarises the time complexity, benefits, and drawbacks of ML models.

Support Vector Machine

Decision Tree
K-Nearest Neighbor
Random Forest
Naïve Bayes
Artificial Neural Network
Recurrent Neural Network
Convolutional Neural Networks
Deep Belief Network

Table 1. An overview of the most commonly used machine learning techniques.

Model	Year	Ref. No	Time Complexity	Description	Limitations
SVM	1995	52	$O(n^2)^1$	• Can be used for classification and regression. • Less overfitting	• Unable to handle large or noisier datasets efficiently. • High computational cost.
Naive Bayes	1960	53	$O(mn)^2$	• A probabilistic classifier that takes less computational time. • Assumes that a feature is entirely independent of all other present features.	• Assigns 0 probability if some category in the test data set is not present in the training data set. • Stores entire training examples • Need massive data to obtain good results.

Random Forest	1995	54	$O(Mm \log n)$[3]	• Composed of many DTs. • Every DT yields a prediction. • The prediction having a maximum number of votes will be the final prediction of the model.	• Computational cost is higher. • Slow prediction generator
ANN	2000	55	$O(emnk)$[4]	• Adaptive and composed of Interconnected Artificial Neurons. Next Layer input depends on Previous Layer • Output.	• High cost and time-consuming. • Black-box model hence shows no relation between input and output variable.
Decision Tree	1979	56	$O(mn^2)$[5]	• Works on an if-then rule to find the best immediate node. • Continue the process until the predicted class is obtained.	• Difficult to change the data without affecting the overall structure. Complex, expensive and time-consuming.
K-mean	1960	57	$O(kmni)$[6]	• Starts from random centroids refine centroids in iterations till the final cluster analysis.	• High dependency on initial centroids. Inefficient clustering for varying cluster sizes
DBN	2006	57	$O\left(m\Sigma_l^L(I_lJ_l)\right)$[7]	• Higher performance and efficiency is achieved because of the addition of the layers. • Better ability to handle noisy data. • Convenient identification of complex relationships between nodes. • Hidden layers are efficiently used.	• Higher hardware resources consumption. • Higher time consumption because of the addition of the layers. • Unable to provide an explanation for the decisions.
RNN	1982	58	-	• Efficiently models sequential data. • Quickly memorize the sequential events • Different various, i.e. LSTM is available.	• Difficult training of the network. • It may face short memory issues while modelling long sequences of data. • Vanishing Gradient and gradient exploding problems.
CNN	1988	59	$O(\sum_{l=1}^{d} n_{l-1} \cdot s_l^2 \cdot n_l \cdot m_l^2)$[8]	• Less number of neurons are needed in contrast with traditional NN. • Different variants, e.g. VGG, AlexNet, are available	• It requires more number of convolutional layers (CL). • A larger tagged dataset is necessary for working.

n=number of instances

[2] n=number of instances, m=number of attributes

[3] n=number of instances, m=number of attributes, M=number of trees

[4] n=number of instances, m=number of attributes, e=number of epochs, k=number of neurons

[5] n=number of instances, m=number of attributes

[6] n=number of instances, m=number of attributes, k=count of clusters, i=iteration count until the threshold is reached

[7] m=number of training samples, I=count of neurons in the input layer, J=count of neurons in the output layer, L=count of RBM models, l=RBM model

[8] l=index of CL, d=count of CLs, n_l= count of filters, s_l-length of filters, m_l=length of the output feature map, n_{l-1}=count of input channels on of l^{th} layer

5. Machine Learning for Network Security - Current State

Cyberattacks and online threats are said to be protected by network security. Only a few instances of network security include the detection and classification of dangerous URLs, financial fraud, spam classification, IDS, malicious domain creation, probing, cyber extortion, and malware. Furthermore, hackers are targeting mobile devices and networks in addition to computer networks as a result of the fast rise of mobile nodes and networks. There has never been a survey that focuses on any aspect of Machine Learning for Network Security assaults on both computer networks and mobile devices in one location, to our knowledge. Figure 10 depicts the important sectors of cyber security, as well as cyberspace attacks and a collection of key machine learning references that target that specific type of attack. Other aspects of cyberspace, such as network security, Internet security, and ICT security, overlap with cyber security.

It has focused on three major cyber security concerns (IDS detection and categorization, spam, and malware), all of which are aided by machine learning approaches. We've gone into greater detail about these risks to mobile devices and computer networks. Intrusion detection systems that can be employed on a computer network include signature-based/misuse-based, anomaly-based, and hybrid-based techniques. Intrusion subtypes are further classified into those that are employed on a computer network vs those that are used on a host. Image, email, SMS, video, and Twitter are all examples of media that can be used to refine spam detection. Malware is also looked into from a static and dynamic standpoint. Machine learning approaches have been utilized to combat several types of cyberattacks in the literature.

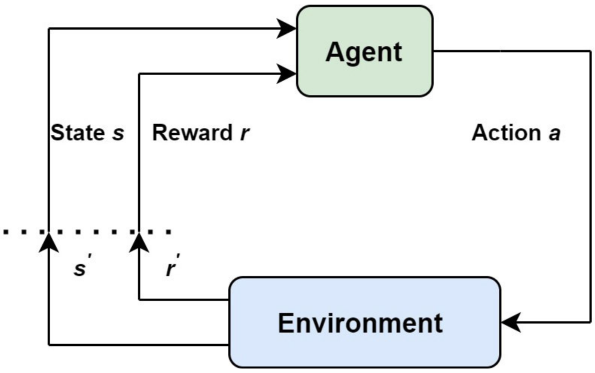


Figure 1. Reinforcement Learning.

Machine learning is one of the strategies for quickly responding to cyberattacks. Machine learning techniques are employed to address such concerns since learning approaches may learn from prior occurrences and respond swiftly to newer attacks. We've included a few links to stories about this form of intrusion. The subheadings below go through each cyber threat to the computer and mobile networks, as well as how cutting-edge machine learning techniques are being utilized to counteract them.

5.1. Computer Network Intrusion Detection

There are two types of cyber security threats in cyberspace: network-based and host-based. On both levels, a cyber defence system provides a defence mechanism. The network-based defence system is in charge of controlling network flow. A host-based defence system, on the other hand, uses a firewall and other protection mechanisms installed on the host to combat incoming data on a workstation/computer [85], [86]. As described in section II-A, the four fundamental types of attacks for instruction detection are Denial of Service (DoS), Phishing/Scanning/Probe, Remote to Local (R2L), and User to Root. (U2R). The crossover between machine learning models and intrusion detection attacks is summarised in the sections below.

5.1.1.DOS Attacks and ML

To detect DoS assaults, Decision Trees with a 97.24 percent accuracy [87], Neural Networks with a 97 percent accuracy [88], Nave Bayes with a 96.65 percent accuracy [87], and SVM with a 91.6 percent accuracy [89] were utilised.

5.1.2.Probe Attacks and ML

Nave Bayes, Fuzzy Association, Decision Tree, Neural Network, and SVM were used to detect probing attacks with accuracy of 88.83 percent, 88.50 percent, 77.92 percent, 71.63 percent, and 36.65 percent, respectively [87], [88], [90].

5.1.3. R2L Attacks and ML

On the KDD dataset, R2L attacks were detected using Neural Net, SVM, and Nave Bayes, with Neural Net achieving the greatest accuracy of 26.68 percent. [87]–[89].

5.1.4. U2R Attacks and ML

Fuzzy association, SVM, DT, and NB were used to identify User to Root assaults, with accuracy rates of 68.60 percent, 12 percent, 13.60 percent, and 11.84 percent, respectively.

5.1.5. HOST-BASED Attacks and ML

Machine learning techniques were used to detect attacks on host and computer networks. Machine learning technologies such as Rule-based, ANN, Fuzzy association rules, and various statistical methodologies were employed to detect misuse-based assaults on a host [91]–[95]. Statistical models, association rules, ANN, and KNN were used to identify anomalous 492-based detection methodologies on a host [96]–[98]. For the hybrid-based intrusion, ANN and association rules were applied over the host [99], [100].

5.1.5.1. Network-Based Attacks and ML

SVM and Decision Tree were used to identify misuse-based attacks on a network [101]–[106]. Random Forest and ANN were used to the network for hybrid-based intrusion detection [107], [108]. Teodoro [109] used machine learning and knowledge-based techniques for anomaly-based intrusion detection.

Machine learning (ML) methodologies for identifying Internet traffic for any cyber data and IP flows were presented by Nguyen [110]. For intrusion detection, others used Fuzzy Logic and Artificial Neural Networks (ANN) [111]. Case-based reasoning is a technique for solving new problems by referring to previously solved similar problems. The answer of previous problem situations is then employed as a starting point for tackling a current challenge [112].

Mansour [113] proposed a case-based reasoning technique for intrusion detection. Unsupervised and semi-supervised techniques such as clustering algorithms in [68], SVM in [114], and neural networks in [115] were employed to detect abnormalities in addition to supervised machine learning techniques. Others have detected irregularities in airports using deep learning models [116] and feature optimization approaches for intrusion detection systems [117].

5.1.6. Techniques (Tools)

For intrusion detection, there are a variety of tools existing on the market. Intrusion detection software is designed to deal with intrusions on either the host or the network. To detect an intrusion on a network, a Network Intrusion Detection System (NIDS) is utilised. A Host Intrusion Detection System (HIDS) is used to identify intrusions on a host based on signatures or anomalies. A number of free ID tools are available. Others, on the other hand, are pricey. Popular commercial ID tools include McAfee NSP [118], Hillstone NIPS [119], Huawei NIP [120], Palo Alto [121], Dark Trace [122], and Cisco Firepower NGIPS [123]. Snort [124], Suricata [125], Samhain [126], Security Onion [127], and Sagan [128] are all free tools. The use of tools is determined by the operating system, detection mechanism (HIDS, NIDS), and detection type (HIDS, NIDS) (anomaly-based, signature-based). Another technique for preventing and mitigating cyberattacks is the Trusted Automated eXchange of Intelligence Information (TAXII). Using Structured Threat Information eXpression (STIX), a language created to convey cyber threat information, TAXII outlines how services and messages interact to become a mechanism of sharing threat information [129].

5.2. Mobile Devices - Intrusion System

5.2.1.Framework

Mobile devices are capable of doing a wide range of complex activities. Every day, smart gadgets face an increasing number of attacks [130], [131]. In wired networks, networks now offer higher transmission speeds ranging from 100 Mbps to 10+ Gbps. IDS was unable to efficiently acquire and analyse network traffic due to the large volume of data. Snort, a Deep Packet Inspection (DPI), can handle data up to 1 Gbps on a wired network and discard after 1.5 Gbps [132]. Attacks on a mobile network can include replaying, traffic analysis, and spoofing [133].

5.2.2.Movement

ML techniques such as supervised ANN, Decision tree, MLP, and SVM are frequently used to detect an intrusion on a mobile network. Decision trees and deep learning algorithms outperformed all other classifiers. Machine learning techniques have evolved to offer new methods of intrusion detection as bandwidth has increased [134].

5.2.3. Approaches and Routine

The two main types of mobile network attacks are active and passive assaults on the network. An active assault is one in which data is modified and the normal functioning of a network is disrupted in order to obtain access and impair network performance. Passive assaults, on the other hand, do not disturb the network's usual flow but instead search it for any relevant information [135].

5.2.3.1. Anomalous Behaviors and ML

Bayes decision rules [136] used to improve the security of cellular networks. The authors of [137] employed supervised ANN to identify malicious performance on mobile communication, like service fraud. [138] used ANN and probabilistic models to identify use irregularities with a TPR of 69 percent. In [139]–[141], ANN is also utilised to detect anomalies in mobile network communication. The authors of [141] proposed the VirusMeter malware detection system and compared it to ANN and decision trees in order to discover unusual behaviours. Self-organizing maps and clustering algorithms were employed to detect abnormal behaviour, with the conclusion that both methods were adequate for network monitoring [142]. [143] compared the accuracy of detecting misuse-based behaviour of users on mobile devices using the BN, KNN, and Random Forest techniques.

On mobile devices, decision tree, KNN, MLP, and SVM were used to detect infiltration, with decision tree outperforming the others with an accuracy of 97.04 percent [144]. SVM was used to detect infiltration on a mobile network, and it performed similarly to a system that wasn't infected [145]. A 90.99 percent accurate deep learning solution for detecting cyberattacks has been proposed [146].

5.2.4. Techniques (Tools)

To safeguard the Android system, there are a variety of programmes accessible on the market. Some of them are free to use, while others with higher quality charge an annual fee. Bitdefender [147], Trend Micro [148], and BullGuard [149] are commercial programmes that charge an annual fee to secure the Android system. Sophos [150], Trustlook [151], and PSafe [152], on the other hand, are examples of ID software that are free to use but have restricted functionalities.

5.3. Computer Network - Malware Detection

Malware is divided into two groups: first, the first generation, and second, the second generation. Malware from the 1st generation has the similar structure. The second generation, on the other hand, modifies its structure and grows into a novel variation while maintaining the same activities [166]. Polymorphic, Metamorphic, Oligormorphic, and Encrypted malware are the second generation's additional classifications based on structure evolution. Malware structural changes are unpredictable and random [167].

5.3.1. Feature Selection and Ml

Feature selection improved accuracy when machine learning algorithms were used. Feature selection was employed by authors in [168], [169], and [171], who claimed that it enhanced malware detection accuracy. Kolter [172] analysed the datasets using a decision tree, TF-IDF, and support vector machine, with the decision tree outperforming the others. A decision tree was also used in conjunction with a hierarchical feature extraction approach in [169].

The AdaBoostM1 and decision tree classification algorithms were utilised by the authors of [173], who reported a 90 percent malware detection accuracy.
The authors of [174] requested that their hyper-grams method for malware identification produced no false alarms. In [175], the semi-supervised technique was found to be 86 percent accurate, whereas SVM [168] was shown to be 95.9% accurate. SVM was also used to detect malware in [176], [177]. The researcher of [178] proposed a new technique for detecting unknown malware that has a 97.95 percent accuracy. In [179], the authors introduced a different dataset named CA and Mal2017, which achieved an 87 percent recall for traffic classification detection and incorporated 80 features.

5.3.2. Zero-Day Malware and ML

An approach for identifying zero-day attacks was proposed by Pierra et al. [180]. Principal Component Analysis (PCA) and artificial neural networks (ANN) were planned to detect and categorise AI-based cyberattacks, with a precision of 90% [181]. In [182], DBN was used to detect malware. Other authors in [183] employed DBN with semi-supervised techniques to enhance accuracy.

5.3.3. Adversarial Inputs and ML

Adversarial malware samples can readily evade the machine learning methods used to identify malware. Because machine learning systems were not created with cyber security in mind, a dodge can readily deceive the ML [184–186]. Adversial training is being researched as a possible option.

5.3.4.Techniques (Tools)

Malware detection tools are available on the market in a variety of forms. However, selecting the appropriate instrument is crucial. Some tools are free to use, while others need an annual fee. The most popular anti-malware programme is Avast Internet Security [187], which accounts for 15.21% of the market [188]. Malwarebytes [189], Norton Power Eraser [190], AVG [191], and Bitdefender Antivirus [192] are also regularly used tools.

5.4. Mobile Devices -Malware Detection

There are three types of malware detection strategies for mobile devices: static, dynamic, and hybrid. Static detection is a method for spotting potentially hazardous patterns in a programme without running it. Dynamic detection, on the other hand, involves running the programme and observing its dynamic behavior [195]–[197]. Hybrid malware detection is a technology that combines static and dynamic analysis to detect malware. [198], [199].

5.4.1. Feature Selection and ML

Others [200] proposed a novel way for categorising related flow behaviours into bags, which was followed by a supervised detection method with a 90% precision. The authors of [201] employed SVM to train their model and predict future assaults using real-world attacks. Decision Tree, KNN, and SVM were used to achieve a 90% accuracy on the model represented by opcode-sequence-frequency [168]. Random Forest, SVM, Logistic Regression, and Nave Bays were used to identify malware, with Random Forest outperforming in terms of TPR/FPR [202].

5.4.2.Android and ML

Existing malware finding methods on Android performed excellently on pre-defined datasets, but they failed to reach a high detection rate in real-world settings. Using permission and API calls, SVM, J48, and Bagging were used to detect malware in Android-based applications, with bagging achieving 96.39 percent accuracy [203]. Another author [204], [205] used permission features and SVM to classify Android malware. The authors of [206] used information gain to establish the most important components. They employed the C4.5 Decision Tree, RIPPER (Repeated Incremental Pruning to Produce Error Reduction), and k-Nearest Neighbour techniques to categorise malware. HOSBAD is a K-NN-based Android malware detection system that can tell the difference between malicious and benign apps [207]. The Nave Bayes technique beat other classification models in detecting malware in [208]–[210].

5.4.3. Detection Techniques and ML Models

Various Android identification approaches for static and dynamic analysis were categorised and assessed by the authors of [211]–[213]. The authors of [214] identified the relevant features by doing static and dynamic analysis on the application, followed by 95 percent accuracy SVM. In [170], [215]–[221], SVM was also employed to detect malware.
If compared to other ML techniques, DeepFlow, a DBN-based deep learning model, was shown to identify Android malware and earned the highest F1 score [222]. The authors of [223] employed the K-mean technique to identify harmful Android business and tool apps with a recall of 71%.

5.4.4. Parallel Combination in ML Models

The authors of [224] offered a concurrent combination of Decision Tree, Simple Logistic Regression, Nave Bayes, PART, and RIDOR algorithms, claiming that evaluating the classifiers individually yielded greater accuracy. The authors of [225] used the DBN architecture to create a deep learning model and compared detection accuracy to SVM, C4.5, and Logistic Regression. The authors discovered that the deep learning model outperformed traditional machine learning models with an accuracy of 96.76 percent.
Ucci [226] conducted a survey on malware analysis using a variety of machine learning methodologies, as well as a correlation between the machine learning techniques used in the analysis, the types of attributes acquired from samples, and the analysis' purpose. They claimed that there was insufficient publicly available data for certain purposes. They emphasized the need of putting new techniques to the test using recent data. Such solutions would be useless in real-life situations otherwise [226].

5.4.5. Techniques (Tools)

Kaspersky mobile antivirus [227], Norton Security and Antivirus [228], and Avira Antivirus Security [229] are examples of high-end mobile device malware detection software.

6. Criteria and Metrics for Evaluation

A variety of indicators and measurements can be used to evaluate an ML model. Every learning task emphasises a variety of measures. A confusion matrix is one of the formal ways to present the aspects of the learning model. A confusion matrix, often called an error matrix, is a table that summarises the performance of a prediction or classification model [230]. Table 4 illustrates a confusion matrix that categorises the binary classification findings into four groups. It generates true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values from the classifier's output, which are then utilised to construct further measures.

In addition to the mistake rate, other factors such as time complexity, space complexity, and the adaptability of learning algorithms should be addressed. The priority of the measure, on the other hand, changes depending on the application. Assume that while determining whether a financial transaction is authentic or fraudulent, false negatives must be taken into account. A single value of FN in a financial transaction might result in a large financial loss. As a result, we are unable to determine which metrics are most important for a specific form of intrusion/attack. The following terms are commonly used to evaluate cyber security classification models:

i. *True Positive: number of accurately categorised normal traffic/nonmalignant/positive samples/applications by the model.*
ii. *The number of attack/malicious/negative samples/applications accurately categorised by the model is known as True Negative.*
iii. *The number of attack/malicious/negative samples/applications misclassified as normal/positive by the model, also known as False Positives or False Alarms.*
iv. *The number of normal traffic/nonmalignant/positive samples/applications that the model incorrectly classifies as False Negative.*

The confusion matrix's aforementioned terms are also used to produce the following metrics:

1. Precision/Positive Predictive Value

It's the proportion of correctly diagnosed benign/positive samples/applications in the dataset to all classified benign/positive samples/applications (Eq. 1). A greater precision number is preferable and indicates that a classifier is doing better.

$$\text{Precision} = TP/(TP + FP) \quad (1)$$

2. Recall/ Sensitivity/True Positive Rate (TPR)

It's a ratio of correctly categorised benign/positive samples/applications to the total number of benign/positive samples/applications in the dataset (Eq. 2). A greater recall value is good and indicates that a classifier is doing better.

$$\text{Recall} = TP/TP + FN \quad (2)$$

3. Specificity/True Negative Rate (TNR)

It's the proportion of attack/malicious/negative samples/applications accurately classified to the total number of attack/malicious/negative samples/applications in the dataset (Eq. 3). A greater specificity value is good and indicates that a classifier is doing better.

$$\text{True Negative Rate} = TN / (TN + FP) \quad (3)$$

4. Accuracy

It's the proportion of correctly identified samples/applications in a dataset to the total number of samples/applications (Eq. 4). The higher the accuracy value, the more accurate the classifier is. It is preferable to have a greater accuracy value.

$$\text{Accuracy} = (TP + TN)/(TN + FP + FN + TP) \quad (4)$$

5. Error Rate

It's the proportion of samples/applications that were erroneously classified to the total number of samples/applications in the dataset (Eq. 5). A lower error rate is preferable and indicates that a classifier is performing better.

$$\text{Error Rate} = (FP + FN)/(TN + FP + FN + TP) \quad (5)$$

6. Fall Out/False Positive Rate (FPR)

It's the proportion of malicious/negative samples/applications that were erroneously classified to the total number of attack/malicious/negative samples/applications in the dataset (Eq. 6). A lower FPR number is preferable and indicates that a classifier is performing better.

$$\text{False Positive Rate} = FP/(FP + TN) \quad (6)$$

7. Miss Rate/False Negative Rate (FNR)

It's the proportion of benign/positive samples/applications that were erroneously classified to the total number of benign/positive samples/applications in the dataset (Eq. 7). A lower FNR value is preferable and indicates higher classifier performance.

$$\text{False Negative Rate} = FN/(FN + TP) \quad (7)$$

8. False Discovery Rate (FDR)

It's the proportion of malicious/negative samples/applications that were mistakenly classified to the total number of classified attack/malicious/negative samples/applications in the dataset (Eq. 8). A lower FDR value is preferable and indicates that a classifier is performing better.

$$\text{False Discovery Rate} = FP/(FP + TP) \quad (8)$$

9. False Omission Rate (FOR)

It is a method of calculating the model's accuracy utilising precision and recall variables (Eq. 10). If the user wants to strike a compromise between recall and precision, and the sample distribution is uneven, this metric will be useful. A higher F1-score indicates that the ML model is outperforming other models.

$$\text{F1-score} = 2.(\text{precision} * \text{recall})/(\text{precision} + \text{recall}) \ (10)$$

10. F1-Score

It is calculated using the classifier's true predicted values (Eq. 11). The accuracy will not project the right picture for positive samples if the number of negative samples is greater than the number of positive ones. In that situation, G-Mean will be of assistance.

$$\text{G-mean}=\sqrt{(((TP/(TP+FN)XTN)/((TN+FP))))} \quad (11)$$

11. G-Mean

The often used graph that plots the values of TPR (y-axis) against FPR to provide a summary of all threshold's performance (x-axis).

12. Received Operating Characteristic (ROC) Curve

AUC refers to the size of the area covered by ROC, which can range from 0.5 to 1.0. A higher AUC value indicates that a classifier is doing better.

13. Area Under Curve (AUC)

The average of the squared difference or error that occurred between the actual values and predicted values of the classifier can be used to construct this metric. A lower MSE score is preferable and indicates that a classifier is performing better.

14. Mean Squared Error (MSE)

The average of the squared difference or error that occurred between the actual values and predicted values of the classifier can be used to construct this metric. A lower MSE score is preferable and indicates that a classifier is performing better.

15. Mean Absolute Error (MAE)

This metric can be generated by averaging the absolute difference or error that occurred between the classifier's actual and projected values. A lower MAE value is preferable and indicates higher classifier performance.

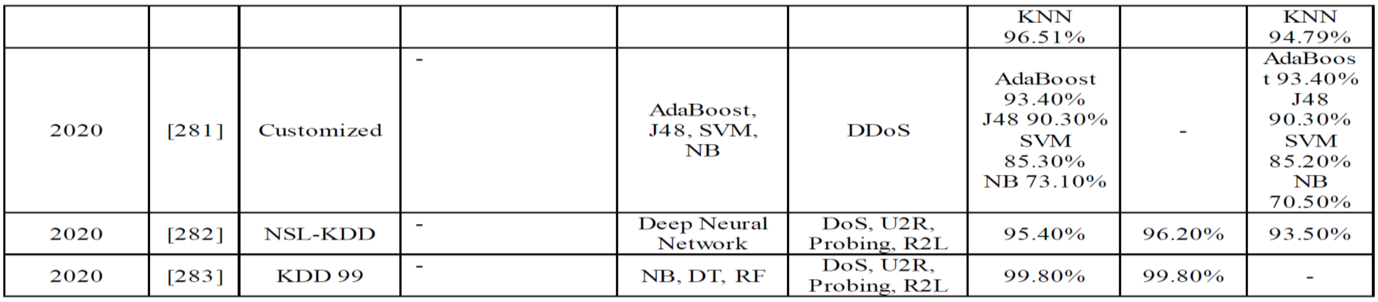
16. Mean Absolute Prediction Error (MAPE)

The MAPE is the average of the absolute difference between the classifier's actual and predicted values. A lower MAPE value is preferable and indicates higher classifier performance.

17. Root MSE (RMSE)

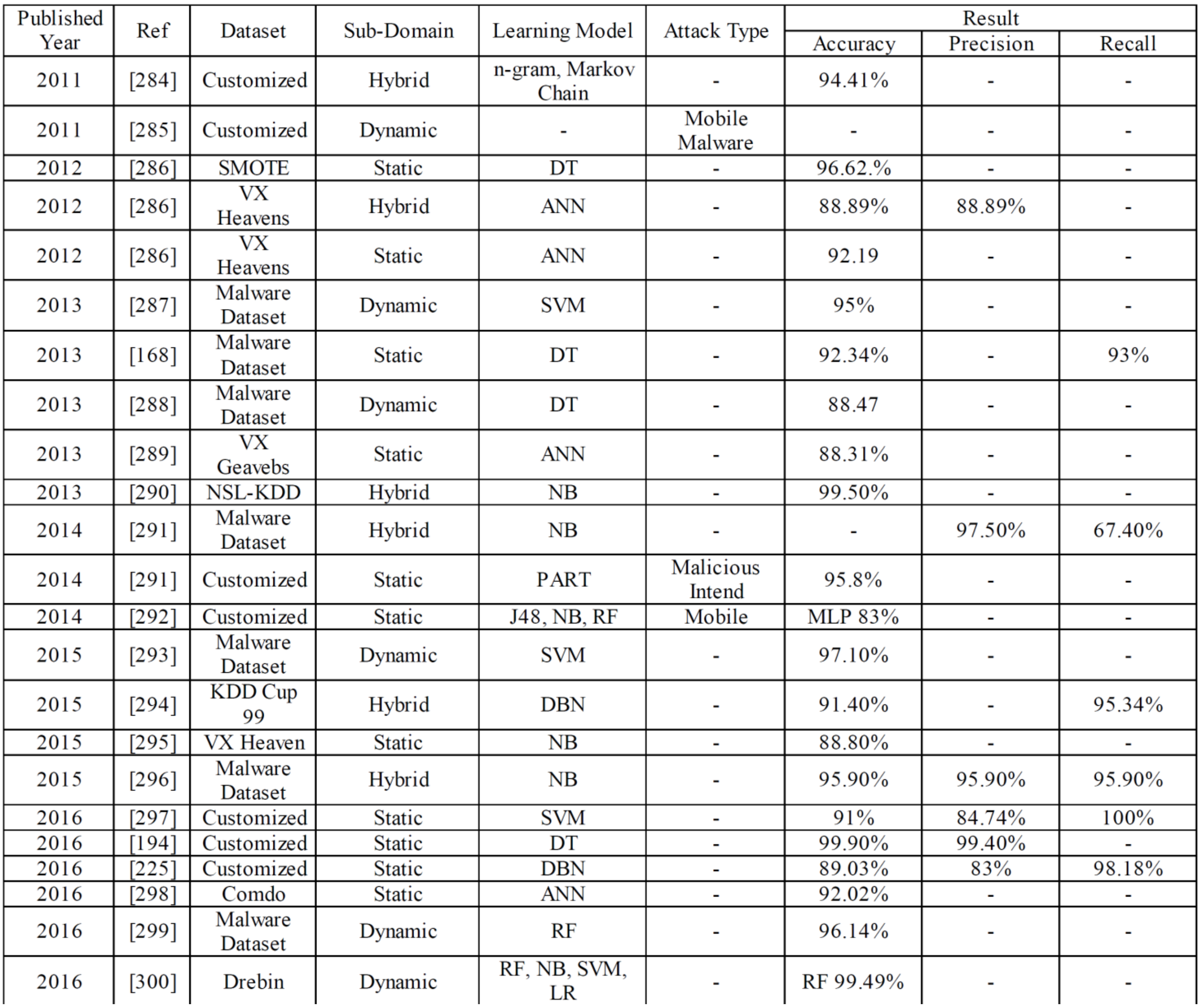
The square root of the mean squared error can be used to determine this metric. A lower RMSE value is preferable and indicates higher classifier performance.

TABLE 2. A comparison and summary of ML models for intrusion

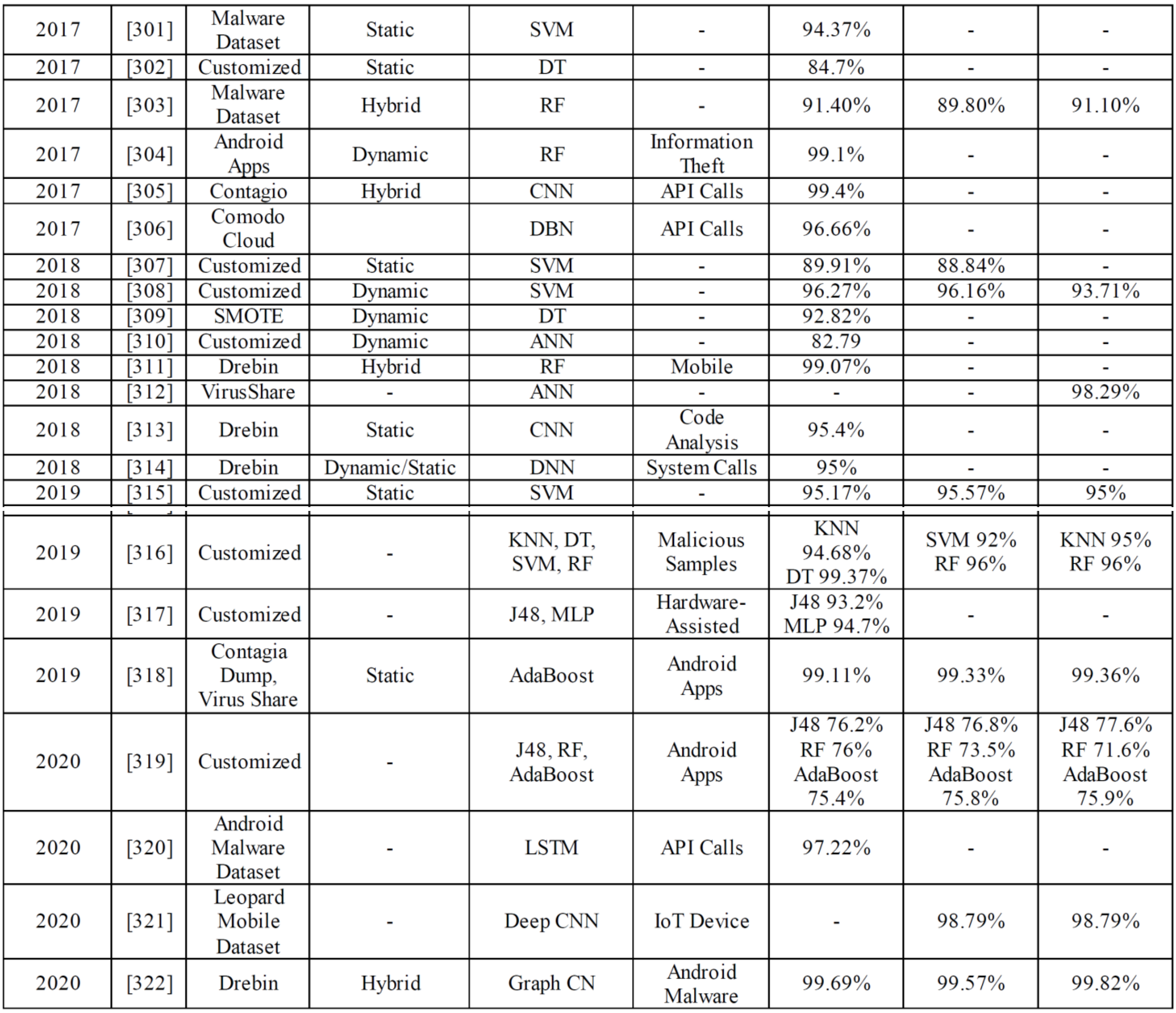


						KNN 96.51%		KNN 94.79%
2020	[281]	Customized	-	AdaBoost, J48, SVM, NB	DDoS	AdaBoost 93.40% J48 90.30% SVM 85.30% NB 73.10%	-	AdaBoos t 93.40% J48 90.30% SVM 85.20% NB 70.50%
2020	[282]	NSL-KDD	-	Deep Neural Network	DoS, U2R, Probing, R2L	95.40%	96.20%	93.50%
2020	[283]	KDD 99	-	NB, DT, RF	DoS, U2R, Probing, R2L	99.80%	99.80%	-

TABLE 3. A comparison and summary of ML models for malware detection



Published Year	Ref	Dataset	Sub-Domain	Learning Model	Attack Type	Result		
						Accuracy	Precision	Recall
2011	[284]	Customized	Hybrid	n-gram, Markov Chain	-	94.41%	-	-
2011	[285]	Customized	Dynamic	-	Mobile Malware	-	-	-
2012	[286]	SMOTE	Static	DT	-	96.62.%	-	-
2012	[286]	VX Heavens	Hybrid	ANN	-	88.89%	88.89%	-
2012	[286]	VX Heavens	Static	ANN	-	92.19	-	-
2013	[287]	Malware Dataset	Dynamic	SVM	-	95%	-	-
2013	[168]	Malware Dataset	Static	DT	-	92.34%	-	93%
2013	[288]	Malware Dataset	Dynamic	DT	-	88.47	-	-
2013	[289]	VX Geavebs	Static	ANN	-	88.31%	-	-
2013	[290]	NSL-KDD	Hybrid	NB	-	99.50%	-	-
2014	[291]	Malware Dataset	Hybrid	NB	-	-	97.50%	67.40%
2014	[291]	Customized	Static	PART	Malicious Intend	95.8%	-	-
2014	[292]	Customized	Static	J48, NB, RF	Mobile	MLP 83%	-	-
2015	[293]	Malware Dataset	Dynamic	SVM	-	97.10%	-	-
2015	[294]	KDD Cup 99	Hybrid	DBN	-	91.40%	-	95.34%
2015	[295]	VX Heaven	Static	NB	-	88.80%	-	-
2015	[296]	Malware Dataset	Hybrid	NB	-	95.90%	95.90%	95.90%
2016	[297]	Customized	Static	SVM	-	91%	84.74%	100%
2016	[194]	Customized	Static	DT	-	99.90%	99.40%	-
2016	[225]	Customized	Static	DBN	-	89.03%	83%	98.18%
2016	[298]	Comdo	Static	ANN	-	92.02%	-	-
2016	[299]	Malware Dataset	Dynamic	RF	-	96.14%	-	-
2016	[300]	Drebin	Dynamic	RF, NB, SVM, LR	-	RF 99.49%	-	-



2017	[301]	Malware Dataset	Static	SVM	-	94.37%	-	-
2017	[302]	Customized	Static	DT	-	84.7%	-	-
2017	[303]	Malware Dataset	Hybrid	RF	-	91.40%	89.80%	91.10%
2017	[304]	Android Apps	Dynamic	RF	Information Theft	99.1%	-	-
2017	[305]	Contagio	Hybrid	CNN	API Calls	99.4%	-	-
2017	[306]	Comodo Cloud		DBN	API Calls	96.66%	-	-
2018	[307]	Customized	Static	SVM	-	89.91%	88.84%	-
2018	[308]	Customized	Dynamic	SVM	-	96.27%	96.16%	93.71%
2018	[309]	SMOTE	Dynamic	DT	-	92.82%	-	-
2018	[310]	Customized	Dynamic	ANN	-	82.79	-	-
2018	[311]	Drebin	Hybrid	RF	Mobile	99.07%	-	-
2018	[312]	VirusShare	-	ANN	-	-	-	98.29%
2018	[313]	Drebin	Static	CNN	Code Analysis	95.4%	-	-
2018	[314]	Drebin	Dynamic/Static	DNN	System Calls	95%	-	-
2019	[315]	Customized	Static	SVM	-	95.17%	95.57%	95%
2019	[316]	Customized	-	KNN, DT, SVM, RF	Malicious Samples	KNN 94.68% DT 99.37%	SVM 92% RF 96%	KNN 95% RF 96%
2019	[317]	Customized	-	J48, MLP	Hardware-Assisted	J48 93.2% MLP 94.7%	-	-
2019	[318]	Contagia Dump, Virus Share	Static	AdaBoost	Android Apps	99.11%	99.33%	99.36%
2020	[319]	Customized	-	J48, RF, AdaBoost	Android Apps	J48 76.2% RF 76% AdaBoost 75.4%	J48 76.8% RF 73.5% AdaBoost 75.8%	J48 77.6% RF 71.6% AdaBoost 75.9%
2020	[320]	Android Malware Dataset	-	LSTM	API Calls	97.22%	-	-
2020	[321]	Leopard Mobile Dataset	-	Deep CNN	IoT Device	-	98.79%	98.79%
2020	[322]	Drebin	Hybrid	Graph CN	Android Malware	99.69%	99.57%	99.82%

7. Discussion

The Table 2 & 3 shows the past ten years data from the year 2010 onwards ML algorithms are used in the network security in different perspective. Table 2 made a comparison of different ML models with intrusion. Table 3 made a comparison of different ML models with malware. From this above two comparison it shows different ML models are very useful to improve QoS and QoE in the infrastructure oriented and infrastructure less networks. This analysis gives positive results to proceed author's research

8. Conclusion

This review gives positive answer. According to the previous researchers, Network can get automated solution for QoS and QoE issues using AI and ML. Reviewed researchers are provides solutions using AI and ML for their domain problems. In the next work author have to analyse the other researchers solution which is related to QoS and QoE issues.

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