Abstract—The widespread significance of Android IoT devices is due to its flexibility and hardware support features which revolutionized the digital world by introducing exciting applications almost in all walks of daily life, such as healthcare, smart cities, smart environments, safety, remote sensing, and many more. Such versatile applicability gives incentive for more malware attacks. In this paper, we propose a framework which continuously aggregates multiple user trained models on non-overlapping data into single model. Specifically for malware detection task, (i) we propose a novel user (local) neural network (LNN) which trains on local distribution and (ii) then to assure the model authenticity and quality, we propose a novel smart contract which enables aggregation process over blockchain platform. The LNN model analyzes various static and dynamic features of both malware and benign whereas the smart contract verifies the malicious applications both for uploading and downloading processes in the network using stored aggregated features of local models. In this way, the proposed model not only improves malware detection accuracy using decentralized model network but also model efficacy with blockchain. We evaluate our approach with three state-of-the-art models and performed deep analyses of extracted features of the relative model.

Index Terms—Android Malware Detection, Blockchain, Federated learning, Deep Learning, Secure IoT Devices

I. INTRODUCTION

The future wireless technologies such as fifth-generation mobile phone networks (5G) and Internet of Things (IoT) are revolutionizing the world by introducing innovative applications and smart systems that can be only imagined in the past, such as smart environment sensing, smart agriculture, smart drones, smart healthcare monitoring, autonomous cars, and many more. For developing such smart systems, heterogeneous electronic devices participate in a common network to communicate with each other as illustrated in Figure 1. A wide range of advanced electronic devices are controlled with a powerful Android platform which enables the integration of smart gadgets such as sensors, smartphones, smartwatches, smart washing machines, etc. Such electronic devices including smartphones encourage people to store and share their personal and confidential information. At the same time, it makes these devices become an intensive target for malicious applications to harm users due to common Android platform [1], [2], [3], [4], [5], [6]. The attacker exploits the Android system by indulging fake applications that will directly affect the users’ privacy and security. It may pose a severe threat by snooping on users’ data such as confidential contracts, photos, contact information, location, account information, and passwords. Additionally, the malicious applications can produce adverse effects not only on the intended node but even can affect other linked devices with a shared network. About 0.7 million applications were reported as malicious and blocked by Google Play store before user downloading in the year 2019 [7]. However, most Android app markets do not provide a way to access whether a mobile app is counterfeited or not. Besides, many users install applications from anonymous sources and do not use antivirus applications to protect from malicious and phishing attacks [8], [9]. Therefore, there exists an urgent need for an evolved approach and framework that can detect malware applications timely.

Conventional malware detection techniques [10], [11], [12], [13], [14], formally classified as signature-based [15], [16], access control-based [17], and sandbox-based mechanisms [18], [19], [20] are significantly dependent on handcrafted features and computationally expensive models. Additionally, most of these techniques are efficient and effective only under some hypothetical constraints which are beyond the real-world scenarios. Recently, deep learning techniques gained significant attention to solve the malware detection problem [10], [13], [21]. Mainly, previous algorithms are highly based on initial feature extraction processes such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM). However, these techniques cannot be directly applied to smartphones and IoT devices due to their limited resources regarding memory, processing power limitations, and so on. For this purpose, we propose a novel technique to integrate blockchain technology with deep neural networks in order to resolve the limitations of previous malware detection techniques. Our approach enables direct implication for IoT devices.

First, we considered the problem of aggregate and training the learning model with a decentralized network. More precisely, each client initialized a multi-layer deep learning model to compute the learning parameters for inspect the malware using a trained model. The overall training process is accomplished by means of five simple steps: (i) Selection of
the important feature using GINI information gain function, (ii) Division of a dataset into different clusters to obtain the fundamental data distribution for a particular group of malware, (iii) Generation of multiple clusters as a sub-tree of each cluster for the huge number of features, (iv) Choosing the best deep learning model for each cluster to classify the malware and benign from the corresponding data distribution, and (v) aggregate the latest weights using the previously trained model. The second problem that we prominently addressed was to track the malware or harmful application when users download certain applications from app networks. We used a blockchain-based authentication mechanism to identify the latest malware information which is detected by the deep learning model. We utilized the InterPlanetary File System (IPFS) based storage of the Android applications and hashes of apps in a blockchain ledger. After uploading the Android app in the IPFS, a deep learning model test (benign, malware) app. Finally, the harmful application information store in the blockchain ledger for future identification. In this way, the smart contract helps to approve or deny an application during the uploading and downloading process.

The third problem that we addressed is related to resource consumption in a malware detection model. We combine the local updates from the various clients into a blockchain ledger, once block is mined, it is appended to the blockchain ledger and broadcast latest malware features to the entire network. The blockchain compute a new version of the global model. The process iterates until global loss function converges or the desired accuracy achieved. In this way, the aggregated deep learning weights and utilize the IPFS technique to reduce the computational cost and achieve the better intelligent network scalability. The integration of the federated learning model and blockchain collects the new types of malicious features for the Android applications from various sources to train the global model itself. It provides security and makes better detection of malware for Android IoT devices in a real-time environment to protect the potential vulnerabilities attacks. In short, our key contributions can be outlined as follows:

1) This paper design smart contract which provide a secure downloading and uploading mechanism for Android applications.
2) This paper proposes a framework that integrates federated learning and blockchain for better malware detection and information sharing regarding Android applications across the network.
3) The enhancement in a multi-level deep learning model is proposed that can extract multiple types of malware features and the training task is distributed in the blockchain network for better prediction.
4) We performed an extensive empirical analysis to prove the significance of the proposed approach by providing multi-level deep learning and secure data sharing via blockchain.

The remaining part of this paper is organized as follows: Section II presents the literature review of Android malware detection, and it discusses the static, dynamic, and hybrid analysis. Section III discusses the preliminaries and need analysis for the proposed framework. Section IV states the formulations and work flow of proposed model based on blockchain and deep learning. Next, Section V analyzes the results and provides a comparison with other works. Finally, we concluded our work in Section VI.

II. RELATED WORK

Deep Learning and blockchain are disruptive technologies that changed the landscape of cyber security research. These models have many advantages over traditional machine learning models, especially when there exists a large amount of data. Android malware detection in IoT devices qualifies as a big data problem because of the growing number of malicious applications, the mystification behavior of Android malware, and the potential protection of huge values of data assets stored on the IoT devices. In this section, we introduced a step-wise progress in malware detection for Android devices. Also, we present a brief overview of blockchain technology for Android IoT security and service enhancements.

A. Android Devices Security For IoT

The Android operating system occupies the worldwide mobile market with billions of devices because of the systems’ flexible nature and accessibility. Every moment, millions of Android apps are ready for end-users for installation through a variety of app stores such as Google Play. Unfortunately, Android attackers take advantage of growing Android apps and spread malicious applications with an over 10 times increment of the number of detected Android malware reported between 2012 and 2018 [22]. Furthermore, according to Google officials, over 12K fresh Android malware samples were encountered daily in 2018. In addition to the existing number of growing attacks, newly released Android malware samples are more sophisticated than the samples that appeared in the past.
With the popularity of IoT devices in digital-world and widespread IoT platforms, users personal information stored in IoT networks got a considerable amount of attackers attention in recent years. To achieve a secure, robust, and reliable communication among IoT devices equipped with camera and microphone, like smartphones, researchers [23], [24] utilize voice and visible light to transmit data among IoT devices. For example, Zou et al. [25] proposed a model to identify a specific individual with his unique gait feature obtained by using RGBD sensors deployed in the house to prevent burglary. A considerable amount of research has been published for the security of IoT environment by designing access control system. For example, Luo et al. [26] proposed contextual model for privacy and security through inferring apps in smart home. Also, Mossain et al. [27] introduced a context-aware framework for detection of hidden terminal emulation attacks in cognitive radio-enabled IoT networks. In the same stream Jia et al. [28] introduced a context-based permission system for IoT platforms that provides contextual integrity and runtime prompts. Kousalya et al. proposed a reliable service availability and access control method for cloud assisted IoT devices. The proposed method is robust for inherent synchronization issues, resource availability and accessibility difficulties. Additionally, Pallavi and Kumar [29] take advantage of fog computing to secure IoT devices by considering a trusted third party authentication scheme. The authentication scheme using fog node offers reliable verification between the data owners and the requester without depending on the arbitrators’ trust. The proposed scheme also, effectively resolve the problems related to the single point of failure in the storage system and offers significant benefits by increasing the throughput and reducing the computation cost. Lee and Lee [30] introduced state-of-the-art research trends and recent developments in IoT security. A plenty of other researchers [31], [32], [33], [34], [35] highlighted significance of malware detection and IoT security for Android devices.

In parallel with machine learning algorithms, the researchers have also started using innovative blockchain technique to protect the underlying IoT smart devices [36], [37], [38], [39], [40], [41], [42]. Blockchain, often confused by some as a synonym to Bitcoin, is the technology behind this in famous cryptocurrency. It is a distributed ledger that stores the data in blocks. These blocks are in order and linked with each other graphically forming a chain in a way that makes it computationally infeasible to alter the data in a particular block [39]. This mechanism ensures transparency, decentralization, verifiability, fault-tolerance, audit-ability, and trust [39], [38]. There is no single consensus on the types blockchain, most commonly the blockchain techniques are distributed as public, private, and consortium. Public or permission-less blockchain technique and is open to everyone, so anyone can access and use them. On the other hand, private or permissioned blockchain techniques are controlled by one or few specified authorities, hence, not everyone can access them. The transactions here are faster and only the selected few are authorized to approve a transaction consensus. A plenty of researchers highlighted inbuilt power of blockchain to protect IoT smart devices [33], [36], [37], [38], [39], [40], [41], [32]. Although, certain machine learning frameworks and blockchain based techniques have been developed to deal with cyber threats in the IoT domain, combining these two is something new that needs to be explored.

B. IoT Platform

IoT platforms are used to build applications that monitor and control the IoT devices. These platforms provide developers with the ability to quickly build, test, deploy, and iterate on IoT-specific applications. According to a technical report by G2 rating database, the global market share of IoT platforms is going to reach till $ 74.74 billion by 2023. The reason behind this growth is the huge demand for IoT devices and other components. Therefore, leading technology stakeholders struggling to win the race of providing sustainable IoT platforms. As per current market share, the most popular IoT platforms includes Google Cloud IoT Core, IBM Watson IoT Platform, AWS IoT Core, Particle, Microsoft Azure IoT Suite, Oracle IoT platform, and many more. Also, these platforms act as a central hub where other smart devices interact with each other and a cloud is used to synchronize device states. These devices collect physical information and send events to the cloud to trigger other events. Mostly, applications for IoT platforms are developed in Groovy language, which is based on JVM, and executed in a Kohsuke sandboxed environment. Compared with Android applications, these are simpler and can be processed in the similar way with Android applications.

III. PRELIMINARIES

This section quickly review the some preliminaries about Android application analysis techniques. We divide this section into four parts i) Static analysis, which contains two approaches the first approach is permission-based, and the second approach is API Call. ii) Dynamic analysis that is used to extract real-time phone features, and iii) Hybrid analysis that combines the static and dynamic features. Final part provides a comparison between all techniques.

A. Static Analysis

Static analysis can check the application’s behavior without executing the app. Several machine learning techniques are proposed to classify benign apps and malicious apps [20], [43] such as content based analysis that reduce the dimensions of the content. The latest research [44], [45], [46], [47] for static analysis based on the API calls and permission features. The malware detection is less effective is such classical techniques [48], [49], [50], [51], [52], [4], [53], [54], [44]. However, low efficiency is demonstrated using these methods for feature extraction. Our main focus to design a multi-level deep learning model, which can support a various kind of features and classify the malware and benign effectively.

1) Permission-based analysis: Android uses a permission-based security model to ensure that sensitive information of the user is restricted, and the actual user only can access it. Indeed, permission is the most effective static feature because attackers apply for permission to reach their malicious goals. Before the
An app gets installed, it asks for some requested permissions from the user. After permission granted, the app installs itself on the device. There are many approaches that extract permissions for malware detection [55], [56], [47], [57]. Wang et al. [56] proposed a methodology for analyzing the permission-based on permission ranking, association rule and similarly based. It finds the permission groups using the correlation coefficient and ranks each permission individually. Verma et al., [58], [42], [20], [59] used the information gain algorithm of feature selection to choose the best features from android apk packed files.

2) API calls: API stands for Application Program Interface. API calls are used by the apps to interact with the Android framework. Some works target API calls and use it as a promised feature to investigate malicious behaviour.

B. Dynamic Analysis

Moreover, dynamic analysis [59] was proposed to observe to real-time behavior of the phone to observe the dynamic behaviors and features of applications. In this perspective, to analysis, the dynamic behavior of malware activities, use the Emulator (Android Virtual Device) to extract the dynamic features such as API calls, Events/Action. There are several tools to use dynamic analysis methods, including the Monkey and the DroidBot tool. Using these tools, Dynalog is an essential file used to input generation methods. It can extract the features of the API calls and system call information that reveals how malware behaves, the features of the dynamic methodology can be observed in [60], [61], [62], [63], [64] and detection of unknown malware that shows similar behavior is also possible using these methods [62], [1], [65]. Also, the API call analysis and control flow are the dynamic analysis methods [57], [59], [66], [67].

The main difference between existing works and ours is that our approach combines both static and dynamic analysis methods with the blockchain [41], [40] and deep learning to increase the detection rate and overcome machine learning weakness. Furthermore, our approach is to distribute the malware information in the blockchain network that can notify benign and malware Android apps at the installation time.

C. Hybrid Analysis

The hybrid analysis combines static analysis and dynamic analysis. The static features are extracted without executing the application. In contrast, dynamic features are extracted by an emulator or on the real device, which is time and resource-consuming. The hybrid analysis illustrates in Figure 4 to combine the static and dynamic analysis. Some researchers focus on hybrid analysis [68], [69], [16], [70], [71], but these methods are time-consuming. To solve this problem, we design the blockchain-based framework that equally distributed resources to all users. Our proposed technique is more sufficient and less time consuming because of the distributed nature of blockchain.

IV. SYSTEM MODEL

A. Proposed Architecture

In this article, we consider the problem of sharing the latest malware features and train the deep learning model in the decentralized network for multiple Android IoT devices. Due to limited resources and power consumption of Android devices. We design a multi-feature deep learning model which support various features form the decentralized network. Then we are focusing the aggregate a previously trained model with new features sets from the latest apps which are uploaded recently. The harmful application information stores
in the blockchain network. Finally, we provide security of the android derives using a smart contract for retrieving the information of the malicious Android applications. Figure 5 shows the architecture of the proposed framework. The steps of proposed framework shown in below:

1) The user uploads app to the network
2) The version of the app will be stored in the InterPlanetary File System (IPFS).
3) The deep learning model extracts the benign and malware features from the uploaded app. More detail in section IV-B.
4) The updated deep learning model store in IPFS system for reducing the cost of blockchain. Additionally, we aggregate the model weights to reduce the computational task in the blockchain nodes. In section IV-C
5) The hash value of app and decision results obtained from deep learning model is stored in a distributed ledger. More details shown in section IV-D
6) During the downloading process of the app: i) the user will send hash value to the network ii) the smart contract will come into action to compare and verify the hash value of the downloaded app iii) Finally, it will notify the user regarding the malicious or benign app. More details shown in section IV-E.

In summarizing Figure 8 provide a more detailed description of uploading or downloading from a developer and user perspective. When a user downloads the Android apps or developers uploading the apps, the smart contract uses for secure data uploading and check the harmful features of the apps automatically. The smart contracts can track malicious apps from the decentralized network. Also, it can help to learn the deep learning model itself and track the malware application when users are downloading the app through the Internet. Additionally, blockchain technology can create a trust-less environment and guarantees the transparency and reliability of the distributed nodes.

B. Proposed Deep learning local model

In this section, we proposed a deep learning-based model based on static and dynamic analysis. Figure 7 shows the overall architecture of the deep learning model for static and dynamic analysis. In the first phase, we combine static and dynamic features. The static features are extracted by decompling the Android apk file, and dynamic features are gathered from Droid Emulator(Android Virtual Environment). The DroidBot Emulator generates the Dynalog file, and for static features, we use CSV file. In the second phase, select the static and dynamic features from the CSV and Dynalog file and rank the features using information gain function. The information gain function score the features such as TelephonyManager-> getDeviceId is 0.98. After that, we found the similarity among the features. In the third phase, deep learning evaluates the performance of benign and malware applications and train the classifier. In the fourth phase, share the features information of malware and benign in the blockchain distributed database for achieving real-time malware detection for Android IoT devices.

1) Feature selection for hybrid malware detection: We used the feature importance property of the model. Feature importance gives a score for each feature of data between zero and one. The higher the score is, the more important or relevant is the feature towards the output variable. This score helps in choosing the most important features and drop the least important ones for model building. Feature importance is an inbuilt class that comes with tree-based classifiers. The information gain (IG) was used to select important features with a high score to classify the data effectively [12]. The information gain express in the 1, 2, and 3 equation.

$$Gain(A) = Info(D) − Info_{A}(D) $$ (1)

$$info(D) = - \frac{pos}{total} \log_{2} \frac{pos}{total} − \frac{neg}{total} \log_{2} \frac{neg}{total} $$ (2)

$$\text{InfoGainRatio}(A) = \frac{Gain(A)}{Info(D)} $$ (3)

2) Deep learning model training: Our main aim is to create a deep learning based model that ensures that Android malware and benign are accurately classified. Furthermore, it detects Android malware from benign apps. The previous paper discusses various techniques for malware detection [10], [11], [73], [13], [14]. These methods are highly efficient, though; however, they can not be applied directly to mobile and the IoT devices. To improve the detection performance of deep learning model, we design the multiple-level of deep learning. Each deep learning model learns from specific features of Android malware data for a single group of malware. Finally, all groups of deep learning models combined and make final prediction. We tested some deep learning models during the training process, which include deep recurrent neural Network, Convolutional Neural Network, Fully Feed Forward Network. One of then us the best for each cluster. Additionally, LSTM avoids the batch normalization vanishing gradient problem for multiple features. We combine the RNN and LSTM to achieve better performance in distinguishing the malware and benign application. In the first step, we select the important feature using information gain function for the static and dynamic analysis. In the second stage, the dataset dived into different clusters that calculate the unique data distribution. In the third stage, multiple clusters generated as a sub-tree of each tree cluster for the huge number of features. In the fourth stage, the best deep learning classifier is selected to distribute the malware and benign from the unique data distribution for every cluster. However, the proposed deep learning model classifies every cluster of each distinct feature for the static and dynamic analysis. The use of multiple deep learning models during the training phase reduces time and provide better accuracy. Finally, our proposed model classifies the malware and benign. The workflow of all stages shown in Figure 9 and deep learning model training is shown in Figure...
Therefore, our model improves the detection performance and efficiency of the traditional deep learning classifier.

Moreover, to save the computational power, the training task is distributed in the blockchain network through the forward propagation and backward propagation. In the forward propagation, the input is passed through the blockchain decentralized network, and after processing the input, the output is shared in the decentralized network. Then, in backward propagation, the weights of neural networks are shared to the blockchain network to reduce the computational power. Therefore, the distribution of the training task reduces time and utilized decentralized resources over the network. Additionally, we simulate the training outputs in the decentralized network through the Proof-of-Work, Proof-of-Stake, and Delegated-Proof-of-Stake. Proof-of-Work reduces the computational power of the deep learning model. Delegated-Proof-of-Stake is using to vote the hash, it avoids the complex hash operation. More precisely, state information of each node in a distributed network is taken as the dataset. The dimensional matrix $(M)$ is the input of the deep neural network, and the average number of becoming the mining node in a term is the capacity label. After training our network, we can get the average transaction number of the $i_{th}$ node as long as $M_i$ is input. Finally, implementation of the deep neural network is aimed to learn itself from the huge volumes of data resources through the blockchain technology. The next section discusses the blockchain technology.

C. Proposed blockchain based Federated Learning model

This section aggregates the local trained model with the new information of the latest feature application features and updated the latest model in the IPFS to track the new harmful
Figure 8. Deep learning model training steps.

Figure 9. Proposed Android multi-feature deep learning model.

The process of combining the blockchain and federated learning technology shown in Algorithm 1. Neural networks are trained through (i) forward propagation (ii) backward propagation are considered to calculate layers’ weights. In the forward propagation, the input is passed through $F = f(x, w) = \bar{y}$, and to processing the code $x$ is input and $w$ parameter vector, the trained malware and benign features set $F = (x_i, y_i); i \in I$ for each devices $(x_i, y_i)$. The output weights are shared in the decentralized network through the IPFS. The loss function of the training feature set is defined as $L(F, w) = \text{loss}$. $F$ is defined as dataset and $l$ is the loss function.

$$\text{loss} = \frac{1}{F} \sum_{(x_i, y_i) \in F} l(y_i, f(x_i, w))$$

Then, in backward propagation, the updated weights of neural networks are using stochastic gradient descent (SGD) defined as below equation:

$$w^{t+1} \leftarrow w^t - \eta \nabla w L(F^t, w^t) \quad (4)$$

As we can see in equation 4, the learning rate is $\eta$, and the $t^{th}$ is the iteration of the $w^t$ parameters, $F^t \subseteq F$ is the each devices mini-batch training dataset.

The above equation is use for single user. Moreover, to learn local model collaboratively and create a global model from the every devices $v \in V$ shown in equation 5

$$w^{t+1} \leftarrow w^t - \sum_{v \in V} \frac{\nabla w L(F^t_v, w^t)}{|V|} \quad (5)$$

In this way the federated learning model identifies the malware app through compute the gradients and send the updated weights to the global blockchain network. The smart contract shares the aggregated updated results. Moreover, when the user downloads the application the smart contract identify the harmful app.

D. Storing information about malware features in blockchain

We store the Android application hashes with the malicious and benign features (static and dynamic) in the blockchain distributed database. The structure of the storing information about malware features shown in Figure 10 and further describes the attributes of the Figure 10 in Table I. Furthermore, the blockchain structure divided into two parts i) Block header and ii) Block data. In the first part of block header stores the version number of apps, Markle root, hash values of all apps, and so on. The second part block data stores all static and dynamic features such as suspicious API, permission, events, calls, etc. The primary purpose to store the malware information in the blockchain distributed database is to ensure the security the identical hash values which can effectively prevent fraud such as de-compile and repacking Android applications by reverse engineering techniques. Therefore, no one can easily create counterfeit applications.

Moreover, an existing system such as VirusTotal has flaws in detecting fake Android mobile apps. The proposed blockchain framework we offer to remove these flaws and recognize Android fake/malicious applications. Furthermore, the blockchain includes actual information in a decentralized malware blockchain database to increase the prediction performance of the malware and run-time detection of malware...
Algorithm 1: Aggregate deep learning weights from the blockchain network

```
1 MD ← MobileDevices;
2 \{F_{n}\}_{n \in \mathbb{N}} ← Malware Features;
3 w^{0} ← global weights;
4 L(w, x) ← Loss;
5 I ← iteration;
6 \theta ← clip bound;
7 for i ∈ [I] do
8     for md ∈ [MD] do
9         sample malware and benign feature data set
10            with probability \frac{|f_{i,md}|}{|f_{md}|} ;
11     end
12     for x ∈ F^{i}_{w} do
13         g_{f_{i,md}}(x) ← \nabla_{w} L (w^{i}, x);
14         g_{f_{i,md}}(x) ← g_{f_{i,md}}(x)/\max \left(1, \frac{||g_{f_{i,md}}(x)||}{\theta}\right);
15     end
16     retrieves the weights or global model from permissioned blockchain;
17     executes IPFS model to aggregation and obtain updated the IPFS model;
18     add the parameters of model as a transaction ;
19 end
20 g_{f_{i,md}} ← \frac{1}{MD} \left(\sum_{n \in [md]} g_{f_{n,md}}\right);
21 w^{i+1} ← w^{i} - \eta \cdot g_{f_{i,md}};
22 retrieves the current updated weights from IPFS, and aggregates the weights;
23 broadcasts new malware information to other delegates for verification, and collects all transactions into a new block;
24 appends the block including the global model to the permissioned blockchain;
```

when the user downloads and upload the Android app into the network.

**E. Designing a Smart Contract to secure the Android devices to check the harmful apps**

This section describes the utilization of Ethererum blockchain and smart contract for verification, tracking of versioning history of Android apps, and further discusses the storing mechanism of hash values in a distributed ledger. The proposed smart contract can track different versions of apps and can provide continuous detection by broadcasting and sharing information regarding every new malicious app. To store an app on the blockchain network will be very expensive and wasteful in terms of resources as most apps have relatively large sizes ranging from several megabytes (MB). That’s why, firstly, the uploaded app by a developer will be stored in the IPFS file system along with its version history, and further only corresponding hash values of apk file will be stored in blockchain distributed ledger. Moreover, the use of the IPFS also provides several other benefits due to its peer-to-peer network feature and support regarding the tracking of the versioning history of every uploaded apk file. Furthermore, our design smart contract interact during the uploading and downloading Android applications. It handles the Android application IPFS version and the hash value of the application. It can approve or deny to upload harmful Android applications during uploading/downloading. Finally, the malicious features are broadcast using smart contracts to all users across the network. Figure 4 interacts between participating entities that are defined as developers, users, approves, deep learning, and the smart contract.

**Smart Contract**: All the interactions among the users and developers are handled by the smart contract. It check the new uploaded applications and provide the information about the malware and benign. Also it store the new information about the new apks. The smart contract interacts with developer and user to approve the application and notify the benign or malware.

| Keywords       | Size | Definition                                                                 |
|----------------|------|-----------------------------------------------------------------------------|
| Pre-Hash       | 32 bytes | preceding block hash value                                                  |
| Version number | 4 bytes | track the protocol or software updates                                      |
| Timestamp      | 5 bytes | records the time a block                                                    |
| Transaction_count | 15 bytes | number of malware results in the current block                             |
| Merkle root    | 32 bytes | it calculate the malicious codes which detected by block                     |
| None           | 15 byte | randomly recognized as a formal block                                       |

**Methods**: Contracts are structures that define the essence of the deal. Several contracts have requirements that only require a certain organization to execute them; others may be accessible to all participants. The strategies used in the smart contract are...
directly related to the effectiveness of the contract.

**Modifiers:** Modifiers changes the behavior of the application features. It can only define variables in this block before execution. It can restrict the access to contract function according to malicious applications.

**Variables:** Variable holds a value and that value can change depends on function call or conditions. Based on the smart contract, variables can be able to store a specific data type.

Algorithm 2: Smart contract approvers uploaded apk

1. Contract is: WaitForCheckingMalware;
2. Developer is: ReadToUploadAP;
3. Approve is: WaitingToSuccessOrFail;
4. if apkHashCheck(distributedLedger) then
   5. Contract is: successSign;
   6. Developer is: successProvidedAP;
   7. Approve = successApproval(If app is not Malware);
5. else
6. Contract is: denySign;
7. Developer is: denyProvidedAP;
8. Approve = denyApproval(If app is Malware);
9. end

Algorithm 3: Smart contract approvers download apk

1. apk ← DownloadedApp;
2. apkHash ← ApplyHash(apk);
3. Approve is: WaitingToSuccessOrFail;
4. if BlockChainLedger(apkHash) then
   5. Approve = successApproval(Malware information not found);
6. else
7. Approve = denyApproval;
8. end

V. PERFORMANCE EVALUATION

In this section, we discuss the experiment results of our proposed framework. It include the dataset, evaluation measures, results and comparison with other works. The proposed model based on deep learning algorithm and blockchain provides the strong evidence of the results, which is obtained from the experiments.

A. Dataset

The dataset that we used contains 18,850 normal Android application packages and 10,000 malware android packages with different features. It collected around 13,000 Android application packages (. apk) as normal apps from different resources and 6971 malicious applications from known sources such as DroidKin dataset [74], Android Malware Genome Project [75] and AndroMalShare [76]. They extracted the permissions at installation and run time after running the collected Android application packages (. apk) using emulator bluestack [77]. In this study, we used the new version of their dataset that contains 18,850 normal Android application packages and 10,000 malware.

B. Experimental setup

In this paper, we extract dynamic and static features. The dynamic analysis is done in real time devices to check the real time performance of the network. We utilized 8 mobiles phones with different configurations, Android 10.0, 6 GB RAM, Processor Kerin 980, 128 GB ROM. Every smart phone process an average 400 apps daily. All phones contains sim card with 4G network connection. The execution of the run time derives are determined when chosen the input generation. Moreover, to analysis the dynamic behavior of malware activities, use the Emulator (Android Virtual Device) to extract the dynamic features such as API calls, Events/Action. After extracting the dynamic and static features, this paper combine and train the model.

C. Evaluation Measures

We used Python; the programming language to conduct our experiment. In order to evaluate malware detection systems efficiency true positive and false positive rate are used in [78], [79] TPR defined as shown in equation 6.

\[ TPR = \frac{T_p}{T_p + F_n} \]  

If True Positive (TP) is the sum of correctly recognized malware samples and False Negative (FN) represents the number of wrongly detected malware samples that are benign. The recognition rate is also known as TPR. Eq 7 is defined as false positive rate (FPR).

\[ FPR = \frac{F_p}{F_p + T_n} \]  

The malware samples incorrectly identified, and true negative (TN) is the number of positive samples. FPR is also referred to as the false alarm rate. Overall Accuracy (ACC): Percentage of correctly identified applications which is shwon in equation 8.

\[ Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \]  

D. Results Discussion

The detailed empirical study of our proposed research work contains two observations. Initially, our key goal is to build a deep learning based model which enable to identify and diagnose Android malware and benign applications. For this purpose, we analyze static and dynamic features based on overall information gain score in At first, inspected information gain based on frequency count of features such as permissions, connections, intents of the static and dynamic features are exploited, as depicted in Figure. From the observed behavior of mentioned features, we can conclude that API calls and services frequency ratio have inverse relationship between benign and malware applications. Whereas
specifically, as shown in Figure 15 frequency count of Intents is much less in benign compared with malware applications. In contrast, the utilization of permission does not help to distinguish between benign and malware due to same frequency count, as shown in Figure 12. Therefore, we exploit useful static and dynamic features to construct a high quality model for training.

The engineered features are then used to train different algorithms including Support Vector Machine (SVM), J48, Naïve Bayes (NB), Random Forest, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Fully Connected Deep Neural Network (FC-DN) and compared with our proposed deep learning model. For ground level evaluation, we report TPR and FPR of all algorithms. As shown in Figure 16, the proposed approach outperformed the previous algorithms by gaining high TPR and accuracy. However, due to conflicting relationship of features between benign and malware, the reported FPR is not better than other approaches except SVM and J48.

Table II shows the performance of the deep learning model with a different combination of hidden layers. These presented results show only dynamic features using the emulator. We apply different layers of neurons to compare the best performance of the deep learning model. Table II applied two, three and four layers of deep learning model, the combination of 200, 200, 200 neurons achieved best compare with other layers and neurons. Similarly, we repeated the same experiment to combine the static and dynamic features shown in Table III. However, this also has the same layers and neurons. The combination of 200,200,200 in 3 layers achieved better performance than other layers and neurons.

Table IV compare the time for different deep learning models. Experiment results indicates that proposed model reduce the computational time and also achieve detection performance for the Android IoT devices.

In Table V we conduct the classification of Android Mal-

![Figure 11. Top ranked info-gain-based apps use the DroidBot (Permission Excluded)](image1)

![Figure 12. Top ranked info-gain-based apps use the DroidBot (Permission Included)](image2)

![Figure 13. Top ranked info-gain based Process](image3)

![Figure 14. Top ranked info-gain based Intents](image4)

![Figure 15. Top ranked info-gain based Intents](image5)
### Table II
**Proposed Deep Learning Model with Different Hidden Layers for Dynamic Features Only**

| No. of layers | No. of Neurons | TPR  | FPR  | Accuracy | Running time (min:sec) |
|---------------|----------------|------|------|----------|------------------------|
| 2             | 200,200        | 0.9663 | 0.337 | 0.9449   | 06:31                  |
| 2             | 400,400        | 0.9903 | 0.2062 | 0.895044 | 13:44                  |
| 3             | 200,200,200    | 0.9719 | 0.0728 | 0.9624   | 09:05                  |
| 3             | 400,400,400    | 0.7219 | 0.0158 | 0.8183   | 20:40                  |
| 4             | 200,200,200,200| 0.9744 | 0.0891 | 0.9508   | 10:39                  |
| 4             | 400,400,400,400| 0.9622 | 0.115  | 0.9339   | 29:28                  |

### Table III
**Proposed Deep Learning Model with Different Hidden Layers for Static and Dynamic Features**

| No. of layers | No. of Neurons | TPR  | FPR  | Accuracy | Running time (min:sec) |
|---------------|----------------|------|------|----------|------------------------|
| 2             | 200,200        | 0.9661 | 0.1229 | 0.9332   | 14:51                  |
| 2             | 400,400        | 0.972  | 0.0918 | 0.9484   | 30:50                  |
| 3             | 200,200,200    | 0.9956 | 0.033 | 0.985    | 17:21                  |
| 3             | 400,400,400    | 0.9764 | 0.0834 | 0.9543   | 38:16                  |
| 4             | 200,200,200,200| 0.9757 | 0.0793 | 0.955    | 20:05                  |
| 4             | 400,400,400,400| 0.9717 | 0.0907 | 0.9486   | 43:52                  |

### Table IV
**Time Comparison of Deep Learning Model Construction**

| No. of layers | No. of Neurons | TPR  | FPR  | Accuracy | Time |
|---------------|----------------|------|------|----------|------|
| 3             | 200,200,200    | Fully Connected | 140  | 96.49    | 3.99 |
| 3             | 200,200,200    | RNN  | 135  | 96.45    | 1.15 |
| 3             | 200,200,200    | CNN  | 120  | 96.45    | 1.15 |
| 3             | 200,200,200    | Our Proposed (Static) | 99   | 96.45    | 1.15 |
| 3             | 200,200,200    | Our Proposed (Dynamic) | 99   | 96.45    | 1.15 |

Figure 16. Comparison between machine and deep learning classifiers

Figure 17. True positive and false positive performance between different classifiers

Table V
**Performance of Federated and Blockchain-Federated Methods**

| Train on | TPR  | FPR  | Accuracy | Time in seconds |
|----------|------|------|----------|-----------------|
| Local user 1 | 97.41 | 17.92 | 93.95    | 189.05          |
| Local user 2 | 96.15 | 15.71 | 95.39    |
| Local user 3 | 95.70 | 13.13 | 93.34    |
| Local user 4 | 95.66 | 14.22 | 93.41    |
| Local user 5 | 96.47 | 14.70 | 95.04    |
| Federated  | 97.34 | 12.41 | 95.25    | 0.052           |
| Blockchain-Federated | 98.64 | 13.21 | 98.05    |

In Android platform there are many clients use many kind of services, so we test the classification performance based on number of clients. Each user choose different 10,000 features for blockchain with 5 users. The training of local model parameters of local epochs is 30 and batch size is 1. We select all kinds of features such as API calls, permissions and intents. The performance of local users and federated learning model shown in Table V. The federated learning takes less time then train the local model. The client required 0.93 mili seconds to send model from client to server. Thus the proposed framework has less communication time. In the way blockchain and deep learning model aggregate the different features i.e., permission, intent, dynamic features and static feature and perform well then other previous approaches.

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### Table VI
**Performance of Different Number of Clients**

| Train on | TPR  | FPR  | Accuracy |
|----------|------|------|----------|
| 2 clients | 96.45 | 13.67 | 96.99    |
| 5 clients | 97.54 | 12.49 | 97.45    |
| 10 clients | 97.43  | 12.18 | 97.74    |
| 15 clients | 97.72 | 13.78 | 97.98    |
| 30 clients | 97.43 | 12.41 | 97.98    |
| 40 clients | 96.54 | 11.89 | 97.45    |
CONSTRAINTS OF DIFFERENT TYPES OF FEATURES

| Feature            | TPR  | FPR  | Accuracy |
|--------------------|------|------|----------|
| API calls          | 95.12| 20.34| 91.41    |
| Permission         | 85.90| 31.14| 81.43    |
| Intents            | 92.34| 19.24| 92.12    |
| Federated          | 98.64| 20.75| 94.42    |
| Federated Blockchain| 99.10| 17.87| 98.62    |

sets randomly form the training dataset to train the local model with various features. According to Table VI the number of clients are increases then the accuracy will increase. Therefore, more users, the model can perform better.

In Android malware datasets have many different features to detect the malware, therefore we classify the different features set in Table VII and compare with the federated learning.

Furthermore, we focus on blockchain integration functionality among the smart contract, hyper ledger, deep learning and users. We implemented the Ethereum smart contract using Remix IDE. All roles have been tested to ensure that the smart contract’s worked properly. The developer uploads the apk files to the blockchain network and stores the hash in to the smart contract. In Remix, for different role different address are stores such as user (0 x435b7d915458ef540ade6d35458dfe2f48e8fa733c) and developer (0 x18965a09aff6a2a60 4d8f8bb4af308fddc180c), to test the smart contract code. Functions are designed to approve or deny the Android apps.

To utilize the IPFS storage, the smart contract transaction and gas execution are recorded as 1808246 and 1338218 respectively. The transaction cost is required to upload the Android apps and the amount of gas is necessary to verify the hash values of the harmful apps. When uploading the apps in the server, the execution cost of the function is USD 0.016. When an Android app is downloading USD 0.0088 is required. When verify the harmful apps the price measured USD 0.0091. Whenever the virus found to form the file then the hash values are stored in the blockchain. Furthermore, the execution and Either cost measured in Figure 18 and 19 respectively.

The Figure 20 shows the simulation results to prove the combination of blockchain and deep neural network increases the performance in terms of reducing the computational cost of the neural network. It shows the training labels increase the prediction performance of the deep learning model is increase. Moreover, the blockchain network calculates the value of nodes by using the deep neural network. And then selects the nodes and calculate the threshold value the features of the dataset taken as the input information to the blockchain nodes. The mining pools provides output to the users. The average number of transaction shown in the Figure 20. The blue label defines the real labels, and the red provides the prediction. Figure 20 (a) the correlation among the computing power ratio and the average transaction is defined as the trend of the blue dots, and red dots show an increasing pattern of the average transaction with the computing power ratio, which is constant with the real world decentralized network. Figure 20 (b) demonstrates the payoff increases, more transactions the node will have. Figure 20 (c) and (d) is the nodes are negatively correlated.

E. Comparison with other works

In this section, we evaluate the efficiency of the proposed deep learning model, and we compare state-of-art deep learning and machine learning approaches. As we can see in Figure 16 compares the accuracy with machine learning and deep learning classifiers. Moreover, we also compare our deep learning model with previous literature shown in Table VIII. Table VIII shows that our method achieve higher accuracy than other techniques.

Furthermore, we compare our work with the [54] and [47] method which introduces the blockchain with Android malware detection. It only proposes and stores the information of malware that is not able to the real-time deployment of blockchain. On the other hand, compared to [54] and [47]
Figure 20. Correlation between the computing power ratio and average transaction number.

Table VIII

| Authors   | Algorithm       | Capacity for feature diversity | Accuracy | F-measure |
|-----------|-----------------|-------------------------------|----------|-----------|
| OURs      | Proposed        | High                           | 96%      | 0.98      |
| [13]      | DNN/RNN         | medium                         | 90%      | NA        |
| [50]      | CNN             | low                            | 90%      | NA        |
| [43]      | Multi-Layer Perception | low                      | 89%      | 0.89      |
| [54]      | KMNN/ANN/FNN    | High                           | 90%      | NA        |
| [51]      | RNN and LSTM    | low                            | 96%      | NA        |
| [12]      | DNN             | High                           | 93.9%    | NA        |
| [81]      | Bayesian        | low                            | 92%      | NA        |
| [82]      | SVM             | low                            | NA       | 0.98      |
| [64]      | Graph Based     | NA                             | 95.4%    | NA        |

Table IX

| Primitive | Block Verify [38] | Sigma Ledger [39] | Stop TheFake [36] | This Work |
|-----------|-------------------|-------------------|-------------------|-----------|
| Blockchain| Private           | Private           | Private           | Private   |
| Target    | Goods             | Goods             | Picture, Video    | Android APK |
| Function  | Detect, Identify  | Tag, Detect       | Detect, Record    | Detect, Identify |
| Smart Contract | Product Label | QRCode, RFID, Copyright, Catalog | Hash, Feature of APK |

our solution has better achievement to secure the IoT devices. Additionally, the Table IX shows the results of the comparative analyses of the blockchain applications. As can be seen in our contribution, a blockchain application is used to identify whether benign or malware when uploading and downloading the apps from the Internet.

VI. CONCLUSION

In this paper, a new approach is presented to integrate the blockchain and multi-level deep learning model for the detection of malware activities in a real-time environment, especially for Android IoT devices. Our proposed framework works as follows: 1) Developer creates a malware 2) Multi-level deep learning model distributes the malware features into various cluster and chooses best deep learning model for each cluster. 3) Moreover, it makes decisions by analyzing the previous data which is already stored in blockchain distributed ledger and stores the new features of the malware activities in the blockchain 4) Finally, the blockchain smart contract provides the notification (of malware) to the user regarding verification of Android app during uploading or download process. To achieve better security for IoT devices regarding malware detection in realtime environments, millions of Android application features (malware and benign) were stored in the blockchain database. Therefore, we designed a multi-layer deep learning model for a large number of malware and benign features that incept the malicious application for Android IoT devices. The proposed model supports the multiple levels of clustering for single data distribution. Furthermore, the smart contract verifies the malicious application to uploading and downloading the Android apps through the network. It can approve or deny to uploading and downloading harmful
Android applications. The proposed model can identify the malware effectively which can provide more security for the Android IoT devices.

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