

ANDROID MOBILE MALWARE DETECTION
MODEL BASED ON PERMISSION FEATURES
USING MACHINE LEARNING APPROACH

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We hereby declare that We have checked this thesis and in our opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science.




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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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ABSTRAK

Penggunaan peranti mudah alih Android telah meningkat dengan pesat dan meraih populariti yang besar dalam pasaran peranti mudah alih. Ia telah menjadi barang paling berharga di seluruh dunia. Populariti dan sistem operasi utama peranti mudah alih Android telah menimbulkan kebimbangan terhadap ancaman perisian hasad. Pengarang yang tidak bertanggungjawab dengan sengaja menggunakan perisian berbahaya seperti root exploit, botnet, Trojan horse, dan spyware dan diterbitkan di Google Play untuk memperoleh keuntungan khusus untuk diri mereka sendiri. Perisian hasad Android ini mempunyai kecekapan untuk mencuri maklumat sulit pengguna dan mengubah sumber maklumat pengguna. Pelbagai teknik yang berbeza telah diadaptasi untuk mengesan dan mencegah penyebaran malware Android, termasuk teknik pengesanan anomali, berdasarkan tanda tangan, dan teknik pengesanan hibrid. Walaupun begitu, teknologi terkini menunjukkan bahawa penyerang perisian hasad Android menemui kaedah yang lebih canggih untuk mengelak daripada dikesan. Kajian ini bertujuan untuk mencadangkan sistem pengesanan perisian hasad Android menggunakan pengelas Bayesian dan pengelas Multilayer perceptron melalui teknik analisis statik untuk memerangi masalah perisian hasad Android. Kajian ini memfokuskan ciri kebenaran pada peranti mudah alih Android. Di samping itu, kajian ini menggunakan dua jenis set data yang diambil daripada Androzoo untuk aplikasi baik dan Drebin untuk aplikasi hasad. Set data pertama mengandungi 10,000 sampel, dan kumpulan data kedua mengandungi 96,074 sampel. Dalam kajian ini, beberapa eksperimen dilakukan untuk mempelajari tingkah laku ciri kebenaran dan mencari ketepatan terbaik mengikut pendekatan yang digunakan. *Chi-square* dan *information gain* adalah dua algoritma yang digunakan dalam pemilihan ciri. Ini bertujuan untuk mengetahui tingkah laku ciri kebenaran yang bertindak balas terhadap ketepatan mengikut bilangan ciri. Kedua-dua sampel set data kemudiannya akan dinilai menggunakan pendekatan pembelajaran mesin dan pembelajaran mendalam dipilih untuk mendapatkan ketepatan terbaik dalam proses pengesanan perisian hasad. Pengesanan melalui pembelajaran mesin memperoleh ketepatan sebanyak 85.4% bagi 96,074 sampel dan 91.1% bagi 10,000 sampel. Manakala pengesanan menggunakan pembelajaran mendalam memperolehi ketepatan sebanyak 98.02% bagi 96,074 sampel dan 98% bagi 10,000 sampel. Kesimpulannya, ketepatan pembelajaran mendalam sesuai bagi set data yang besar dan juga set data yang kecil manakala pembelajaran mesin menghasilkan pengesanan yang baik dalam set data yang lebih kecil.

ABSTRACT

The use of Android mobile devices has increased exponentially and gained massive popularity in the mobile market. It has become the most valuable item to humans across the world. The popularity and primary operating system of the Android mobile device have raised concerns over malware threats. Unscrupulous authors have deployed malicious software such as root exploit, botnet, Trojan horse, and spyware and published it on Google Play to gain profits. Android malware has the ability to abduct user credentials and cause a resource to maltreat. Different techniques have been adopted to detect and prevent the spread of Android malware, including anomaly, signature-based, and hybrid detection techniques. Nevertheless, current technologies indicate that Android malware attackers have found novel ways to avoid detection. This study aims to propose an Android malware detection model using Bayesian classifier and Multilayer perceptron classifier via static analysis technique to address the Android malware issue. This study focused on the permission feature of Android mobile devices. This study obtained two types of datasets which were retrieved from Androzoo and Drebin database. The first dataset contains 10,000 samples, and the second dataset contains 96,074 samples. Several experiments were conducted to learn the permission features' behaviour and find the best accuracy for the approaches used. Chi-square and information gain algorithms were used for features selection. The aim is to learn the behaviour of permission features that react to the accuracy according to the number of features. Both samples of datasets then were evaluated using machine learning and deep learning approaches to analyse the best accuracy of malware detection. The validation of machine learning obtained 85.4% accuracy for 96,074 samples and 91.1% accuracy for 10,000 samples. The validation in deep learning obtained 98.02% accuracy for the 96,074 samples and 98% accuracy for the 10,000 samples. These best achievements for both datasets were from the deep learning approach. In conclusion, the accuracy of deep learning is always greater in smaller or larger datasets, and machine learning produces great detection in smaller datasets.

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