

# Android Mobile Malware Detection Using Fuzzy AHP

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**Abstract**— Android mobile is very challenging because it is an open-source operating system that is also vulnerable to attacks. Previous studies have shown various mobile malware detection methods to overcome this problem, but still, there is room for improvement. Mobile users mostly ignore long lists of permissions because these are difficult to understand. Therefore, to distinguish benign or malware applications and the probability of each permission request is understood, it is necessary to evaluate Android mobile applications. This research proposed a multi-criteria decision-making based (MCDM) mobile malware detection system using a risk-based fuzzy analytical hierarchy process (AHP) approach to evaluate the Android mobile application. This study focuses on static analysis, that uses permission-based features to assess the mobile malware detection system approach. Risk analysis is applied to increase the awareness of the mobile user in granting any permission request to contain a high-risk level. The evaluation used 10,000 samples taken from Drebin and AndroZoo. The results show a high accuracy rate of 90.54% values that can effectively classify the Android application into four different risk levels.

**Keywords:** Android mobile, mobile malware detection system, fuzzy analytical hierarchy process, risk analysis

## 1. Introduction

The use of mobile devices is growing every year. Statista revealed that the number of mobile users has increased from 2.7 billion in 2012 to 3.2 billion in 2019. It foresees a rise of up to 3.8 billion in 2021 (Statista, 2020). Mobile applications are no longer limited to communication and are also widely used in education, social media, shopping, industry, and banking. Its widespread use causes large quantities of data containing highly-sensitive information to be provided. This scenario presents an opportunity for a malicious code explosion designed to target mobile devices. Over 30 million mobile malwares were detected in 2018 (Mcaffee, 2019). Based on Nokia Threat Intelligence Report 2019 (Nokia, 2019), Android has recorded a higher percentage of malware among smartphone devices. Android smartphones accounted for the highest percentage, with

malware applications, and researchers need to focus on these results to improve the security of Android mobile.

In the future, a comparative study between fuzzy AHP and other MCDM approaches can be conducted to validate the significant methods to improve mobile malware detection systems. Moreover, as one of the steps to increase awareness among Android users, the security vulnerabilities of Android applications that exposed users at risk of malware attacks should also be considered to be extended by this study. Furthermore, it is strongly recommended to use updated real-world data and applications existing in App Stores to assess the performance of the developed model, and it will be extremely important to evaluate the Android mobile malware detection system in the future.

The limitation of this study is that it only focused on permission-based features. Additional static features such as Java code and the intent filter can be select to expand the research. The results of this study will assist future researchers in improving the Android mobile malware detection system.

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### **References**

- Adewole, K. S., Anuar, N. B., Kamsin, A., Varathan, K. D., & Razak, S. A. (2017). Malicious accounts: Dark of the social networks. *Journal of Network and Computer Applications*, 79, 41–67. <https://doi.org/10.1016/j.jnca.2016.11.030>
- Alali, M., Almogren, A., Hassan, M. M., Rasan, I. A. L., & Bhuiyan, M. Z. A. (2018). Improving risk assessment model of cyber security using fuzzy logic inference system. *Computers and Security*, 74, 323–339. <https://doi.org/10.1016/j.cose.2017.09.011>
- Alazab, M., Alazab, M., Shalaginov, A., Mesleh, A., & Awajan, A. (2020). Intelligent mobile malware detection using permission requests and API calls. *Future Generation Computer Systems*, 107, 509–521.

<https://doi.org/10.1016/j.future.2020.02.002>

Allix, K., Bissyandé, T. F., Klein, J., & Le Traon, Y. (2016). AndroZoo: Collecting millions of Android apps for the research community. *Proceedings - 13th Working Conference on Mining Software Repositories, MSR 2016*, 468–471.

<https://doi.org/10.1145/2901739.2903508>

Alshahrani, H., Mansourt, H., Thorn, S., Alshehri, A., Alzahrani, A., & Fu, H. (2018). DDefender: Android application threat detection using static and dynamic analysis. *2018 IEEE International Conference on Consumer Electronics, ICCE 2018, 2018-Janua*, 1–6. <https://doi.org/10.1109/ICCE.2018.8326293>

Alshehri, A., Hewins, A., McCulley, M., Alshahrani, H., Fu, H., & Zhu, Y. (2017). Risks behind Device Information Permissions in Android OS. *Communications and Network*, 09(04), 219–234. <https://doi.org/10.4236/cn.2017.94016>

Arp, D., Spreitzenbarth, M., Hübner, M., Gascon, H., & Rieck, K. (2014). Drebin: Effective and Explainable Detection of Android Malware in Your Pocket. *NDSS, August*. <https://doi.org/10.14722/ndss.2014.23247>

Arslan, R. S., Dogru, I. A., & Barisci, N. (2019). Permission-Based Malware Detection System for Android Using Machine Learning Techniques. *International Journal of Software Engineering and Knowledge Engineering*, 29(1), 43–61. <https://doi.org/10.1142/S0218194019500037>

Bai, H., Xie, N., Di, X., & Ye, Q. (2020). FAMD: A Fast Multifeature Android Malware Detection Framework, Design, and Implementation. *IEEE Access*, 8, 194729–194740. <https://doi.org/10.1109/access.2020.3033026>

Baraiya, D., & Diwanji, P. H. (2017). A Survey on Android Malware Detection Techniques. *DEStech Transactions on Computer Science and Engineering*, 3(wcne), 143–147. <https://doi.org/10.12783/dtcse/wcne2016/5088>

Bernardi, M. L., Cimitile, M., Martinelli, F., & Mercaldo, F. (2017). A fuzzy-based process mining approach for dynamic malware detection. *IEEE International Conference on Fuzzy Systems*. <https://doi.org/10.1109/FUZZ-IEEE.2017.8015490>

- Buchanan, W. J., Chiale, S., & Macfarlane, R. (2017). A methodology for the security evaluation within third-party Android Marketplaces. *Digital Investigation*, 23, 88–98. <https://doi.org/10.1016/j.diin.2017.10.002>
- Chen, Z., Yan, Q., Han, H., Wang, S., Peng, L., Wang, L., & Yang, B. (2018). Machine learning based mobile malware detection using highly imbalanced network traffic. *Information Sciences*, 433–434, 346–364. <https://doi.org/10.1016/j.ins.2017.04.044>
- D'Angelo, G., Ficco, M., & Palmieri, F. (2020). Malware detection in mobile environments based on Autoencoders and API-images. *Journal of Parallel and Distributed Computing*, 137, 26–33. <https://doi.org/10.1016/j.jpdc.2019.11.001>
- Feizollah, A., Anuar, N. B., Salleh, R., & Wahab, A. W. A. (2015). A review on feature selection in mobile malware detection. *Digital Investigation*, 13, 22–37. <https://doi.org/10.1016/j.diin.2015.02.001>
- Hasegawa, C., & Iyatomi, H. (2018). One-dimensional convolutional neural networks for Android malware detection. *Proceedings - 2018 IEEE 14th International Colloquium on Signal Processing and Its Application, CSPA 2018, March*, 99–102. <https://doi.org/10.1109/CSPA.2018.8368693>
- Jerlin, M. A., & Marimuthu, K. (2018). A New Malware Detection System Using Machine Learning Techniques for API Call Sequences. *Journal of Applied Security Research*, 13(1), 45–62. <https://doi.org/10.1080/19361610.2018.1387734>
- Karbab, E. M. B., Debbabi, M., Derhab, A., & Mouheb, D. (2018). MalDozer: Automatic framework for android malware detection using deep learning. *DFRWS 2018 EU - Proceedings of the 5th Annual DFRWS Europe*, 24, S48–S59. <https://doi.org/10.1016/j.diin.2018.01.007>
- Kaspersky. (2016). *EXPLOIT.LINUX.LOTOOR*. <https://threats.kaspersky.com/en/threat/Exploit.Linux.Lotoor/#:~:text=Linux.,Lotoor&text=This program is a conditionally,CVE-2009-1185>.
- Kaspersky. (2019). *Mobile malware evolution 2018*. <https://securelist.com/mobile-malware-evolution-2018/89689/>

- Kaspersky. (2021). *TROJAN-SMS.ANDROIDOS.FAKEINST*.  
<https://threats.kaspersky.com/en/threat/Trojan-SMS.AndroidOS.FakeInst/>
- Kedziora, M., Gawin, P., Szczepanik, M., & Jozwiak, I. (2019). Malware Detection Using Machine Learning Algorithms and Reverse Engineering of Android Java Code. *International Journal of Network Security & Its Applications*, 11(01), 01–14.  
<https://doi.org/10.5121/ijnsa.2019.11101>
- Kim, H., Cho, T., Ahn, G. J., & Hyun Yi, J. (2018). Risk assessment of mobile applications based on machine learned malware dataset. *Multimedia Tools and Applications*, 77(4), 5027–5042. <https://doi.org/10.1007/s11042-017-4756-0>
- Kim, K., Kim, J., Ko, E., & Yi, J. H. (2020). Risk Assessment Scheme for Mobile Applications Based on Tree Boosting. *IEEE Access*, 8, 48503–48514.  
<https://doi.org/10.1109/ACCESS.2020.2979477>
- Kouliaridis, V., Kambourakis, G., Geneiatakis, D., & Potha, N. (2020). Two anatomists are better than one-Dual-level android malware detection. *Symmetry*, 12(7), 1–21.  
<https://doi.org/10.3390/sym12071128>
- Kouzinopoulos, C. S., Spathoulas, G., B, K. M. G., Votis, K., Pandey, P., Tzovaras, D., Katsikas, S. K., Collen, A., & Nijdam, N. A. (2018). Security in Computer and Information Sciences. In *Security in Computer and Information Sciences* (Vol. 821).  
<https://doi.org/10.1007/978-3-319-95189-8>
- Kumar, K. A., Raman, A., Gupta, C., & Pillai, R. R. (2020). The recent trends in malware evolution, detection and analysis for android devices. *Journal of Engineering Science and Technology Review*, 13(4), 240–248.  
<https://doi.org/10.25103/jestr.134.25>
- Li, J., Sun, L., Yan, Q., Li, Z., Srisa-An, W., & Ye, H. (2018). Significant Permission Identification for Machine-Learning-Based Android Malware Detection. *IEEE Transactions on Industrial Informatics*, 14(7), 3216–3225.  
<https://doi.org/10.1109/TII.2017.2789219>
- Liu, K., Xu, S., Xu, G., Zhang, M., Sun, D., & Liu, H. (2020). A Review of Android

- Malware Detection Approaches Based on Machine Learning. *IEEE Access*, 8, 124579–124607. <https://doi.org/10.1109/ACCESS.2020.3006143>
- Liu, X., Lin, Y., Li, H., & Zhang, J. (2020). A novel method for malware detection on ML-based visualization technique. *Computers and Security*, 89. <https://doi.org/10.1016/j.cose.2019.101682>
- Malleswari, D. N., Dhavalaya, A., Sai, V. D., & Srikanth, K. (2018). A detailed study on risk assessment of mobile app permissions. *International Journal of Engineering and Technology(UAE)*, 7(1.1 Special Issue 1), 297–300. <https://doi.org/10.14419/ijet.v7i1.1.9706>
- Martinelli, F., Mercaldo, F., Nardone, V., Santone, A., & Vaglini, G. (2020). Model checking and machine learning techniques for HummingBad mobile malware detection and mitigation. *Simulation Modelling Practice and Theory*, 105(March), 102169. <https://doi.org/10.1016/j.simpat.2020.102169>
- Mat, S. R. T., Razak, M. F. A., Kahar, M. N. M., Arif, J. M., Mohamad, S., & Firdaus, A. (2021). Towards a systematic description of the field using bibliometric analysis: malware evolution. In *Journal of Scientometrics* (Issue 0123456789). Springer International Publishing. <https://doi.org/10.1007/s11192-020-03834-6>
- Mathur, A., Podila, L. M., Kulkarni, K., Niyaz, Q., & Javaid, A. Y. (2021). NATICUSdroid: A malware detection framework for Android using native and custom permissions. *Journal of Information Security and Applications*, 58(January), 102696. <https://doi.org/10.1016/j.jisa.2020.102696>
- Mcafee. (2019). *McAfee Mobile Threat Report Q1*. <https://www.mcafee.com/enterprise/en-us/assets/reports/rp-mobile-threat-report-2019.pdf>
- Mercaldo, F., & Santone, A. (2020). Deep learning for image-based mobile malware detection. *Journal of Computer Virology and Hacking Techniques*, 16(2), 157–171. <https://doi.org/10.1007/s11416-019-00346-7>
- Naderi, H., & Kiani, B. (2020). Security Challenges in Android Mhealth Apps

- Permissions: A Case Study of Persian Apps. *Frontiers in Health Informatics*, 1–6.  
<https://doi.org/10.30699/fhi.v9i1.224>
- Nokia. (2019). Nokia Threat Intelligence Report – 2019. *Network Security*, 2019(12), 4.  
[https://doi.org/10.1016/s1353-4858\(18\)30122-3](https://doi.org/10.1016/s1353-4858(18)30122-3)
- Olukoya, O., Mackenzie, L., & Omoronyia, I. (2020). Security-oriented view of app behaviour using textual descriptions and user-granted permission requests. *Computers and Security*, 89, 101685. <https://doi.org/10.1016/j.cose.2019.101685>
- Pan, Y., Ge, X., Fang, C., & Fan, Y. (2020). A Systematic Literature Review of Android Malware Detection Using Static Analysis. *IEEE Access*, 8, 116363–116379.  
<https://doi.org/10.1109/ACCESS.2020.3002842>
- Rashidi, B., Fung, C., & Bertino, E. (2017). Android resource usage risk assessment using hidden Markov model and online learning. *Computers and Security*, 65, 90–107. <https://doi.org/10.1016/j.cose.2016.11.006>
- Razak, M. F. A., Anuar, N. B., Othman, F., Firdaus, A., Afifi, F., & Salleh, R. (2018). Bio-inspired for Features Optimization and Malware Detection. *Arabian Journal for Science and Engineering*, 43(12), 6963–6979. <https://doi.org/10.1007/s13369-017-2951-y>
- Razak, M. F. A., Anuar, N. B., Salleh, R., & Firdaus, A. (2016). The rise of “malware”: Bibliometric analysis of malware study. *Journal of Network and Computer Applications*, 75, 58–76. <https://doi.org/10.1016/j.jnca.2016.08.022>
- Razak, M. F. A., Anuar, N. B., Salleh, R., Firdaus, A., Faiz, M., & Alamri, H. S. (2018). “Less Give More”: Evaluate and zoning Android applications. *Measurement: Journal of the International Measurement Confederation*, 133, 396–411.
- Salah, A., Shalabi, E., & Khedr, W. (2020). A lightweight android malware classifier using novel feature selection methods. *Symmetry*, 12(5), 1–16.  
<https://doi.org/10.3390/SYM12050858>
- Salah, Y., Hamed, I., Nabil, S., Abdulkader, A., & Mostafa, M. M. (2019). Mobile Malware Detection : A Survey. *International Journal of Computer Science and*

*Information Security*, 17(1).

- Sayadi, H., Patel, N., D, S. M. P., Sasan, A., Rafatirad, S., & Homayoun, H. (2018). Ensemble learning for effective run-time hardware-based malware detection. *2018 55th ACM/ESDA/IEEE Design Automation Conference (DAC)*, 1–6.  
<https://doi.org/10.1145/3195970.3196047>
- Sharma, A., Gandotra, E., Bansal, D., & Gupta, D. (2019). Malware Capability Assessment using Fuzzy Logic. *Cybernetics and Systems*, 50(4), 323–338.  
<https://doi.org/10.1080/01969722.2018.1552906>
- Sharmeen, S., Huda, S., Abawajy, J., & Hassan, M. M. (2020). An adaptive framework against android privilege escalation threats using deep learning and semi-supervised approaches. *Applied Soft Computing Journal*, 106089.  
<https://doi.org/10.1016/j.asoc.2020.106089>
- Statista. (2020). *Smartphone users worldwide 2016-2021 Published by S. O’Dea, Dec 10, 2020 How many people have smartphones worldwide? The number of smartphone users worldwide today surpasses three billion and is forecast to further grow by several hundred million in the n.*  
<https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/>
- Taheri, R., Ghahramani, M., Javidan, R., Shojafar, M., Pooranian, Z., & Conti, M. (2020). Similarity-based Android Malware Detection Using Hamming Distance of Static Binary Features. *Future Generation Computer Systems*, 105, 230–247.  
<https://doi.org/10.1016/j.future.2019.11.034>
- Wang, S., Chen, Z., Yan, Q., Yang, B., Peng, L., & Jia, Z. (2019). A mobile malware detection method using behavior features in network traffic. *Journal of Network and Computer Applications*, 133(January), 15–25.  
<https://doi.org/10.1016/j.jnca.2018.12.014>
- Yan, P., & Yan, Z. (2018). A survey on dynamic mobile malware detection. *Software Qual J*, May 2017, 891–919. <https://doi.org/10.1007/s11219-017-9368-4>
- Zaburko, J., & Szulzyk-Cieplak, J. (2019). Information security risk assessment using

the AHP method. *IOP Conference Series: Materials Science and Engineering*,  
710(1). <https://doi.org/10.1088/1757-899X/710/1/012036>