

# Android Mobile Malware Detection using Machine Learning Techniques

R. Mariammal<sup>1</sup>, Bommanaboina Haribabu<sup>2</sup>, Konka Venkatesh<sup>3</sup>, Korsipati Rahul Reddy<sup>4</sup>

Assistant Professor, Dhanalakshmi College of Engineering, Chennai, India<sup>1</sup>

Students, Dhanalakshmi College of Engineering, Chennai, India<sup>2,3,4</sup>

**Abstract:** *With the growth of malware and improvements in cyberattacks, malware detection is crucial to maintaining cyber security. These attacks frequently employ previously undetectable malware that is not the focus of security firms, and it is inevitable that solutions will be found to learn from unlabelled sample data. This paper introduces SHERLOCK, a deep learning model for malware detection based on self-monitoring and the Vision Transformer (ViT) architecture. Using binary representation based on images, SHERLOCK is a novel malware CA detection technology that learns distinctive traits to separate malware from the benign programmes they employ. Self-supervised learning can achieve accuracy 97% for binary malware classification, which is higher than current state-of-the-art algorithms, according to experimental results employing 1.2 million Android apps hierarchy of 47 categories and 696 families. With macro-F1 scores of 0.497 and 0.491, respectively, the suggested model can also outperform cutting-edge methods for multi-class malware classification types and families.*

**Keywords:** Supervised Learning, Deep Learning, Malware Detection, Android Security

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