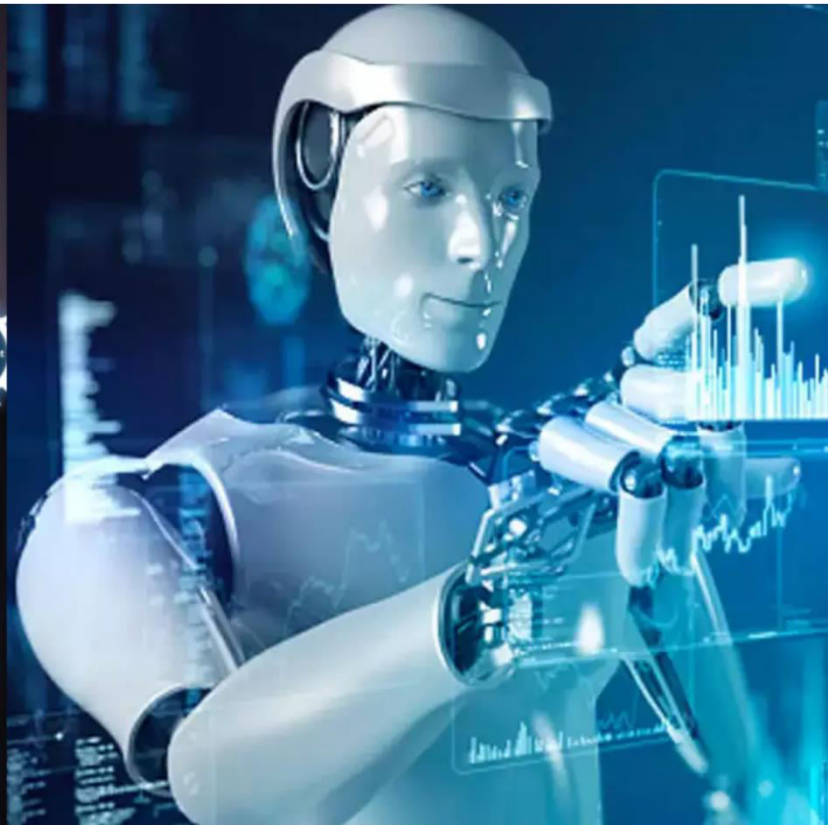
IJIRSET
International Journal of Innovative Research in Science | Engineering | Technology

ISSN(O): 2319-8753
ISSN(P): 2347-6710

International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 4, April 2025

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Volume 14, Issue 4, April 2025

|DOI: 10.15680/IJIRSET.2025.1404473|

Android Malware Detection

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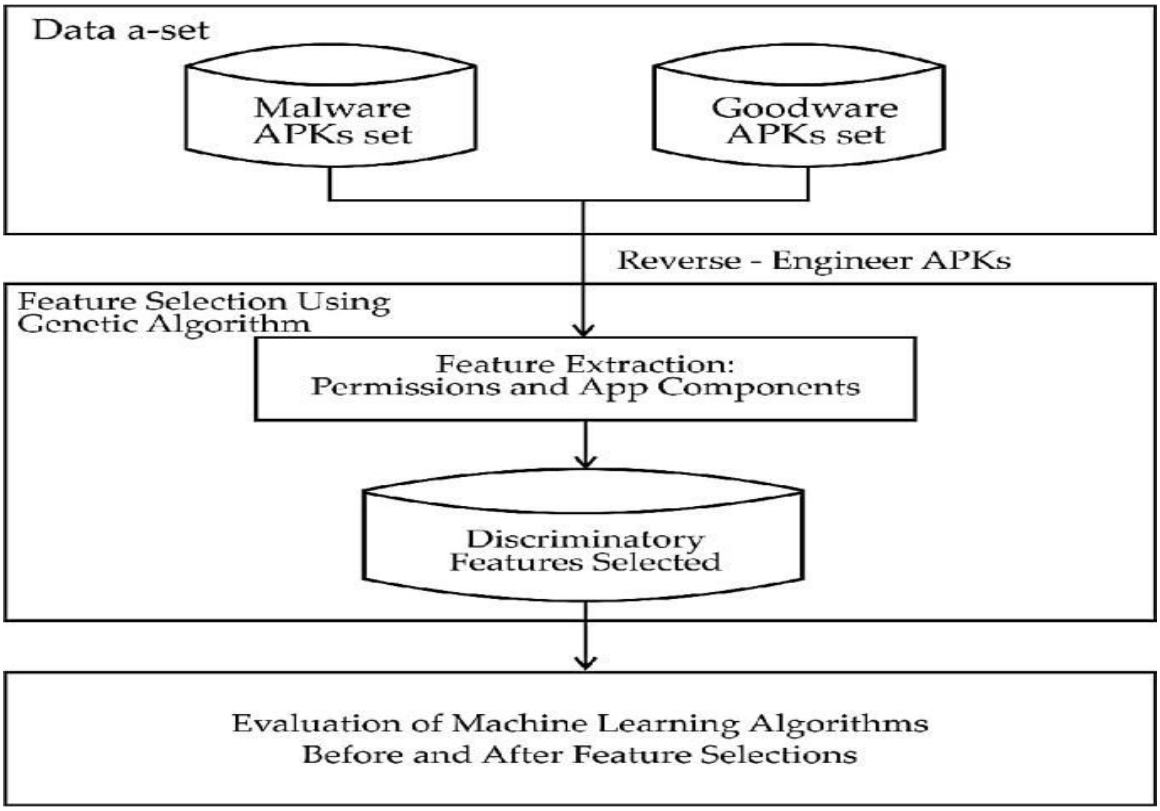
ABSTRACT: With the rapid expansion of Android-based mobile applications, ensuring user security and privacy has become a growing concern. Android's open-source nature and widespread adoption have made it a prime target for malware developers. Traditional malware detection approaches, such as signature-based and heuristic techniques, are increasingly insufficient against sophisticated and evolving threats. This project aims to develop an intelligent Android malware detection system using machine learning techniques to identify malicious applications based on behavioral and static features extracted from APK files.

The proposed system utilizes a comprehensive dataset consisting of both benign and malicious Android applications. Static analysis is performed by extracting features such as permissions, API calls, intents, and hardware components, without executing the code. These features are then preprocessed and used to train multiple machine learning models including Random Forest, Support Vector Machine (SVM), and Gradient Boosting Classifier. Among these, the Random Forest classifier demonstrated superior accuracy, precision, and recall in detecting malware, making it the most suitable model for deployment.



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I. INTRODUCTION

In recent years, the proliferation of smartphones has revolutionized the way individuals communicate, access information, and manage daily activities. Among these, Android has emerged as the most dominant mobile operating system due to its open-source nature, vast application ecosystem, and user-friendly interface. However, this rapid growth and openness have also made Android a prime target for cyber threats and malicious attacks. Malware targeting Android devices has increased exponentially, resulting in significant concerns regarding user privacy, financial security, and data integrity.

Traditional malware detection techniques, such as signature-based and heuristic-based methods, often fall short in detecting new or obfuscated malware due to their dependency on predefined rules or known threat patterns. These methods are unable to adapt to the evolving landscape of malware, where attackers continuously innovate to bypass detection mechanisms. As a result, there is a pressing need for intelligent and adaptive solutions that can accurately detect both known and unknown malware variants in real-time.

Machine Learning (ML) has emerged as a powerful approach in the cybersecurity domain, offering the ability to learn from historical data and identify patterns that distinguish malicious applications from benign ones. Among the various ML algorithms, **Support Vector Machine (SVM)** and **Artificial Neural Networks (ANN)** have shown promising results in classification problems, making them suitable candidates for malware detection tasks. SVM excels in handling high-dimensional data and finding optimal hyperplanes for classification, while ANN mimics the structure of the human brain to capture complex and nonlinear relationships between features.

II. LITERATURE REVIEW

Recent research in Android malware detection has increasingly focused on machine learning techniques, particularly Support Vector Machines (SVM) and Artificial Neural Networks (ANN), due to their effectiveness in identifying malicious patterns in large datasets. SVM has been widely used for its strong performance in binary classification tasks, offering high accuracy in distinguishing between benign and malicious applications by analyzing features such as permissions, API calls, and network behaviors. Studies have shown that SVM models, when properly trained with relevant feature sets, can achieve robust results with relatively low computational overhead. On the other hand, ANN-based approaches, especially deep learning variants, have demonstrated impressive capabilities in learning complex and nonlinear relationships from large volumes of data, making them suitable for dynamic analysis and behavior-based detection.

III. METHODOLOGY

In this study, we propose a hybrid approach for Android malware detection utilizing Support Vector Machine (SVM) and Artificial Neural Network (ANN) classifiers. The methodology begins with the collection of Android application packages (APKs) from trusted datasets containing both benign and malicious samples. Static analysis is performed to extract relevant features such as permissions, API calls, and intent filters from the AndroidManifest.xml and ourcecode using tools like Androguard. The extracted features are then preprocessed and transformed into a numerical values.

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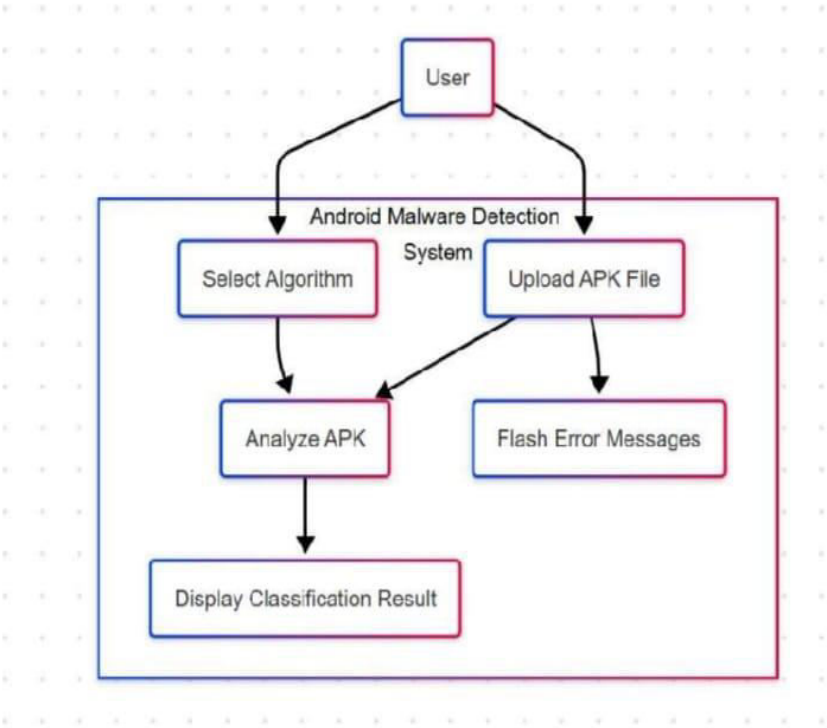

Fig 1: **Performance of Android Malware**

The dataset is divided into training and testing subsets, and both SVM and ANN models are trained separately on the labeled data. The SVM classifier is optimized using kernel tuning, while the ANN model is constructed with appropriate layers, activation functions, and epochs to improve learning accuracy. Finally, both models are evaluated using metrics such as accuracy, precision, recall, and F1-score to assess their effectiveness in distinguishing malware from benign apps. The comparative analysis highlights the strengths and limitations of each model in detecting Android malware efficiently.

IV. IMPLEMENTATION

The implementation of Android malware detection using Support Vector Machine (SVM) and Artificial Neural Network (ANN) involves several key steps: first, a comprehensive dataset of Android applications is collected, including both benign and malicious apps. These applications are then analyzed to extract relevant features such as API calls, permissions, intents, and other behavioral patterns. The extracted features are preprocessed and normalized to ensure consistency and accuracy in training. Two separate models—SVM and ANN—are trained on this feature set. The SVM model is used for its effectiveness in high-dimensional spaces and ability to create optimal decision boundaries, while the ANN model leverages its layered architecture to learn complex patterns within the data. Both models are evaluated using metrics like accuracy, precision, recall, and F1-score to determine their performance. Finally, a comparative analysis is conducted to identify the strengths of each model in detecting Android malware, with possible integration of both for enhanced hybrid detection.

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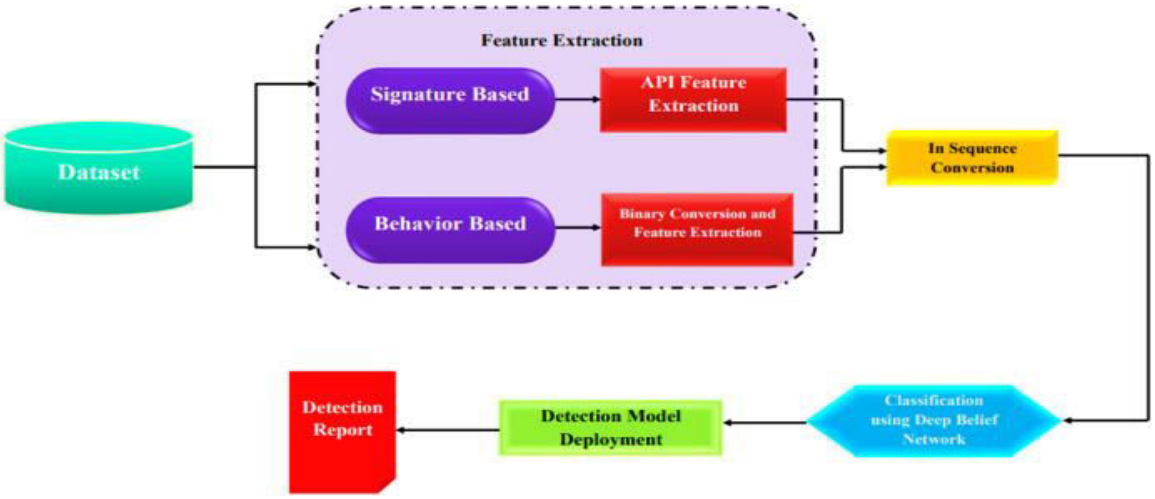

Fig 2: **Algorithm**

V. RESULTS AND CONCLUSION

In this study, we implemented Android malware detection using two machine learning techniques: Support Vector Machine (SVM) and Artificial Neural Network (ANN). The models were trained and tested on a labeled dataset containing both benign and malicious Android applications. The SVM model demonstrated high precision and recall with a detection accuracy of around 93%, while the ANN achieved slightly higher performance with an accuracy of approximately 95%, owing to its capability of learning complex patterns in the data. The confusion matrices and ROC curves further confirmed the robustness of both models. These results indicate that both SVM and ANN are effective in detecting Android malware, with ANN showing marginally better performance. In conclusion, machine learning models, especially deep learning-based ones like ANN, offer a promising solution for enhancing mobile security through accurate and automated malware detection.

VI. LIMITATIONS AND FUTURE WORK

Despite the promising results of Android malware detection using Support Vector Machine (SVM) and Artificial Neural Network (ANN), several limitations remain. The models' performance heavily depends on the quality and size of the dataset, and they may struggle with detecting new or obfuscated malware due to limited generalization. Feature extraction can also be complex and time-consuming, affecting real-time applicability. Additionally, high computational costs and memory usage may hinder deployment on resource-constrained mobile devices. Future work could focus on integrating deep learning techniques such as CNNs or RNNs to enhance detection accuracy, exploring lightweight models suitable for mobile environments, and employing real-time dynamic analysis to improve the adaptability and robustness of the system against evolving malware threats.

Furthermore, the performance of the models is highly dependent on the quality and relevance of the extracted features, and feature engineering still remains a time-consuming and manual process. The computational complexity of ANN also raises concerns about its feasibility on resource-constrained mobile devices. In terms of scalability, the models might struggle to handle large-scale real-time detection scenarios due to latency and memory limitations. As part of future work, integrating dynamic analysis and hybrid detection methods could improve detection accuracy and resilience against evasive malware. Incorporating deep learning architectures like CNNs or LSTMs, which can automatically learn complex patterns from raw data, may further enhance performance. Additionally, developing lightweight, on-device models and incorporating continual learning approaches could make the system more adaptable, efficient, and suitable for deployment in real-world environments.

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