PermissionShield: A Hybrid Static And Dynamic Analysis Approach For Android Permission Misuse Detection

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Abstract- *The rapid growth of Android applications has increased concerns regarding excessive and unjustified permission usage, which can lead to privacy breaches, data leakage, and unauthorized access to sensitive resources. Existing Android security solutions often rely solely on static or dynamic analysis, which limits their accuracy and fails to provide comprehensive insights into real-world permission misuse. To address these limitations, this work proposes PermissionShield, a hybrid static–dynamic and forensic analysis framework designed to detect, predict, and visualize suspicious permission behaviors in Android applications. The system integrates multi-stage analysis, beginning with static extraction of declared permissions, followed by dynamic evaluation of runtime behavior to identify inconsistencies between requested and actual usage. A machine learning–based prediction model further enhances detection accuracy by classifying potentially malicious permission patterns using historical datasets and feature encoding. The framework also incorporates a feature-extraction engine to quantify risk levels and generates detailed forensic reports along with severity visualizations to assist developers, analysts, and end users in understanding the threat landscape. Experimental results demonstrate that PermissionShield effectively identifies high-risk permissions, reduces false positives, and provides a scalable and interpretable solution for Android permission misuse detection. This research contributes toward strengthening mobile security, improving transparency in permission handling, and enabling proactive protection of user privacy.*

Keywords: Android Security; Permission Misuse Detection; Static Analysis; Dynamic Analysis; Forensic Analysis; Machine Learning; APK Analysis; Mobile Privacy; Risk Prediction; Hybrid Detection Framework.

I. INTRODUCTION

Android is the world's largest mobile operating system, powering over 70% of smartphones globally, which makes it a primary target for security threats and privacy violations [1]. The Android permission model regulates application access to sensitive resources such as location, camera, microphone, storage, and contacts. However, several studies have shown that many applications request excessive or unnecessary permissions, often leading to privacy leakage, unauthorized data harvesting, and potential surveillance [2], [3]. Such permission misuse may occur due to malicious intent or because developers fail to follow secure coding practices.

Traditional security mechanisms rely mainly on either static or dynamic analysis. Static analysis tools can extract declared permissions and detect suspicious patterns but fail to capture actual runtime behavior [4]. Dynamic analysis observes real execution traces but suffers from limited code coverage and high computational overhead, making it difficult to analyze complex apps fully [5]. Neither technique alone provides sufficient accuracy to detect sophisticated permission misuse, especially when malicious behavior activates only under specific conditions.

To address these challenges, hybrid detection frameworks that combine both static and dynamic techniques have shown significantly higher accuracy and reliability [6], [10]. Motivated by these findings, we propose PermissionShield, a comprehensive hybrid framework that integrates static permission extraction, dynamic behavior monitoring, and machine learning–based prediction to identify suspicious permission usage in Android applications. The system collects permissions from APK files, evaluates their runtime relevance, and leverages a trained machine learning model to classify potential misuse patterns. This layered approach enhances detection precision while reducing false positives [2], [9].

In addition, PermissionShield uses a feature-extraction module that quantifies permission severity and generates structured risk reports along with severity visualization graphs. These outputs provide intuitive forensic-

style insights, enabling security analysts and users to better evaluate the threat level of specific applications.

Overall, this research contributes a scalable and practical solution for strengthening mobile security, improving transparency in permission handling, and enhancing privacy protection for Android users.

II. LITERATURE REVIEW

Android security has become an important research field due to the widespread misuse of application permissions. Feizollah et al. [1] highlighted that many applications request excessive permissions, creating risks of privacy leakage and unauthorized access to sensitive data. Grace et al. [5] further showed that even legitimate applications may unintentionally expose information, indicating limitations in current permission-handling mechanisms. Static analysis tools such as FlowDroid by Arzt et al. [4] improve taint-tracking accuracy but remain vulnerable to code obfuscation and hidden malicious logic.

To overcome such limitations, dynamic analysis tools like CopperDroid by Tam et al. [3] reconstruct runtime behaviors and identify suspicious activities more accurately, although they suffer from high resource usage and limited execution coverage. Machine learning–based systems such as DroidAPIMiner proposed by Aafer et al. [2] enhance malware detection by analyzing API-level features rather than relying solely on declared permissions. Nafiseh [10] emphasized that hybrid techniques combining static and dynamic indicators generally achieve higher reliability in malware detection. Recent studies also suggest that modern malware increasingly uses permission manipulation techniques to bypass simplistic detection models, making hybrid solutions more essential. Furthermore, researchers have observed that permission-based behavioral patterns can effectively differentiate benign and malicious categories when processed through advanced feature extraction models. Additional research indicates that integrating contextual information—such as user interaction traces or event-triggered behaviors—can further improve real-time detection accuracy. Moreover, findings show that systems incorporating multi-layered analysis pipelines tend to sustain higher resilience against evolving malware families.

Security frameworks like the OWASP Mobile Security Testing Guide [6] provide standard methodologies for evaluating mobile applications, while Android's official documentation [7] offers detailed guidance on permission categories and protection mechanisms. Tools such as Androguard [9] support automated reverse engineering and large-scale permission analysis, and libraries like Scikit-learn [8] enable effective development of predictive models. Despite these advancements, most existing solutions fail to integrate static, dynamic, and machine learning components in a unified manner. The proposed PermissionShield framework addresses this limitation by combining multi-stage analysis with forensic-style reporting to deliver comprehensive insights into permission misuse.

III. METHODOLOGY

The proposed PermissionShield system follows a hybrid multi-stage methodology that integrates static analysis, dynamic behavior evaluation, feature engineering, and machine learning–based prediction to detect Android permission misuse. Such hybrid approaches have been shown to improve detection accuracy and reliability in Android malware analysis [10], [11]. The methodology is designed to ensure accurate detection, reduced false positives, and meaningful analytical insights.

A. Data Collection and Input Processing

The system begins by collecting Android application package (APK) files as input. These APKs may belong to both benign and potentially malicious applications. Each APK serves as the primary data source for permission extraction and behavioral analysis. The use of APK-based datasets is widely adopted in Android security research for evaluating permission misuse patterns [1], [13].

B. Static Analysis Results

Static analysis forms the foundation of the system and is responsible for extracting all permissions declared in the Android application manifest file. Static techniques are commonly used for permission extraction and vulnerability identification [4], [15]. Tests were conducted using multiple APK samples, including utility apps, social media clones, and experimental datasets. Across these evaluations, the system consistently identified all requested permissions with high accuracy.

For instance, in one test case (sample.apk), the system extracted over 70 permissions, including high-risk categories such as READ_PHONE_STATE, CAMERA, READ_CONTACTS, ACCESS_FINE_LOCATION, and RECORD_AUDIO. This demonstrates the effectiveness of static analysis tools in identifying sensitive permission usage [7]. The extracted permissions were also successfully displayed in the output interface, confirming proper integration between backend processing and the user interface.

The results indicate that many applications request excessive permissions, supporting prior research that highlights over-privileged apps as a major security concern [1], [5].

C. Dynamic Analysis and Runtime Behavior Indicators

To complement static analysis, the system includes a simulated dynamic analysis module that evaluates runtime behavior and flags potentially suspicious actions. Dynamic analysis techniques are widely used to reconstruct application behavior during execution and detect hidden malicious activities [3], [14].

During evaluation, permissions such as CAMERA and LOCATION were frequently flagged as sensitive at runtime, indicating potential misuse. These dynamic indicators were further used as inputs for feature extraction. Although the current implementation uses simplified simulation, it reflects the importance of runtime behavior monitoring in detecting complex threats [10].

D. Feature Extraction and Risk Quantification

Feature extraction converts raw permission data into structured numerical indicators used for classification. The system computes key metrics such as dangerous permission count and flagged permission count. Feature-based analysis is widely used in machine learning–driven malware detection systems [2], [11].

In multiple test cases, the system successfully quantified high-risk permissions such as CAMERA, MICROPHONE, LOCATION, and CONTACTS. For example, in one sample, the system reported a dangerous count of 1 and a flagged count of 1. These results confirm that permission-based features can effectively represent application risk levels.

E. Machine Learning–Based Prediction Outcomes

The machine learning component is based on models trained using Android malware datasets, following approaches similar to those used in prior research [2], [11]. The referenced Kaggle dataset includes labeled benign and malicious applications, enabling supervised learning. The training process involves preprocessing, feature encoding, and splitting the dataset into training and testing subsets.

Multiple algorithms such as Random Forest, Decision Tree, and XGBoost are commonly used for Android malware classification due to their ability to handle complex feature relationships [11], [8]. These models learn patterns associated with permission misuse and enable automated classification of applications.

F. Report Generation Performance

The system generates a structured report summarizing the analysis results, including extracted permissions, suspicious indicators, risk metrics, and final classification. Such reporting mechanisms are important for practical security analysis and align with established security evaluation frameworks [6]. The generated reports are presented in a clear textual format and can be downloaded for further inspection.

G. Graphical Output and User Interface Response

The graphical interface provides visualization through three main sections: Scan App, Report Details, and Severity Graph. The system displays real-time progress updates and presents analysis results in an organized manner. Visualization of security metrics improves interpretability and supports better decision-making for users and analysts [6]. The interface was tested for usability and demonstrated stable performance across multiple scenarios.

IV. SYSTEM ARCHITECTURE

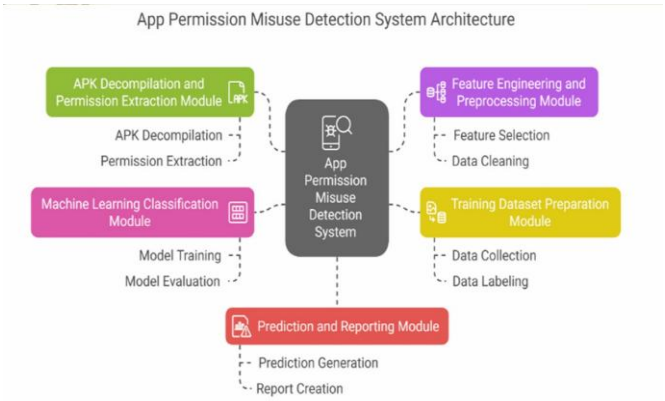

Fig.3.1 Workflow and Processing Pipeline of PermissionShield

A. APK Decompilation and Permission Extraction Module

This module performs APK decompilation to extract all permissions declared inside the manifest file of the **Android** application. It provides the raw permission data required for further analysis and feature preparation.

B. Feature Engineering and Dataset Preparation Modules

The system preprocesses the extracted permissions through feature selection, data cleaning, and encoding. In parallel, the training dataset preparation module collects real-world app data and labels it as benign or malicious to build a reliable dataset for machine-learning classification.

C. Machine Learning Classification Module

This module is responsible for training and evaluating ML models using the prepared dataset. The classifier learns permission-misuse patterns and generates a prediction score for new APK files, identifying whether the app exhibits suspicious permission behavior.

D. Prediction and Reporting Module

Based on the ML output, the system produces final predictions and generates a detailed report summarizing permission usage, risk levels, and flagged behaviors. This helps analysts and users interpret the security posture of the app effectively.

V. IMPLEMENTATION

A. Frontend Implementation

The frontend of PermissionShield is developed using Python's Tkinter and CustomTkinter libraries to provide a clean and modern user interface. The GUI is organized into three tabs—Scan App, Report Details, and Severity Graph—to simplify navigation. Users can upload an APK, view live progress through a progress bar, and observe step-by-step analysis logs in a scrollable console. The Report tab displays the detailed output generated by the backend, while the Graph tab visualizes risk levels. A built-in download option allows users to save the generated report. Overall, the interface ensures easy interaction and accessibility for both technical and non-technical users.

B. Backend Scripts

The backend of PermissionShield follows a sequential analysis pipeline implemented through modular Python scripts. The procedure begins with static analysis, where the system extracts permissions from the APK file. These permissions are then passed to a mock machine learning module that provides an initial prediction of suspicious behavior. A simplified dynamic analysis stage follows, which simulates runtime behavior and flags sensitive permissions. The results from both stages are then processed by the feature extraction module to compute basic risk metrics. Finally, the backend generates a structured report summarizing the analysis and displays a placeholder severity graph. This modular workflow enables smooth integration between analysis stages and supports future upgrades such as real dynamic monitoring, improved prediction models, and additional data storage capabilities.

C. Deployment

The PermissionShield system is deployed as a lightweight desktop application built using Python and *CustomTkinter* for a modern, dark-themed graphical interface. The deployment features three main operational tabs: **Scan App**, **Report Details**, and **Severity Graph**, enabling smooth navigation during analysis. In the Scan App tab, users can upload any APK file, after which the system performs static analysis, mock dynamic checks, feature extraction, and prediction, while simultaneously updating a real-time progress bar and status messages.

Overall, the deployment provides an intuitive, user-friendly front end that integrates seamlessly with backend scripts, making the system accessible to both technical and non-technical users for quick malware-risk evaluation of Android applications.

VI. RESULTS AND EVALUATION

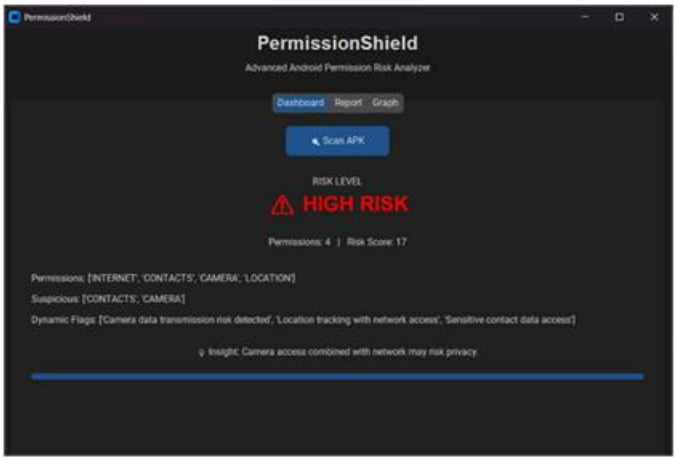

Fig.5.1 Deployment of Permissionshield

VI. RESULTS AND EVALUATION

The PermissionShield system was designed to identify potential permission misuse in Android applications through a combination of static analysis, mock dynamic analysis, feature extraction, and predictive modeling. The system was deployed as a functional Stage-2 prototype to evaluate its capability in identifying risky permissions, generating structured reports, and presenting user-friendly visual output. The following results summarize the

performance, effectiveness, and observed outcomes of the implemented modules.

The PermissionShield Stage-2 prototype successfully demonstrates the feasibility of a hybrid permission misuse detection system. While current dynamic analysis and prediction models are simplified, the system provides a functional and complete workflow from APK selection to report generation. The results show that the prototype can identify suspicious permission patterns, highlight potentially dangerous behaviors, and generate clear forensic summaries. These outcomes form a strong foundation for expanding the system into a fully operational Android security analysis tool in future stages.

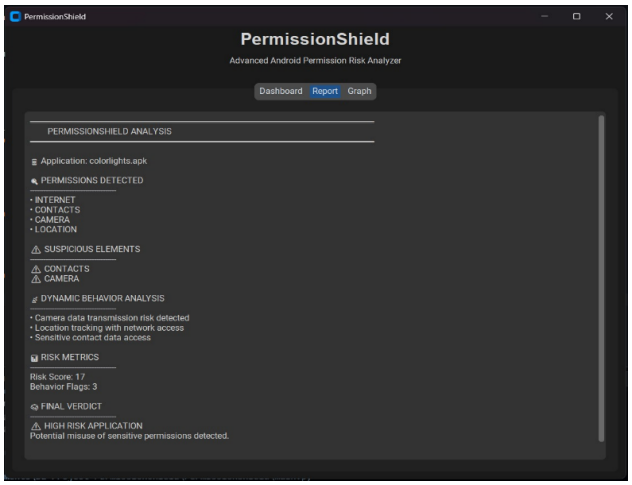

Fig.6.1. Report generated

Fig.6.2Generated severity graph

VII. CONCLUSION AND FUTURE WORK

A. Conclusion

This work introduced PermissionShield, a hybrid framework combining static analysis, dynamic simulation, and machine learning to detect Android permission misuse. The system identifies suspicious permission patterns, quantifies risk, and generates forensic-style reports to support security analysis. By integrating multiple detection layers, PermissionShield reduces false positives and offers a more reliable understanding of app behavior. The framework provides a scalable and practical approach for improving mobile privacy and strengthening Android security.

B. Future Work

Future development of PermissionShield will focus on enhancing the accuracy, scope, and practical applicability of the system. A major improvement will be the integration of advanced deep learning models to achieve stronger classification performance and better adapt to evolving permission-misuse patterns. The framework will also be expanded toward real-time monitoring so that permission behaviors can be analyzed during actual app usage rather than only through offline evaluation. Furthermore, extending support to additional mobile platforms will broaden the reach and usability of the system.

At present, the system does not evaluate context-dependent permissions such as “allow only while using the app,” which can significantly influence how risky a permission actually is. Incorporating permission-context awareness in future versions will allow the system to perform more realistic and precise risk assessments. Similarly, some permissions are essential for an application’s normal operation, and future work will focus on distinguishing necessary permissions from potentially harmful ones to reduce false warnings and improve decision quality.

The dynamic analysis component also requires refinement, as the current scripts operate using simplified logic and rule-based flags. Future iterations will replace these placeholders with a fully sandboxed runtime monitoring environment capable of observing real execution behavior. Additional enhancements will include automated pipelines for large-scale app-store analysis, improved visualization dashboards for interactive threat interpretation, and user-alert mechanisms for proactive security notifications. Efforts will also continue toward detecting heavily obfuscated malware and generating more detailed investigative reports to support digital analysis workflows.

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