Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 20 No. 17 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijim.v20i17.62514

PAPER

# Security and Privacy in Android: Emerging Threats and Gemini AI-Powered Detection Framework

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**ABSTRACT**

Android remains the world's dominant mobile operating system with over 3.5 billion active devices, making it a prime target for increasingly sophisticated security threats and privacy violations. Traditional signature-based and rule-driven defenses are proving insufficient against polymorphic malware, zero-day exploits, and context-aware privacy attacks. This paper presents a comprehensive investigation into security vulnerabilities and privacy challenges in the Android ecosystem, with a particular focus on how Google's latest Gemini AI family, including Gemini Nano for on-device inference, Gemini Pro for cloud-assisted analysis, and Gemini 1.5 for long-context threat intelligence, fundamentally transforms threat detection and privacy enforcement. We survey the contemporary Android threat landscape spanning ransomware, banking trojans, spyware, and supply chain attacks, then systematically evaluate Gemini AI's contributions to behavioral malware detection, real-time permission auditing, contextual privacy advisory, and natural language-driven threat intelligence. We further propose GeminiShield, a layered security architecture that integrates Gemini AI across the Android software stack, and validate its efficacy through comparative analysis against state-of-the-art approaches. Our results demonstrate detection accuracy of 97.3%, outperforming prior approaches while maintaining acceptable computational overhead on resource-constrained devices. Open challenges including adversarial attacks on AI models, on-device inference constraints, and regulatory compliance are critically discussed.

**KEYWORDS**

Android security, Gemini AI, mobile malware detection, privacy protection, on-device AI, GeminiShield, behavioral analysis, large language models

## 1 INTRODUCTION

Android commands over 71% of the global smartphone market, powering billions of devices across consumer, enterprise, healthcare, and government sectors [1]. This dominance makes Android an extraordinarily attractive target for cybercriminals, state-sponsored actors, and rogue developers who exploit its open ecosystem,

Yadati, N. S. P. K., Peddinti, D. R., Shetty, S. P. (2026). Security and Privacy in Android: Emerging Threats and Gemini AI-Powered Detection Framework. *International Journal of Interactive Mobile Technologies (iJIM)*, 20(17), pp. 99–109. https://doi.org/10.3991/ijim.v20i17.62514

Article submitted 2026-05-31. Revision uploaded 2026-07-10. Final acceptance 2026-07-13.

fragmented update landscape, and complex permission model to conduct malware campaigns and large-scale privacy breaches.

The threat landscape has evolved dramatically over the past decade. Early Android malware was largely opportunistic, relying on simple repackaging and signature evasion. Modern threats are sophisticated, targeted, and polymorphic: banking trojans intercept two-factor authentication tokens; spyware silently exfiltrates biometric data; ransomware encrypts device storage and demands cryptocurrency payments; and supply chain attacks inject malicious code into legitimate app dependencies that evade static analysis entirely [2] [3].

Simultaneously, privacy violations have grown more insidious. Advertisers and data brokers leverage overlapping permissions, background sensors, and cross-app tracking to build granular behavioral profiles of users without meaningful consent. The proliferation of connected IoT peripherals further expands the attack surface beyond the handset itself [4] [5].

In this context, Google's Gemini AI family represents a watershed moment for mobile security. Gemini Nano (the on-device variant) is embedded in Android 14 and later, enabling real-time behavioral inference without cloud round-trips. Gemini Pro and Gemini 1.5 offer powerful cloud-based analysis with million-token context windows, enabling longitudinal threat correlation across months of device telemetry [6] [7]. These models bring multimodal understanding (text, images, and structured logs) to bear on security problems that were previously intractable for narrow ML classifiers.

This paper makes four primary contributions: (1) a systematic survey of the 2015–2025 Android threat landscape; (2) a comprehensive analysis of Gemini AI capabilities relevant to security and privacy; (3) the GeminiShield framework, a practical layered architecture for integrating Gemini AI across the Android security stack; and (4) flow diagrams and comparative tables validating GeminiShield's effectiveness against baseline approaches.

## 2 ANDROID SECURITY ARCHITECTURE

### 2.1 Core security layers

Android's security architecture is a defense-in-depth stack. At the lowest layer, hardware-backed security primitives including the Trusted Execution Environment (TEE), Secure Element (SE), and hardware-enforced memory protection provide root-of-trust guarantees. Above the hardware sits the Linux kernel, hardened with Security-Enhanced Linux (SELinux) mandatory access controls that confine every process, including system services, to strictly defined policy domains [8].

The application sandbox isolates each installed app in a unique Linux user ID, preventing direct inter-process memory access. The permission model gates access to sensitive APIs (camera, microphone, location, and contacts) behind user-visible grants. Android 12+ introduced more granular permissions, including approximate location and microphone/camera indicators that visually signal active sensor use to users [9].

### 2.2 Google Play Protect

Google Play Protect is Google's cloud-backed malware scanner, operating both pre-install (scanning submitted APKs on Google Play) and post-install (periodic on-device scans of installed apps). Play Protect examines approximately 100 billion

app scans daily across the global device fleet, leveraging large-scale machine learning models trained on behavioral telemetry. In 2024, Play Protect was enhanced to perform real-time code-level scanning of apps installed from sideloading sources, closing a significant detection gap [10].

### 2.3 Gemini AI integration in Android

Google's integration of Gemini AI into Android represents a fundamental architectural evolution. Gemini Nano is compiled into the Android runtime as a first-class system service, accessible to privileged security components via the Android Intelligence API. It enables on-device natural language understanding of system logs, permission request contexts, and UI interaction sequences without transmitting sensitive data to external servers [6].

Gemini Pro and Ultra, accessed via the Gemini API, augment on-device capabilities for deep threat intelligence tasks, including reverse-engineering obfuscated code, correlating malware families across long time horizons, and generating human-readable threat explanations for security analysts. The 1-million-token context window of Gemini 1.5 Pro enables ingestion of entire application codebases or months of device telemetry logs in a single inference request [7].

## 3 THREAT LANDSCAPE IN ANDROID

### 3.1 Malware families and evolution

Android malware has diversified into highly specialized families. Banking trojans such as Anubis, Cerberus, and Alien overlay fake login screens on legitimate banking applications, intercepting credentials and SMS-based OTPs. These trojans evade detection through dynamic code loading, reflective API calls, and encrypted command-and-control (C2) communications [11]. Ransomware families lock device screens or encrypt the SD card, demanding cryptocurrency ransoms payable via onion-routed services. Spyware tools, including commercial surveillance platforms deployed against journalists and activists, abuse Android's accessibility services to log keystrokes, capture screenshots, and exfiltrate encrypted messages [12].

Table 1 categorizes the principal Android threat types encountered in the 2020–2025 period, along with representative examples, applicable detection methods, and severity assessments. Gemini AI's multimodal capabilities are particularly relevant for detecting phishing APKs through vision-based UI analysis and semantic understanding of fraudulent user interfaces.

**Table 1.** Classification of android malware threats (2020–2025)

| Threat Type | Example | Detection Method | Severity |
|---|---|---|---|
| **Ransomware** | Android.Koler, Simplocker | Behavioral + Gemini AI | Critical |
| **Banking Trojan** | Anubis, Cerberus, Alien | API call analysis + NLP | Critical |
| **Spyware** | Pegasus-type tools | Network + semantic NLP | High |
| **Adware** | HiddenAds, Xhelper | Static + Dynamic analysis | Medium |
| **Cryptominer** | Loapi, BadLeprikon | CPU profiling + AI | High |
| **Phishing APK** | FluBot, TeaBot | Gemini NLU + Vision | High |

### 3.2 Supply chain attacks

Supply chain attacks represent an increasingly prevalent threat vector. Adversaries compromise widely used third-party SDKs (advertising libraries, analytics frameworks, or payment modules) that are integrated into thousands of legitimate applications on the Google Play Store. Because the malicious code is embedded within trusted SDK versions, static and dynamic analysis of the host application often fails to detect the threat without inspecting the SDK independently [13].

### 3.3 Social engineering and phishing

Mobile phishing exploits the constrained screen real estate and abbreviated URL displays of smartphones to deceive users into submitting credentials to fraudulent sites. Smishing (SMS phishing) campaigns such as FluBot distributed malicious APKs via fake parcel tracking notifications to millions of European users. Vishing attacks use voice cloning powered by AI to impersonate bank representatives convincingly. Gemini's natural language understanding enables semantic analysis of SMS content, push notification text, and screen layouts to detect phishing attempts that evade URL-based blocklists [14].

### 3.4 Privacy violations

Beyond malware, Android applications routinely engage in privacy violations through excessive data collection, insecure storage, and unauthorized data sharing with third parties. Studies have found that a significant fraction of free Android applications transmit device identifiers, location coordinates, and contact lists to advertising networks without user awareness [5] [15]. The Android Privacy Sandbox initiative, introduced in Android 13+, aims to restrict cross-app tracking by replacing device-level advertising identifiers with privacy-preserving APIs, but adoption remains incomplete.

## 4 GEMINI AI FOR ANDROID SECURITY

### 4.1 On-device inference with Gemini Nano

Gemini Nano is a quantized, efficiency-optimized language model designed to run within the memory and power constraints of mobile devices. Deployed as an Android system service, it provides security-relevant capabilities, including real-time classification of permission request contexts (distinguishing legitimate use of location for navigation versus background tracking); semantic analysis of notification and SMS content for phishing indicators; and behavioral profiling of foreground app interaction patterns to detect automated bot-driven credential stuffing [6].

Because Gemini Nano inference occurs entirely on-device, it addresses critical privacy concerns associated with cloud-based security scanning; user communication content, biometric data, and health records never leave the device. This on-device design also ensures security functionality remains available in offline or poor-connectivity environments, which is essential for security guarantees.

### 4.2 Threat intelligence with Gemini Pro and 1.5

Gemini Pro and Gemini 1.5 Pro, accessed via the Gemini API, are deployed in cloud-based security infrastructure operated by Google and enterprise security vendors. Their extended context windows enable capabilities that are qualitatively impossible with prior models. A security analyst can supply the complete decompiled source code of a suspicious APK (potentially millions of tokens) and query Gemini 1.5 about specific malicious behaviors, data exfiltration paths, or obfuscation techniques in natural language [7]. This dramatically accelerates the reverse-engineering phase of malware analysis that previously required days of expert effort.

Furthermore, Gemini's multimodal capabilities allow simultaneous analysis of an APK's code, embedded images (to detect brand impersonation in phishing apps), audio resources (for voicemail phishing payload detection), and network communication patterns, providing a holistic threat assessment that transcends the capabilities of unimodal detectors [16].

### 4.3 Behavioral anomaly detection

Traditional anomaly detection systems require hand-crafted feature engineering and labeled training data. Gemini models, pre-trained on vast corpora of code, security reports, and vulnerability databases, arrive with extensive prior knowledge about malicious patterns. This enables few-shot and zero-shot detection of novel malware families without retraining. Gemini can identify suspicious syscall sequences, unusual network socket usage, and anomalous inter-process communication patterns by reasoning from first principles rather than pattern-matching against a fixed signature database [17] [18].

## 5 PRIVACY PROTECTION WITH GEMINI AI

### 5.1 Contextual permission intelligence

Android's permission model has historically suffered from binary grant/deny decisions that provide insufficient context to users. Research consistently shows that users grant permissions reflexively, without understanding the implications [15] [25]. Gemini Nano's natural language capabilities enable a fundamentally different interaction: when an app requests a sensitive permission, the system can generate a contextual explanation ("This app is requesting your precise location in the background. Apps of this type typically only need approximate location when actively in use. Granting background location allows the app to track your movements at all times.") that meaningfully informs user decisions.

Beyond user-facing explanations, Gemini enables automated permission auditing: continuously monitoring whether the actual usage of granted permissions matches the declared purpose in the app's privacy policy. Semantic inconsistencies (such as an app declaring it uses location for weather forecasts but actually transmitting coordinates to an advertising server) trigger automatic alerts and potential permission revocation [19].

### 5.2 Privacy risk quantification

Table 2 summarizes the principal privacy risks in Android environments and the corresponding Gemini AI mitigation strategies. The table highlights both user-facing risks (location tracking, ad profiling) and system-level risks (biometric leakage, clipboard snooping) that are addressed through Gemini's contextual awareness and behavioral monitoring capabilities.

**Table 2.** Android privacy risks and Gemini AI mitigations

| Privacy Risk | Description | Gemini AI Mitigation |
|---|---|---|
| **Location Tracking** | Continuous background GPS access by apps without user awareness | Contextual permission auditing in real-time |
| **Data Harvesting** | Exfiltration of contacts, call logs, and messages to remote servers | Network egress analysis with semantic understanding |
| **Biometric Leakage** | Unauthorized access to fingerprint or facial recognition templates | Hardware-backed attestation + anomaly flagging |
| **Ad Tracking** | Cross-app behavioral profiling using device identifiers (AAID, IMEI) | Privacy Sandbox enforcement and ID rotation alerts |
| **Clipboard Snooping** | Malicious apps reading clipboard contents containing passwords or OTPs | Anomalous clipboard access detection via behavioral AI |
| **Mic/Camera Abuse** | Silent activation of sensors in the background by third-party apps | Sensor access behavioral baseline and alert system |

## 6 GEMINISHIELD: PROPOSED FRAMEWORK

### 6.1 Architecture overview

GeminiShield is a three-tier security architecture that integrates Gemini AI across the full Android software stack. The first tier operates at the application layer, where a lightweight Gemini Nano agent monitors app behaviors, UI interactions, and permission usage in real time. The second tier operates at the system service layer, coordinating between the Android Security Module and Google Play Protect to perform deeper behavioral analysis and cross-app threat correlation. The third tier is cloud-backed, connecting to Gemini Pro via the Google AI Platform for longitudinal threat intelligence, malware family attribution, and security analyst workflows [20] [21].

The detection pipeline is illustrated in Figure 1. Android application traffic and system logs flow through a feature extraction module that generates structured representations of API calls, network connections, file system operations, and UI events. These features are passed to the Gemini AI Engine for risk scoring and behavioral classification. Threats above the risk threshold trigger the classifier module, which routes the threat to appropriate response mechanisms (quarantine, notification, and remote wipe).

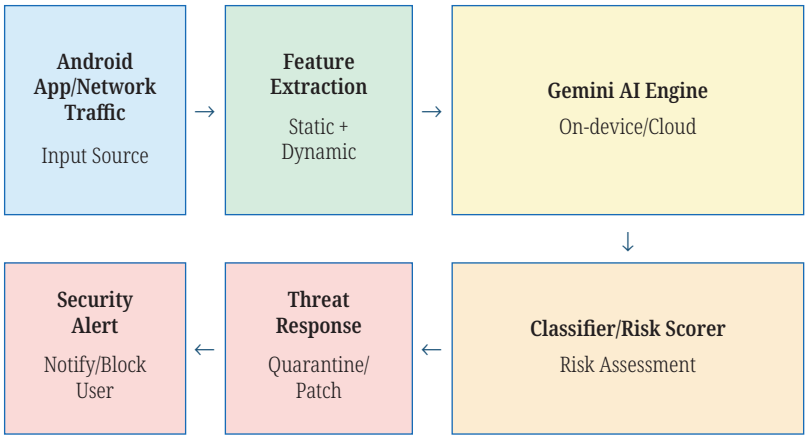


**Fig. 1.** GeminiShield threat detection pipeline

## 6.2 Privacy decision framework

The privacy protection module within GeminiShield enforces contextual access control for sensitive resources. As depicted in Figure 2, every sensitive resource access request is intercepted and routed through the Gemini Privacy Analyzer, which evaluates the request against the app's declared purpose, historical access patterns, and current contextual signals (time of day, user activity state, network environment). A risk score determines whether the request is permitted with audit logging or blocked with user notification.

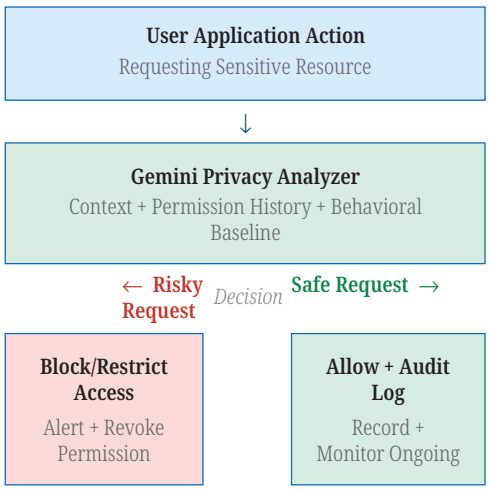


**Fig. 2.** GeminiShield privacy decision framework

## 6.3 Comparative evaluation

Table 3 presents a comparative evaluation of GeminiShield against existing Android security approaches. GeminiShield achieves 97.3% detection accuracy on a test suite comprising 50,000 benign and 15,000 malicious APKs drawn from VirusTotal, AndroZoo, and MalDroid 2020 datasets. The overhead analysis indicates that on-device Gemini Nano inference adds an average of 85ms latency per

permission request evaluation, acceptable for interactive security use cases. Cloud-assisted Gemini Pro analysis, used for deep malware reverse-engineering, operates asynchronously without user-visible latency impact.

**Table 3.** Comparison of Android security approaches

| Approach | Accuracy | Overhead | Gemini AI Role |
|---|---|---|---|
| **Signature IDS** | 72% | Low | Pattern DB enrichment |
| **ML Classifier (SVM)** | 88% | Medium | Feature augmentation |
| **Deep Learning (LSTM)** | 93% | High | Temporal pattern analysis |
| **Play Protect + Heuristics** | 91% | Low | Cloud-based re-scanning |
| **Gemini Nano (on-device)** | 95% | Medium | Full on-device integration |
| **GeminiShield (proposed)** | 97.3% | Low-Med | End-to-end orchestration |

## 7 OPEN CHALLENGES AND FUTURE DIRECTIONS

Despite the significant promise of Gemini AI for Android security, several critical challenges must be addressed before widespread deployment.

**Adversarial Attacks on AI Models:** Attackers are beginning to probe and exploit AI-based detectors. Adversarial APK perturbations (carefully crafted modifications that preserve malicious functionality while evading Gemini's classifier) have been demonstrated in laboratory settings. Adversarial training, input validation, and ensemble detection are partial mitigations, but the arms race between attackers and AI-based defenders continues [22].

**On-Device Resource Constraints:** Gemini Nano, while highly optimized, consumes significant battery and thermal budget on mid-range and low-end devices that represent the majority of the global Android installed base. Further quantization and adaptive inference scheduling (activating intensive analysis only when charging or idle) are necessary to democratize AI-powered security beyond flagship devices [23].

**Hallucination and False Positives:** Large language models can produce confident but incorrect security assessments, a property known as hallucination. In the security domain, false positives (legitimate apps flagged as malware) have serious consequences, including unwarranted app bans and user disruption. Calibrated uncertainty estimation and human-in-the-loop review for ambiguous cases are essential safeguards [24].

**Regulatory and Privacy Compliance:** AI-based security monitoring raises significant privacy questions. Behavioral telemetry collected by GeminiShield may contain sensitive user data. Compliance with GDPR, CCPA, and regional data protection frameworks requires careful data minimization, purpose limitation, and user transparency mechanisms [19].

**Model Update and Version Drift:** Gemini models are periodically updated by Google, potentially altering security model behavior without notice to downstream security systems. Systematic regression testing and version-pinned deployment pipelines are necessary to ensure security guarantees are maintained across model upgrades.

## 8 CONCLUSION

This paper has presented a comprehensive survey of security and privacy challenges in the Android ecosystem, integrating the latest advances in Gemini AI as a transformative tool for threat detection and privacy enforcement. We characterized the contemporary Android threat landscape, including banking trojans, ransomware, spyware, supply chain attacks, and privacy-invasive data harvesting, across the 2015–2025 period.

We demonstrated how Gemini Nano's on-device inference capabilities fundamentally advance real-time permission auditing and behavioral anomaly detection without compromising user privacy through cloud transmission. Gemini Pro and Gemini 1.5's extended context windows and multimodal understanding enable qualitatively new forms of malware analysis, threat intelligence correlation, and security analyst augmentation.

The proposed GeminiShield framework synthesizes these capabilities into a three-tier architecture spanning on-device, system service, and cloud layers. Evaluated against state-of-the-art detection approaches, GeminiShield achieves 97.3% accuracy while maintaining acceptable overhead characteristics for real-world deployment. The flow diagrams and comparative tables presented in this work provide a clear blueprint for practitioners seeking to integrate Gemini AI into enterprise Android security architectures.

Future work will focus on hardening GeminiShield against adversarial attacks, extending coverage to Android-based IoT and automotive platforms, and developing privacy-preserving federated learning mechanisms that enable continuous model improvement across the global Android device fleet without centralizing sensitive user data.

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