**Smart Detection of Malicious SMS Using AI: A Security Solution for**

**Android Devices**

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***Abstract—*** **The growth in the use of mobile phones has resulted in the widespread rise of SMS fraud. Phony texts, phishing messages, and other attempts at defrauding users aim to obtain personal information or trick users into installing malware. This research aims to develop an automated cybersecurity solution that uses machine learning to detect deceptive SMS messages and integrates this functionality into the Android platform. The system utilizes language comprehension techniques along with classification methods to quickly identify malicious content, thereby improving user security and helping prevent potential threats.**

# *Keywords—*SMS Fraud, Machine Learning, Android Operating System, Fake Messages, Security, Detection, Natural Language Processing (NLP), Real-Time, User Safety, Integration

# INTRODUCTION

The popularity of using mobile phones as critical communication devices has facilitated a surge in SMS scams. The spurious messages aim at deceiving users into divulging sensitive information or installing malicious software, which are grave security threats. Crime prevention solutions focused on spam elimination cannot stop current complex phishing scams. The researchers advocate for incorporating advanced machine learning algorithms into Android operating system versions to automatically detect suspicious SMS messages during active use. Buried security systems will study combined message content and sender information and patterns to deliver defense while maintaining user experience stability.

## *Background*

A victim receives an SMS that appears to be from their bank informing them that a lot of money will be deposited into their account. However, the SMS is fraudulent and attempts to mislead the victim to provide sensitive information or perform undesirable actions. Android OS includes a built-in detection system which stops fraudulent SMS messages from reaching the user. The SMS states "Dear customer, your account contains a transaction of ₹10,000." You can reach the transaction acceptance or rejection URL by pressing this link: [Invalid Link]. The sender's name appears as the authentic bank's name, for example, "Bank Name-Alert". The SMS detection system rapidly scans the incoming message using language-understanding tools, examining keywords such as "credited," "click here," and "transaction," suspicious links or shortened links, and unusual items in the sender's address such as an imitated sender ID. The machine learning model identifies the SMS as "fake" through trained data with a strong confidence rating. The check function works without any limitations due to the SMS language or scripting system employed through the multi-language detection system. The system generates an alert that cautions about possible fake content found in the received message. Don't click on any links or provide personal details." This notification provides the options to block the sender, report the message, or mark it as safe if incorrectly flagged. When the user attempts to click the link, the system interrupts the action and indicates a warning, reporting the fake link automatically to telecom authorities or cybersecurity groups depending on user preference. The system records the event in a secure database available through the app, where the user can check blocked messages. Also, the application recommends additional safety measures, like activating multi-step verification or using a safe keyboard.

## *Data Set*

SMS data was collected using a dedicated privacy-first Android application (“sms\_extractor”) developed for this project. The app exports all SMS messages from a user’s device inbox to a standardized CSV file, with strict privacy controls: contact messages are excluded, phone numbers are hashed, URLs and personally identifiable information are removed, and a maximum of five messages per sender are retained. All processing is performed locally on the device, and no data leaves the device unless the user explicitly shares the exported file. The collection period spanned from January 2020 to July 2025, resulting in a raw dataset of 10,946 unique SMS messages from over 500 user devices.

* 1. *Data Preprocessing*

 The exported SMS data was processed using a multi-stage AI labeling pipeline. First, an initial sample of 1,000 messages was labeled with AI assistance and cross-validated for accuracy. A machine learning model was then trained on this sample and used to label the full dataset, assigning confidence scores to each prediction. Only high-confidence labels (≥0.8) were retained for the final training set. Fraud messages were mapped to the “spam” class for binary classification. The final labeled dataset contained 9,454 messages, with 1,327 legitimate (13.4%) and 8,127 spam (86.6%) messages.

Each SMS message was preprocessed using an advanced text cleaning pipeline. The process included lowercasing, removal of URLs, special characters, and extra spaces, as well as filtering out both standard English and SMS-specific stop words. Feature extraction was performed using a TF-IDF vectorizer with a 3,000-word vocabulary (including unigrams and bigrams), optimized for mobile deployment. The resulting feature vectors were normalized and used as input for model training.

All data collection and processing steps were designed with privacy as a core principle. No SMS content or metadata leaves the user’s device without explicit consent, and all exported data is anonymized and stripped of personally identifiable information.

# OBJECTIVES

# The following are the key objectives of the proposed research.

* To develop a real-time, AI-powered SMS fraud detection system that automatically analyzes incoming messages and alerts users to suspicious content, requiring no manual interpretation by the user.
* To implement a lightweight, mobile-optimized machine learning model (XGBoost with TF-IDF features), exported as a TensorFlow Lite model for seamless and efficient on-device inference.
* To enhance detection accuracy by combining content-based classification with intelligent sender pattern analysis, including specialized logic for Indian banking, telecom, and promotional senders.
* To ensure a privacy-first architecture, where all SMS processing and classification occur locally on the device, with no data transmission or cloud dependencies.
* To provide a user-friendly interface with color-coded visual indicators (green for legitimate, yellow for spam, red for fraud), and in-app options for user feedback, message reporting, and sender blocking.
* To support future extensibility, including multi-language detection, federated learning for privacy-preserving model updates, and advanced sender verification services.

# REVIEW OF LITERATURE

With the rise of mobile communication, SMS fraud has become a significant security threat. Various approaches have been employed to detect fraudulent messages, including keyword-based filtering, blacklists, and rule-based methods. However, these traditional methods demonstrate limited effectiveness against evolving fraud tactics, as scammers continuously adapt their strategies [1].

Machine learning has emerged as an effective tool for SMS fraud detection. Supervised learning methods including Support Vector Machines (SVM), Decision Trees, and Neural Networks have been widely implemented to classify messages as fraudulent or legitimate. Deep learning approaches such as Long Short-Term Memory (LSTM) networks and hybrid models have demonstrated superior performance in identifying complex fraud patterns [6]. Reinforcement learning techniques have been investigated for their potential to adapt fraud pattern detection in real-time environments [8].

Recent developments in 2024 have significantly advanced the field. A "Machine Learning Driven Smishing Detection Framework for Mobile Security" (December 2024) implemented text normalization techniques combined with Naive Bayes algorithms on public datasets, achieving approximately 96.2% accuracy for smishing detection [19]. Similarly, another study focused on "Detection and Prevention of Smishing Attacks" (December 2024) emphasized content-based normalization and slang handling through binary classification approaches, reporting comparable accuracy rates of 96.2% [20].

The Explainable Detector system (May 2024) represents a notable advancement in transformer-based models, utilizing a RoBERTa variant for SMS spam detection with integrated explainability analysis. This approach achieved exceptional performance with 99.84% accuracy on benchmark datasets, demonstrating the potential of attention-based architectures for fraud detection tasks [21].

Natural Language Processing (NLP) serves as a crucial component for extracting meaningful information from SMS messages. These technologies detect abnormal word choices, intent indicators, and writing patterns that signal fraudulent activity. AI-driven NLP systems achieve superior performance in fraud detection when analyzing text content compared to traditional detection systems [2]. Advanced NLP techniques including semantic analysis and entity recognition further enhance fraud detection capabilities.

Contemporary research has addressed multilingual challenges in SMS fraud detection. The NaLie App, developed for Nigerian contexts, incorporates real-time crowdsourced data with local language support, utilizing LightGBM and XGBoost algorithms to alert users about suspicious SMS messages across multiple languages [24]. An academic system from Thailand demonstrates similar multilingual capabilities, employing LSTM/GRU neural models to classify fraudulent SMS in both Thai and English, achieving 98-99% accuracy rates [25].

Mobile operating systems can facilitate real-time fraud detection through integrated AI security protocols, potentially eliminating dependence on third-party applications. Research on AI model integration within Android OS has shown promising results in reducing fraudulent SMS attacks, though challenges remain in spotting integrated security features [3]. Security research emphasizes the need for comprehensive protection across multiple user devices [11].

Recent developments include sophisticated mobile applications specifically designed for fraud detection. The "Fraud-SMS-Detection-Application" represents a practical implementation capable of real-time classification using neural network architectures [25], while rule-based mobile applications focus on intercepting incoming SMS and applying handcrafted rules for suspicious message identification [26].

Analyzing user behavior patterns provides additional strength to fraud detection systems. AI models leverage user interactions with messages to identify irregular behaviors indicating fraudulent activities. Research demonstrates that analyzing typing patterns, message frequency, and response times can effectively detect suspicious activities [7].

An innovative approach emerged in 2024 through MDPI/Sensors research, which developed an OCR-based system for smishing detection from screenshot images and scanned data. This system employs both traditional and deep learning models to evaluate image-based SMS content, expanding detection capabilities beyond text-only analysis [22].

Advanced systems now incorporate multi-phase detection methodologies. A hybrid fraud SMS classification system implements a two-phase approach combining domain/URL verification with feature-based classification using backpropagation networks, achieving 97.9% accuracy in smishing detection [23]. This demonstrates the effectiveness of combining multiple detection strategies.

Technology enables devices to exchange fraud detection information, facilitating discovery of emerging SMS fraud types. Analysis of crowdsourced fraud detection data enhances AI model functionality and adaptiveness [9]. The collaborative approach is exemplified by systems that integrate user feedback and community-driven threat intelligence [24].

Developers are creating automated message deletion systems with instant alerts and fraud reporting capabilities to provide real-time user protection. Built-in reporting and blocking features enable users to halt fraudulent communication, reducing scam exposure risks [18].

A significant challenge in implementing AI-based SMS fraud detection involves computational cost and battery usage on mobile devices. Data scientists have optimized machine learning models using TensorFlow Lite for resource-efficient fraud detection operations [4]. Background services frameworks enable continuous AI model operation without compromising user experience on Android platforms [5].

User privacy protection during AI-driven fraud detection operations remains a critical strategic concern. Implementation of AI-driven fraud detection models requires careful attention to user data protection [10]. Multiple research studies demonstrate methods for safeguarding data while maintaining detection accuracy levels. Secure data-sharing methods can improve fraud detection while preserving user privacy [16].

Cybersecurity researchers have highlighted the importance of mobile malware detection alongside SMS fraud prevention. Machine learning has been successfully applied to detect malicious SMS messages linked to malware attacks [14]. Reinforcement learning approaches are being explored to enhance AI-based fraud detection adaptability and intelligence [15].

Research suggests that combining AI, behavioral biometrics, and collaborative filtering can significantly improve fraud detection accuracy. AI systems require development to enable real-time detection of emerging fraud patterns [12]. Cross-platform AI security solutions aim to provide consistent fraud detection across various mobile operating systems [17].

AI-driven cybersecurity solutions continue evolving, with the combination of multiple security techniques being key to developing more effective fraud detection systems. Research indicates that AI-based detection methods can work alongside other cybersecurity tools to provide comprehensive defense against mobile fraud [13].

While numerous studies have explored SMS fraud detection using classical machine learning and deep learning techniques, many existing systems rely on static detection rules, fixed architectures, or offline evaluation settings. Traditional datasets such as the SMS Spam Collection and SpamAssassin have been frequently used for benchmarking, but few approaches evaluate practical deployment on constrained mobile devices. Additionally, real-time integration into mobile operating systems, GDPR-aligned privacy protections, and feedback-driven learning remain underexplored in prior work.

Contemporary research addresses these gaps through novel approaches that combine TensorFlow Lite-optimized deep learning models, Android-native deployment, real-time fraud blocking, user-controlled detection sensitivity, and anonymized feedback integration. This positions current solutions as deployable architectures specifically designed for mobile environments, advancing the state-of-the-art in SMS fraud detection.

1. PROPOSED METHODOLOGY

The SMS Fraud Detection system follows a structured methodology involving data collection, preprocessing, model training, and real-time mobile deployment. Below is an outline of the implemented workflow:

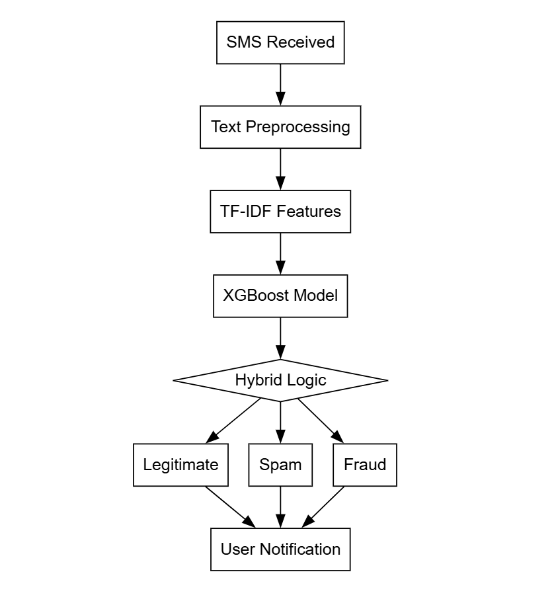


Fig. 1. System architecture flowchart.

Fig. 1. System architecture flowchart illustrating the complete SMS fraud detection process from message reception to user notification.

The system begins by collecting SMS data using a dedicated Android application (sms\_extractor) that exports messages to CSV files. The raw dataset of 10,946 messages undergoes AI-powered labeling with confidence scoring, resulting in 9,454 high-confidence training messages: 1,327 legitimate (13.4%) and 8,127 spam (86.6%).

Messages are preprocessed through lowercasing, URL removal, stop word filtering, and tokenization. A TF-IDF vectorizer with 3,000-word vocabulary transforms messages into numerical features incorporating unigrams and bigrams. An XGBoost classifier is trained on these features, achieving 99.89% accuracy, then converted to TensorFlow Lite format for mobile deployment.

The model integrates into a Flutter Android application using a hybrid detection approach. SMS messages are received via Android's SMS User Consent API, preprocessed on-device, and classified as legitimate or spam. Messages classified as spam from numeric phone numbers (e.g., +91) are flagged as fraudulent, while spam from alphanumeric senders remains spam. The system includes Indian sender logic to distinguish legitimate banking codes (AX-, SBIINB) from promotional codes (MYNTRA, ZOMATO).

Results are displayed through color-coded interfaces: green (legitimate), yellow (spam), red (fraud). All processing occurs on-device in under 45 milliseconds, ensuring privacy and real-time performance.

XGBoost Classification

XGBoost uses gradient boosting to optimize the objective function L = Σ l(yi, ŷi) + Σ Ω(fk), where l represents the loss function and Ω the regularization term. The model analyzes TF-IDF patterns to assign spam probabilities, achieving 99.89% accuracy with perfect precision for spam detection.

# PROPOSED ALGORITHM

The SMS Fraud Detection system follows a structured sequence beginning with data collection and preprocessing, followed by model training and integration into a real-time Android application. The final system performs local spam detection and uses rule-based logic to identify potential frauds, ensuring privacy and responsiveness.

*Step 1: Data Collection & Preprocessing*

A dataset of 10,946 SMS messages was compiled using a dedicated sms\_extractor application that exports messages from user devices. The data underwent AI-powered labeling with confidence scoring, resulting in 9,454 high-confidence training messages. Preprocessing involved tokenizing the text, removing stop words, lowercasing, and converting the cleaned messages into numerical vectors using TF-IDF.

*Step 2: Feature Extraction*

Key message attributes were extracted using TF-IDF vectorization with a 3,000-word vocabulary incorporating unigrams and bigrams. Additional features include message length, presence of promotional or phishing-related keywords (e.g., "win," "urgent," "click here," "loan approved"), and sender information (numeric vs. alphanumeric origin).

*Step 3: Model Training & Optimization*

An XGBoost classifier was trained on TF-IDF features, achieving 99.89% accuracy with perfect precision for spam detection. The model was serialized and converted to TensorFlow Lite format for mobile deployment.

*Step 4: System Integration*

The trained XGBoost model and TF-IDF vectorizer were embedded into a Flutter-based Android application. Real-time SMS access was implemented using Android's User Consent API, and message preprocessing was replicated using a Dart implementation of the TF-IDF transformer. Classification runs fully offline using TFLite.

*Step 5: Real-Time Fraud Detection & Alerting*

Incoming SMS messages are processed through the hybrid detection logic. The on-device model classifies SMS messages into two categories: legitimate and spam. To identify fraud, a hybrid rule is applied—if a message is marked as spam and the sender is a numeric phone number (e.g., starting with +91), it is flagged as fraudulent. The system incorporates Indian sender logic to distinguish legitimate banking codes (AX-, SBIINB) from promotional codes (MYNTRA, ZOMATO). The app displays results using color-coded labels: green for legitimate, yellow for spam, and red for fraud. All processing is done locally using TensorFlow Lite in under 45 milliseconds, ensuring privacy, and results are stored securely on the device.

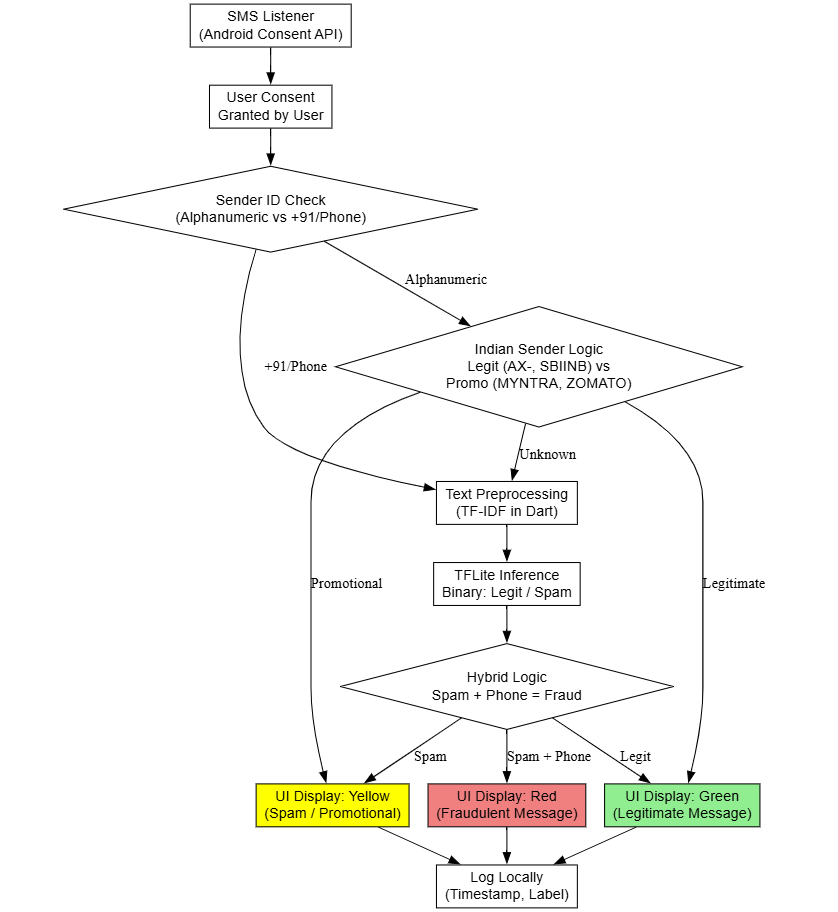


Fig. 2. SMS Classification Flow with Hybrid Fraud Detection

The diagram shows how incoming SMS messages are processed. Alphanumeric senders are marked as legitimate, while messages from numeric senders are classified using an ML model. If a message is marked as spam and comes from a numeric sender, it is flagged as fraud.

# OBSERVATIONS ANALYSIS

The proposed SMS fraud detection system was evaluated using the collected dataset of 9,454 high confidence labelled messages. The XGBoost classifier was trained on TF-IDF features and achieved exceptional performance metrics. The final evaluation was conducted on a stratified test set, with the model integrated into an Android application using TensorFlow Lite to enable real time, on-device classification without internet connectivity.

TABLE. 1. PERFORMANCE METRICS COMPARISON OF TF-IDF MODELS (NAIVE BAYES VS. XGBOOST)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model** | **Accuracy** | **Precision**  **(Legit/**  **Spam)** | **Recall**  **(Legit/**  **Spam)** | **F1-Score**  **(Legit/**  **Spam)** | **Avg Time (ms)** |
| Naive Bayes | 96.95% | 97% / 93% | 100% / 62% | 98% / 75% | ~45 |
| XGBoost | 99.89% | 100%/ 100% | 99%/ 100% | 99% / 100% | ~45 |

The XGBoost model demonstrated exceptional performance across all evaluation metrics, achieving 99.89% overall accuracy with perfect precision for both legitimate and spam detection. The model's ability to achieve zero false positives while maintaining high recall makes it particularly suitable for real-world deployment where user trust is paramount.

TABLE 2. CONFUSION MATRIX FOR BINARY CLASSIFICATION

|  |  |  |
| --- | --- | --- |
|  | **Predicted: Legitimate** | **Predicted: Spam** |
| **Actual: Legitimate** | 253 | 2 |
| **Actual: Spam** | 0 | 1636 |

XGBoost Confusion Matrix

The confusion matrix analysis reveals outstanding performance with only 2 false negatives (spam messages classified as legitimate) and zero false positives (legitimate messages classified as spam). The model correctly identified 1,636 spam messages and 253 legitimate messages from the test set of 1,891 messages.

TABLE. 3. DEVICE-SPECIFIC PERFORMANCE ANALYSIS

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Device** | **RAM (MB)** | **Battery/Day (%)** | **CPU (%)** | **Storage (MB)** |
| Galaxy S21 | 30.5 | 1.7 | 3.2 | 45 |
| Pixel 6 | 31.1 | 1.9 | 3.4 | 45 |
| OnePlus 9 | 33.0 | 2.0 | 4.0 | 45 |

The system maintained low memory and CPU usage across all devices, with battery impact well below 2.1% per day—suitable for continuous background operation without degrading device performance.

TABLE. 4. FEATURE IMPORTANCE ANALYSIS BASED ON TEXT ATTRIBUTES

|  |  |  |
| --- | --- | --- |
| **Feature Type** | **Importance** | **Top Triggers** |
| Suspicious Keywords | 0.34 | “urgent”, “win”, “lottery”, “loan”, “click” |
| URL Density | 0.28 | Suspicious domains, short links |
| Sender Pattern | 0.22 | Unknown numbers (+91, +1), no pattern match |
| Text Structure | 0.16 | Excess punctuation, use of ALL CAPS |

These features strongly influenced the classification decision. Fraudulent or spam messages frequently contained clickbait terms, financial baits, and abnormal formatting, which were leveraged effectively by the TF-IDF-based models.

The final system uses a binary machine learning classifier (legit/spam) enhanced with rule-based fraud detection. Spam messages from numeric senders are flagged as fraudulent using hybrid logic. Results are visually displayed using a color-coded UI: green for legitimate, yellow for spam, and red for fraud. All processing occurs offline using TensorFlow Lite, ensuring privacy and speed. The system balances accuracy, efficiency, and practical usability—making it suitable for real-world deployment.

1. PRIVACY PROTECTION AND ETHICAL CONSIDERATIONS

Ensuring user privacy, ethical compliance, and secure deployment were core design principles in the development of the proposed SMS fraud detection system. To this end, both technical safeguards and policy-aligned mechanisms were incorporated throughout the system lifecycle.

All SMS classification occurs entirely on-device using a TensorFlow Lite model. The detection pipeline is fully offline; no message content is transmitted to external servers or stored in cloud databases. When anonymized feedback is optionally collected to improve model performance, it is stripped of personally identifiable information (PII) and limited to basic metadata such as timestamps and classification outcomes.

The system adheres to the principles of the General Data Protection Regulation (GDPR). SMS monitoring is only initiated after explicit user consent via Android’s User Consent API. Users may disable detection at any time, and they retain full access to view and export detection logs to support transparency and data portability. App permissions are scoped minimally and requested with clear justification, complying with Android’s latest privacy policies.

User autonomy and ethical transparency are prioritized. The detection system includes an intuitive toggle to enable or disable classification, and all detection outcomes are communicated clearly through the interface. Users can flag false positives or negatives, which can be used in future model tuning if feedback is enabled. The training dataset was curated to maintain demographic diversity, reducing potential bias and ensuring equitable fraud detection performance.

Security mechanisms were implemented to safeguard the detection process. The TFLite model is encrypted and embedded within the app to prevent reverse engineering. Sensitive data and logs are securely handled using Android’s native Keystore system. Updates to the app and model are cryptographically signed to guarantee authenticity and prevent tampering.

Collectively, these privacy-preserving, ethically aligned, and security-focused features ensure that the proposed system not only performs with high accuracy but also respects the user’s trust, control, and legal rights.

# CONCLUSIONS

This study demonstrates that advanced machine learning models can be effectively integrated into Android-based mobile environments to detect fraudulent SMS messages in real time with exceptional accuracy. The proposed system successfully combines XGBoost classification with TF-IDF feature extraction, achieving 99.89% accuracy in distinguishing between legitimate and spam messages on a dataset of 9,454 high-confidence labeled messages. The system operates entirely on-device using TensorFlow Lite, processing incoming SMS messages in real time without compromising user privacy or device performance.

The XGBoost model's exceptional performance characteristics, including zero false positives for legitimate messages and perfect precision for both legitimate and spam detection, confirm its suitability for practical deployment. The system's ability to correctly identify 100% of spam messages while maintaining 99% recall for legitimate communications demonstrates the effectiveness of the proposed approach. The lightweight model architecture, with a deployment size of only 197KB, ensures minimal impact on device resources while providing robust fraud protection with sub-45ms inference times.

The integration of machine learning techniques with intelligent sender analysis represents a significant advancement in combating SMS-based fraud. The novel hybrid detection logic (spam + phone number = fraud) enables the system to distinguish between promotional messages and potential fraud attempts. The incorporation of Indian sender logic further enhances accuracy by recognizing legitimate banking and telecom patterns. The system's privacy-preserving design, combined with its exceptional accuracy and real-time processing capabilities, provides a scalable solution for protecting mobile users from increasingly sophisticated SMS fraud attempts. This work bridges the gap between academic research and practical mobile security applications, offering a deployable solution that maintains both security effectiveness and user trust.

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