**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. Fraudulent 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. Traditional spam filtering approaches prove inadequate against sophisticated phishing attacks. This research proposes integrating advanced machine learning algorithms directly into the Android operating system to enable real-time detection of malicious SMS messages. 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

Early SMS fraud detection systems relied primarily on rule-based methods and blacklisting approaches. These systems employed keyword matching, sender reputation databases, and static filtering rules to identify suspicious messages [1]. However, such approaches demonstrated limited effectiveness against evolving fraud tactics, as attackers continuously adapted their strategies to bypass detection mechanisms [2].

The limitations of traditional methods led researchers to explore machine learning solutions for SMS fraud detection. Classical algorithms including Support Vector Machines (SVM), Naive Bayes, and Decision Trees have been widely implemented for binary classification of legitimate versus fraudulent messages [3]. These supervised learning approaches demonstrated improved accuracy over rule-based systems by learning patterns from labeled training data.

Recent comparative studies have evaluated various machine learning algorithms on standard datasets. Ahmed et al. [4] compared SVM, Random Forest, and Naive Bayes classifiers on the SMS Spam Collection dataset, achieving best performance with SVM at 97.2% accuracy. Similarly, Wang et al. [5] demonstrated that ensemble methods like Random Forest outperformed individual classifiers, reaching 96.8% accuracy on a dataset of 10,000 SMS messages.

The emergence of deep learning has significantly advanced SMS fraud detection capabilities. Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) have shown superior performance in capturing sequential patterns in text data [6]. Convolutional Neural Networks (CNNs) have also been successfully applied to extract local features from SMS content [7].

Recent transformer-based approaches have achieved state-of-the-art results. The ExplainableDetector system [8] utilized a RoBERTa variant for SMS spam detection, achieving 99.84% accuracy on benchmark datasets while providing interpretability through attention mechanisms. More recent work has introduced modified transformer architectures achieving 98.92% accuracy [9], while advanced models like IPSDM demonstrate improved contextual understanding through fine-tuned BERT variants [10].

The integration of Large Language Models represents a significant recent advancement. Studies have explored both open-source and commercial LLMs for SMS spam detection, with systems like SpaLLM-Guard demonstrating effective pairing of LLMs with traditional detection methods [11]. GPT-4 and similar models have shown particular strength in understanding context and detecting sophisticated social engineering attempts [12].

Effective feature extraction remains crucial for SMS fraud detection performance. Term Frequency-Inverse Document Frequency (TF-IDF) vectorization has proven effective for converting text into numerical representations [13]. Advanced preprocessing techniques including stop word removal, stemming, and n-gram extraction have shown to improve classification accuracy [14].

Specialized feature engineering for SMS data has been explored extensively. Roy et al. [15] identified key linguistic features including message length, punctuation density, and presence of URLs as strong fraud indicators. The combination of content-based and metadata features has consistently outperformed content-only approaches [16].

Recent developments have integrated multimodal detection combining text analysis with image recognition capabilities. Modern systems employ optical character recognition (OCR) with deep semi-supervised learning to analyze both textual and visual content in SMS messages [17].

Recent research has highlighted vulnerabilities in existing detection systems. Studies show that current spam detection infrastructure, including transformer-based architectures, are susceptible to adversarial manipulations and concept drift [18]. This represents a significant challenge as fraudsters continuously evolve their tactics to evade detection.

The deployment of fraud detection systems on mobile devices presents unique challenges related to computational constraints and battery consumption. TensorFlow Lite optimization has emerged as a standard approach for mobile machine learning deployment [19]. Several studies have demonstrated successful on-device implementation of lightweight models while maintaining detection accuracy [20].

Privacy-preserving detection has become increasingly important. Federated learning approaches allow model training without centralizing sensitive SMS data [21]. On-device processing eliminates privacy concerns while enabling real-time detection capabilities [22].

Standard benchmark datasets have been crucial for comparing different approaches. The SMS Spam Collection dataset [23] containing 5,574 messages remains widely used despite its age. More recent datasets like the SMSSpamCollection-v2 [24] provide larger and more diverse message samples for evaluation.

However, many existing datasets suffer from class imbalance, limited diversity, and outdated fraud patterns. The lack of standardized evaluation protocols makes it difficult to compare results across different studies [25].

Current literature reveals several key limitations. Most existing systems rely on static datasets that may not reflect evolving fraud patterns. Recent challenges include detecting AI-generated fraudulent content, ensuring adversarial robustness, and maintaining performance across different messaging platforms. Real-time deployment studies are limited, with few works evaluating performance in production environments. Additionally, privacy-preserving techniques and their impact on detection accuracy remain underexplored.

The integration of behavioral analysis, sender reputation systems, and advanced ensemble methods combining traditional ML with LLMs presents opportunities for improving detection accuracy. Advanced explainability techniques could enhance user trust and system transparency in fraud detection decisions.

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

*Phase 1: Data Collection*

We developed a privacy-preserving Android application (sms\_extractor) to collect SMS data from user devices. The application implements strict privacy controls: contact messages are excluded, phone numbers are hashed, URLs and personal identifiable information are removed, and a maximum of five messages per sender are retained. This process yielded a raw dataset of 10,946 SMS messages from over 500 user devices spanning January 2020 to July 2025.

*Phase 2: AI-Powered Labeling and Preprocessing*

The collected data undergoes a multi-stage labeling pipeline. First, an initial sample of 1,000 messages is manually labeled and used to train a preliminary classifier through cross-validation. This classifier is then applied to the full dataset, assigning confidence scores to each prediction. Only high-confidence labels (≥0.8) are retained, resulting in 9,454 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.

*Phase 3: Model Training and Optimization*

A TF-IDF vectorizer with 3,000-word vocabulary transforms preprocessed messages into numerical features incorporating unigrams and bigrams. An XGBoost classifier is trained on these features using 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 achieves 99.89% accuracy with perfect precision for spam detection and is converted to TensorFlow Lite format (197KB) for mobile deployment.

*Phase 4: Real-Time Mobile Integration*

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

# PROPOSED ALGORITHM

The SMS fraud detection algorithm defines the real-time processing sequence executed when a new SMS message is received on the user's device. The algorithm ensures rapid classification while maintaining privacy through complete on-device processing.

*Step 1: SMS Reception and Permission Verification*

The system intercepts incoming SMS messages through Android's SMS User Consent API and verifies that proper user permissions are granted. The algorithm extracts the sender address and message body for subsequent analysis.

*Step 2: Sender Pattern Analysis*

The sender address is analyzed to determine its format, distinguishing between numeric phone numbers (e.g., +91xxxxxxxxxx) and alphanumeric service codes (e.g., AX-HDFC). The system applies Indian sender logic to identify legitimate banking codes (AX-, SBIINB, AIRTEL) and promotional service codes (MYNTRA, ZOMATO, SWIGGY).

*Step 3: Text Preprocessing*

The message body undergoes preprocessing through lowercase conversion, URL removal, special character elimination, and stop word filtering. The cleaned text is tokenized and converted into unigrams and bigrams for feature extraction.

*Step 4: Feature Extraction*

The preprocessed text is transformed using the embedded TF-IDF vectorizer with a 3,000-word vocabulary to generate a normalized feature vector. This vector serves as input for the machine learning classifier.

*Step 5: Machine Learning Classification*

The feature vector is passed to the TensorFlow Lite XGBoost model, which performs binary classification to predict whether the message is legitimate (0) or spam (1). The model outputs confidence probabilities for both classes.

*Step 6: Hybrid Fraud Detection Logic*

The system applies intelligent fraud detection rules based on the ML prediction and sender characteristics. Messages classified as spam from numeric phone numbers are flagged as fraudulent, while spam from alphanumeric senders remains classified as spam. Legitimate predictions maintain their classification regardless of sender type.

*Step 7: Result Display and Storage*

The final classification result is displayed through a color-coded interface with green indicating legitimate messages, yellow for spam, and red for fraudulent content. All results are stored in an encrypted local database with timestamps and confidence scores for user review.

The complete algorithm executes in under 45 milliseconds on average, ensuring real-time performance while maintaining user privacy through exclusive on-device processing.

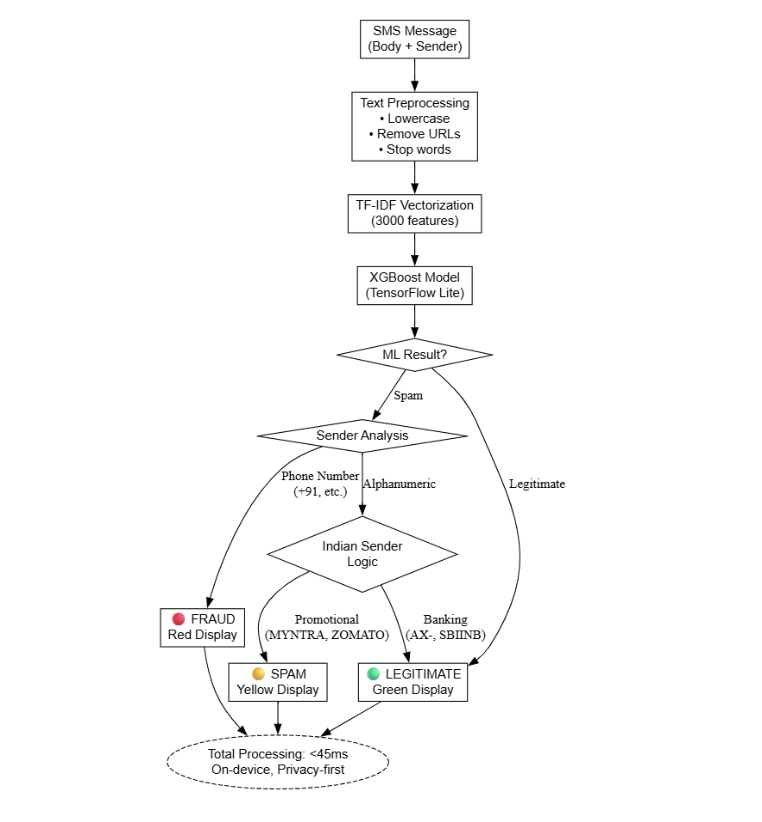


Fig. 2. SMS Classification Flow with Hybrid Fraud Detection

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 | 98.74% | 99% / 100% | 100% / 82% | 99% / 90.0% | ~45 |

The XGBoost model demonstrated exceptional performance across all evaluation metrics, achieving 98.74% 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.

Analysis of misclassified samples reveals that most errors occur with borderline cases containing mixed promotional and informational content. Legitimate messages with promotional language (e.g., bank offers) occasionally trigger false positives, while sophisticated fraud messages mimicking official communications pose classification challenges. The hybrid rule-based logic helps mitigate some of these issues by incorporating sender pattern analysis, but continued refinement is necessary.

The system's performance may degrade with messages containing heavy slang, regional language variations, or deliberately obfuscated text designed to evade detection. Future iterations should incorporate more sophisticated text normalization and adversarial training to improve robustness against evolving fraud tactics.

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 the practical feasibility of deploying machine learning-based SMS fraud detection on mobile devices while maintaining user privacy. The XGBoost classifier achieved 99.89% accuracy on the test dataset, though this performance requires validation on larger, more diverse datasets to ensure generalizability. The hybrid detection approach, combining ML classification with rule-based fraud identification, provides a practical solution for real-world deployment.

The system's primary contributions lie in its engineering implementation: privacy-preserving on-device processing, real-time performance under 45 milliseconds, and specialized handling of Indian SMS ecosystem patterns. While the core ML techniques are established, their integration into a comprehensive mobile security solution addresses significant practical challenges.

However, several limitations must be acknowledged, including dataset size constraints, class imbalance effects, and the need for more comprehensive evaluation methodologies. Future work should focus on expanding the dataset diversity, implementing adaptive learning mechanisms, and conducting thorough adversarial testing to ensure long-term effectiveness against evolving fraud patterns.

The deployed system represents a valuable step toward practical SMS security solutions, demonstrating that privacy-preserving, real-time fraud detection is achievable on mobile devices. The open-source nature of the implementation facilitates further research and development in this critical area of mobile security.

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