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Intelligent Fraud and Dispute Management Systems

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Abstract: Fraud and dispute complaints in banking are often received through multiple channels such as online banking, mobile applications, customer service, and branch offices. Handling these complaints manually can lead to delays, incorrect case routing, duplicate complaints, inconsistent investigation, and difficulty in tracking case progress. The proposed Intelligent Fraud and Dispute Management System provides a centralized platform to manage fraud and dispute cases in an organized and efficient manner. The system collects customer and transaction details, validates the information, classifies the complaint based on its type, prioritizes cases according to their urgency, identifies possible duplicate cases, and assigns them to the appropriate investigation team. Investigators can access the case details, record investigation findings, update the case status, and take appropriate action based on the available information. The system maintains a complete record of each case from complaint registration to final resolution, allowing bank staff to monitor the progress and customers to receive timely information about their complaints. The proposed system helps streamline the overall case management process, minimize processing delays and errors, improve coordination between teams, and provide a more transparent and reliable way of handling fraud and dispute complaints.

Keywords: Financial Fraud Management, Dispute Management, Machine Learning, TF-IDF, Logistic Regression, Text Classification, Automated Complaint Categorization, Priority-Based Complaint Routing, Investigation Management.

I. INTRODUCTION

The Intelligent Fraud and Dispute Management System (FraudGuard) is a web-based application developed to improve the management of financial complaints using Machine Learning (ML). The system uses Term Frequency–Inverse Document Frequency (TF-IDF) to convert complaint descriptions into numerical features and the Logistic Regression algorithm to classify complaints into five categories: Unauthorized Transaction, Duplicate Charge, Cash Withdrawal Issue, Payment Failure, and Other. This automated classification helps organize complaints consistently and reduces the need for manual categorization.

In addition to machine learning-based classification, FraudGuard assigns complaint priorities and routes cases to appropriate investigation teams based on predefined rules. The system provides separate interfaces for customers, investigators, and administrators. Customers can submit complaints and track their status, investigators can review cases and record investigation remarks, evidence, and outcomes, and administrators can monitor complaint statistics and investigation progress. By combining automated classification with a structured workflow, the system supports more organized complaint handling while retaining human involvement in investigation and decision-making.

The application is developed using Python and the Flask web framework, with an SQLite database to store complaint details and related investigation records. The machine learning model is trained using a dataset of 200 complaint samples and integrated into the application to classify newly submitted complaints. FraudGuard aims to demonstrate how machine learning and workflow automation can support financial dispute management. However, the predicted category is based on the complaint text and does not independently confirm whether fraud has occurred. Further testing with larger and more diverse datasets is required to evaluate the model's accuracy, reliability, and suitability for real-world use.

II.THEORETICAL BACKGROUND

The Intelligent Fraud and Dispute Management System (FraudGuard) is based on machine learning and automated complaint management techniques. Machine learning enables the system to identify patterns in previously labeled complaint data and classify new financial complaints into predefined categories. This helps organize customer complaints and supports a more structured dispute management process.

The system uses Term Frequency–Inverse Document Frequency (TF-IDF) to convert complaint descriptions into numerical features that can be processed by a machine learning algorithm. Logistic Regression is then used to classify complaints into five categories: Unauthorized Transaction, Duplicate Charge, Cash Withdrawal Issue, Payment Failure, and Other. The predicted category is based on the text submitted by the customer.

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FraudGuard also uses rule-based logic to assign complaint priorities and route cases to the appropriate teams. The system provides separate interfaces for customers, investigators, and administrators. Customers can submit complaints and track their status, investigators can record remarks, evidence, and investigation outcomes, and administrators can monitor complaint statistics and case progress.

The system is developed using Python and the Flask web framework, with an SQLite database for storing complaint and investigation details. By combining machine learning-based classification with rule-based workflow management, FraudGuard aims to improve the organization and handling of financial disputes. However, the predicted category does not confirm that fraud has occurred; the final investigation outcome depends on human review and available evidence.

III.FOUR-TIER TAXONOMY

Tier 1:
This tier collects financial complaints submitted by customers through the FraudGuard application. Customers provide complaint descriptions related to unauthorized transactions, duplicate charges, cash withdrawal issues, payment failures, and other financial problems. The collected information is passed to the classification process.

Tier 2:
This tier classifies complaints using machine learning techniques. TF-IDF converts the complaint text into numerical features, and the trained Logistic Regression model predicts one of five predefined complaint categories. This helps categorize complaints automatically based on their descriptions.

Tier 3:
This tier manages complaint priority assignment and team allocation using predefined rules. Based on the predicted category, complaints are assigned appropriate priority levels and investigation teams. Investigators can review complaints, add remarks and evidence, and update investigation outcomes.

Tier 4:
This tier stores complaint details, status updates, and investigation records in an SQLite database. The administrator can monitor complaint statistics and investigation progress, while customers can track their complaint status. This tier supports organized record keeping and monitoring throughout the complaint management process.

IV.LITERATURE REVIEW

Several researchers have proposed machine learning and deep learning techniques for financial fraud detection. Carcillo et al. (2018) developed SCARFF for streaming credit card fraud detection using Apache Spark. Wang et al. (2019) proposed FdGars, which uses Graph Convolutional Networks to identify fraudsters in online app reviews.

Mosa et al. (2024) explored machine learning and meta-heuristic techniques for credit card fraud detection, while Li et al. (2024) investigated financial fraud using relationship-based analysis. Prince (2025) studied machine learning models for real-time fraud detection, and Cai (2026) explored Convolutional Neural Networks for detecting financial fraud and anomalies in corporate transactions.

Although these studies focus on fraud detection, they do not cover the complete customer complaint management process. Therefore, the proposed FraudGuard system uses TF-IDF and Logistic Regression to classify financial complaints and integrates priority assignment, team allocation, complaint tracking, and investigation management into a centralized platform.

TABLE I: LITERATURE REVIEW SUMMARY

No.	Author(s) and Year	Paper Title	Technique Used	Limitations
1	Carcillo et al. (2018)	SCARFF: A Scalable Framework for Streaming Credit Card Fraud Detection with Spark	Streaming data processing and Machine Learning	Focuses on transaction fraud detection rather than complete complaint management.

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2	Wang et al. (2019)	FdGars: Fraudster Detection via Graph Convolutional Networks in Online App Review System	Graph Convolutional Networks (GCN)	Focuses on fraud detection in app reviews rather than financial dispute management.
3	Mosa et al. (2024)	CCFD: Efficient Credit Card Fraud Detection Using Meta-Heuristic Techniques and Machine Learning Algorithms	Meta-heuristic techniques and Machine Learning	Concentrates on credit card fraud detection rather than complaint handling and case tracking.
4	Li et al. (2024)	An Intelligent Financial Fraud Detection Support System Based on Three-Level Relationship Penetration	Relationship analysis and Machine Learning	Focuses on financial fraud detection rather than customer complaint classification and investigation management.
5	Prince (2025)	Developing Machine Learning Models for Real-Time Fraud Detection in Online Transactions	Machine Learning and real-time transaction processing	Emphasizes transaction monitoring rather than end-to-end dispute resolution.
6	Cai (2026)	Detecting Financial Fraud and Anomalies in Corporate Transactions with Convolutional Neural Networks	Convolutional Neural Networks (CNN) and financial anomaly detection	Focuses on detecting financial anomalies rather than complaint classification and workflow automation.

TABLE I: LITERATURE REVIEW SUMMARY

V COMPARATIVE ANALYSIS

Traditional financial complaint management systems primarily rely on manual processes for complaint registration, classification, prioritization, and assignment. In these systems, employees must examine each complaint and determine its category and appropriate handling procedure. This approach can be time-consuming, increase the workload of financial institutions, and lead to delays in complaint resolution. Manual processing may also result in inconsistent classification and difficulties in managing a large number of complaints efficiently.

In contrast, machine learning-based complaint management systems automate the classification process by analyzing the textual information provided in customer complaints. FraudGuard uses Term Frequency–Inverse Document Frequency (TF-IDF) to convert complaint text into numerical features and Logistic Regression to classify complaints into five predefined categories. This approach helps organize incoming complaints systematically and reduces the need for repeated manual classification. The effectiveness of the classification process depends on the quality, diversity, and quantity of the training dataset.

Another important difference is that many basic complaint management systems concentrate mainly on complaint registration and classification. FraudGuard extends these functionalities by incorporating rule-based priority assignment, team allocation, complaint status tracking, and investigation record management. Based on predefined rules, complaints can be assigned an appropriate priority level to support more efficient handling. The team allocation feature helps direct complaints to the responsible personnel, while status tracking allows users to monitor the progress of each complaint. Investigation records also help maintain relevant information for subsequent review and decision-making.

FraudGuard additionally provides separate interfaces for customers, investigators, and administrators, ensuring that each user can access the functionalities relevant to their role. Customers can submit complaints and monitor their status, investigators can review assigned cases and maintain investigation details, and administrators can oversee complaint allocation and management activities. This role-based approach supports better coordination, organized record keeping, and improved transparency throughout the dispute management process. Compared with systems that depend heavily on manual communication and record maintenance, the proposed system offers a more centralized and structured workflow.

Furthermore, the integration of machine learning with rule-based decision-making provides a practical approach to financial complaint management. While the machine learning model predicts the complaint category, predefined rules

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can support priority assignment and workflow decisions. Combining these techniques allows FraudGuard to automate selected tasks without relying entirely on machine learning predictions. However, the quality of the results depends on the accuracy of the trained model, the effectiveness of the predefined rules, and the correctness of the complaint information submitted by users.

Despite these advantages, FraudGuard has certain limitations that require further investigation. The classification model may produce incorrect predictions when complaints contain ambiguous language, spelling errors, incomplete information, or terms that were not sufficiently represented in the training dataset. In addition, rule-based priority assignment may not capture every complex financial dispute scenario. Therefore, the system should be evaluated using larger and more diverse datasets, appropriate performance metrics, and real-world complaint examples. Future improvements may include testing alternative classification algorithms, refining priority rules, strengthening data security, and incorporating feedback from investigators to improve the reliability and effectiveness of financial complaint management.

VI.METHODOLOGY

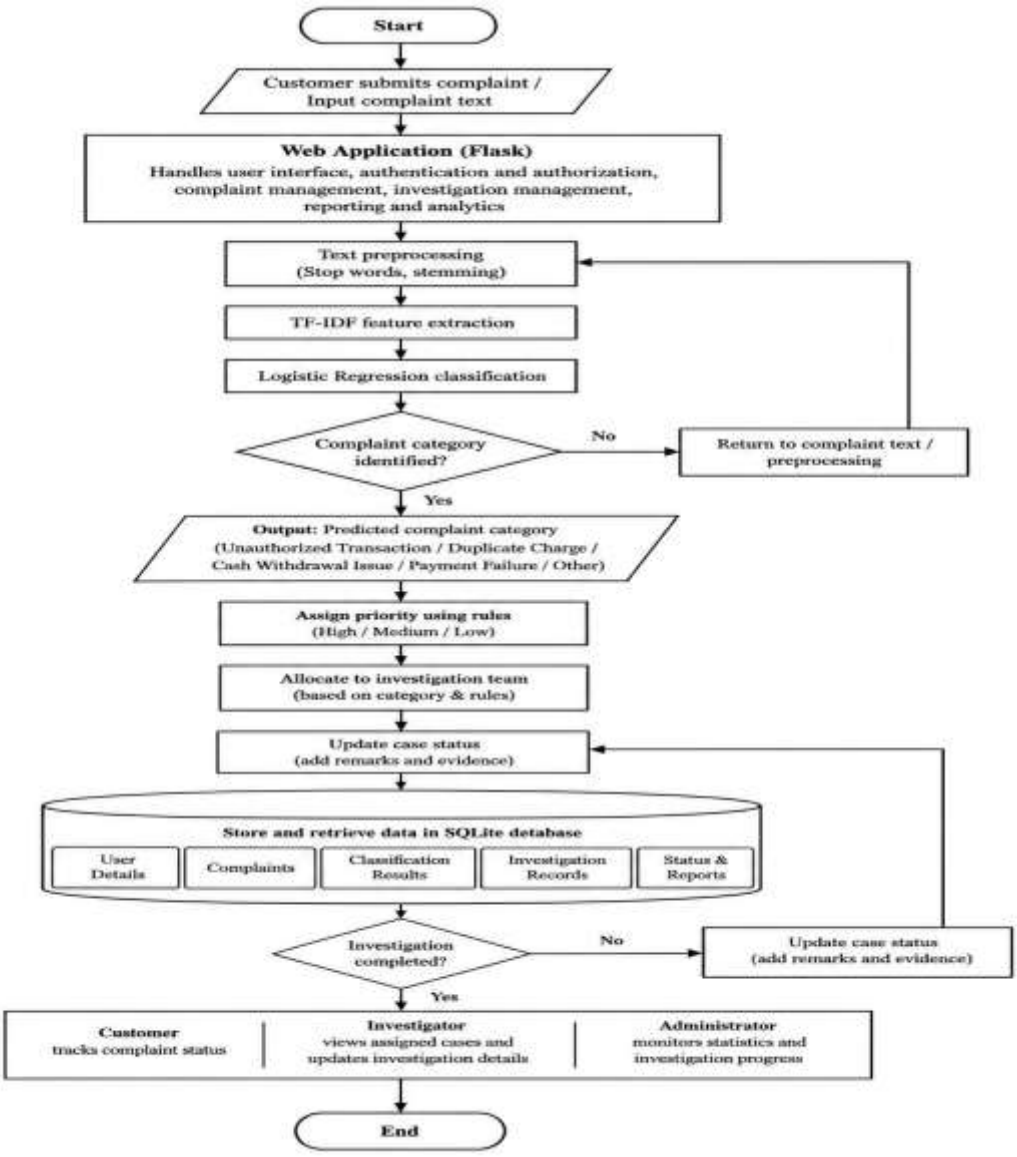


FIG I. FLOWCHART: INTELLIGENT FRAUD AND DISPUTE MANAGEMENT SYSTEM

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The proposed Intelligent Fraud and Dispute Management System (FraudGuard) follows a machine learning-based approach to classify financial complaints and manage their investigation process.

1. Complaint Submission: The customer submits a complaint through the Flask web application by providing the complaint details and description.

2. Text Preprocessing: The complaint text is cleaned by removing unnecessary words and applying text preprocessing techniques such as stop-word removal and stemming.

3. Feature Extraction: TF-IDF (Term Frequency–Inverse Document Frequency) converts the preprocessed complaint text into numerical features for machine learning.

4. Complaint Classification: The Logistic Regression model classifies the complaint into one of five categories: Unauthorized Transaction, Duplicate Charge, Cash Withdrawal Issue, Payment Failure, or Other.

5. Priority Assignment: Based on predefined rules, the system assigns a priority level of High, Medium, or Low to the complaint.

6. Investigation Team Allocation: The complaint is assigned to the appropriate investigation team based on its predicted category and predefined rules.

7. Case Management: Investigators review the assigned complaints, add remarks and evidence, and update the case status during the investigation.

8. Database Management: The SQLite database stores user details, complaints, classification results, investigation records, case statuses, and reports.

9. Investigation and Monitoring: If the investigation is incomplete, investigators update the case details and continue the investigation. Once completed, customers can track complaint status, investigators can review case details, and administrators can monitor statistics and investigation progress.

10. Final Outcome: The investigation outcome is recorded, and the case status is updated to complete the complaint management process.

VII. RESEARCH GAP

Gap 1: Manual Complaint Classification
Traditional financial complaint management systems often depend on manual processes to classify customer complaints. This increases the workload of employees, consumes time, and may lead to inconsistent categorization. An automated complaint classification approach is required to improve efficiency.

Gap 2: Limited Automated Priority Assignment
Many existing systems do not provide sufficient automation for determining complaint priority. As a result, urgent complaints may not receive timely attention. A rule-based priority assignment mechanism is needed to categorize complaints according to predefined conditions and support timely handling.

Gap 3: Lack of Integrated Team Allocation
Existing systems may require manual intervention to assign complaints to the appropriate investigation teams. The absence of integrated team allocation can cause delays and inefficient distribution of work. An automated or rule-based allocation mechanism can help direct complaints to the relevant teams.

Gap 4: Inadequate Complaint Tracking and Investigation Management
Some complaint management systems focus mainly on complaint registration and classification, with limited integration of status tracking and investigation records. This makes it difficult to monitor complaint progress and maintain organized investigation information. A centralized system is required to manage complaints throughout the investigation process.

Gap 5: Limited Integration of Machine Learning and Rule-Based Techniques
Many approaches concentrate on either complaint classification or predefined workflow rules rather than integrating both within a single platform. Combining machine learning-based classification with rule-based priority assignment and team allocation can provide a more organized and efficient complaint management process.

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Gap 6: Need for Improved Classification Evaluation
Machine learning models may produce incorrect predictions when complaint descriptions are unclear, incomplete, or different from the training examples. The reliability of such models must be evaluated using appropriate performance metrics and diverse datasets. Further testing is required to determine their suitability for practical financial complaint management.

Gap 7: Lack of a Unified, Role-Based Platform
Managing customer complaints, investigation activities, and administrative operations through separate tools can lead to fragmented information and communication difficulties. A unified platform with separate interfaces for customers, investigators, and administrators can improve coordination, transparency, and record management.

VIII. CONCLUSION

FraudGuard is a machine learning-based financial complaint and dispute management system designed to improve the efficiency of complaint classification and investigation. The system uses Term Frequency–Inverse Document Frequency (TF-IDF) for text feature extraction and Logistic Regression to classify customer complaints into five predefined categories. This approach helps organize complaints systematically and reduces the need for manual classification.

In addition to complaint classification, FraudGuard integrates rule-based priority assignment, team allocation, complaint status tracking, and investigation record management. It provides separate interfaces for customers, investigators, and administrators, supporting centralized record keeping, better coordination, and a more structured complaint handling workflow. By combining machine learning techniques with rule-based mechanisms, the system helps reduce manual effort and improve the organization of financial complaints.

In the future, FraudGuard can be enhanced by evaluating the model with larger and more diverse datasets, comparing different machine learning algorithms, and improving classification performance. Additional features, such as automated notifications, analytical reports, enhanced data security, and integration with financial institution systems, can further improve its usefulness. Overall, FraudGuard provides a foundation for more efficient and organized financial complaint and dispute management, while final fraud verification and investigation remain essential.

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