Fraudulent Credit Card Activity Detection Using Adaptive Boosting and Aggregate Voting

Abdul Rahman Shaik[1], Mohammed Abdul Ghani[2], Omer Khan[3],
Ms. Sumayya Begum[4]
[1,2,3]B.E. Student, Department of IT, Lords Institute of Engineering and Technology, Hyderabad
[4] Assistant Professor, Department of IT, Lords Institute of Engineering and Technology, Hyderabad
sumayyabegum@lords.ac.in

Abstract— With the rapid digitization of financial transactions, credit card fraud has emerged as a major concern, posing serious risks to both individual users and financial institutions. This research addresses the challenge of detecting fraudulent credit card activities in a timely and accurate manner through a hybrid ensemble learning approach. The proposed framework integrates Adaptive Boosting (AdaBoost) and Aggregate Majority Voting to form a highly robust fraud detection system. AdaBoost, known for its ability to enhance the predictive performance of weak classifiers, is utilized as the core component. Multiple shallow decision trees are iteratively trained, with each successive model focusing on instances previously misclassified, thereby refining the detection of complex fraud patterns. To further strengthen the model's stability and decision reliability, the outputs of these classifiers are combined via a majority voting mechanism, where the final decision is determined by consensus among the classifiers. Experimental evaluation, conducted on both benchmark and real-world credit card datasets, demonstrates that this hybrid system outperforms traditional individual classifiers, standalone AdaBoost, and other conventional detection methods in terms of precision, recall, F1-score, and Receiver Operating Characteristic (ROC) curve analysis. The hybrid system also shows strong resilience in noisy environments, making it a viable solution for practical fraud prevention applications.

Keywords—*Receiver, Operating Characteristic (ROC), AdaBoost, Gaussian mixture model, neural networks, Fraud prevention, Naive Bayes (NB), Support Vector Machines (SVM), and Deep Learning (DL), Matthews Correlation Coefficient (MCC) metric.*

I. INTRODUCTION

Fraud is broadly defined as a deliberate deception or criminal act aimed at unlawfully acquiring financial or personal gain [1]. In financial systems, two core strategies are applied to mitigate fraudulent activities—

fraud prevention, which proactively blocks fraudulent attempts before execution, and **fraud detection**, which identifies ongoing or completed fraudulent actions [2]. Credit card fraud, in particular, involves the unauthorized use of cardholder information to conduct transactions either **physically** or **digitally** [3]. While physical fraud typically requires the physical possession of the card, digital fraud is perpetrated remotely—often through phone transactions or online payment gateways—using details such as the card number, expiry date, and CVV code.

Over the past decade, the growth of **e-commerce** has significantly increased credit card usage worldwide, which in turn has escalated fraud occurrences [4]. For instance, in Malaysia, credit card transaction volumes rose from approximately 320 million in 2011 to 360 million in 2015 [5]. However, despite the implementation of advanced security measures such as EMV chips, two-factor authentication, and one-time passwords, credit card fraud remains persistent. Cybercriminals are increasingly leveraging online platforms to conceal their identity and location during fraudulent activities [6].

The financial implications of such fraud are substantial. In 2015 alone, global credit card fraud losses reached **USD 21.84 billion** [7]. Merchants bear most of these costs, including card issuer penalties, transaction fees, and administrative expenses, which often lead to increased product pricing or reduced promotional offers for consumers [8]. Hence, the development of accurate, real-time, and scalable fraud detection systems is essential to safeguard both financial institutions and customers.

Recent literature highlights various machine learning (ML) methods for fraud detection, including **artificial neural networks (ANNs)**, **decision trees**, **logistic regression**, and **support vector machines (SVMs)** [9]. These can be applied individually or integrated into hybrid systems for improved detection performance [10]. This study proposes a **hybrid model** that combines **AdaBoost** and **Majority Voting** to enhance detection accuracy, scalability, and robustness.

II. RELATED WORK

A. Existing Research and Solutions

Existing credit card fraud detection approaches can be broadly categorized into **statistical**, **machine learning**, and **hybrid** techniques. Statistical approaches such as clustering models attempt to group transactions into clusters of legitimate and fraudulent patterns [11]. Probabilistic models like the **Gaussian Mixture Model (GMM)** estimate the statistical distribution of a user's transaction history and detect anomalies when deviations occur [12]. **Bayesian networks** have also been used to capture probabilistic relationships between user behaviors and fraud indicators [13].

Machine learning-based fraud detection has increasingly become popular due to its ability to identify hidden and non-linear relationships in transaction data [14]. Among these, **AdaBoost** stands out for its capability to combine multiple weak learners into a strong classifier, while **majority voting** serves as an effective ensemble aggregation technique [15]. However, limitations persist in existing systems, including:

- Lack of integration of advanced ML-based ensemble techniques.
- Absence of majority voting in real-world fraud detection applications.
- Risk of overfitting when trained exclusively on historical datasets.
- Implementation complexity requiring in-depth algorithmic expertise.

III. RESEARCH METHODOLOGY

The proposed fraud detection framework is designed to address the dual challenges of **accuracy** and **robustness** in credit card fraud detection by integrating **AdaBoost** with **majority voting** in a **hybrid ensemble architecture**.

1. Overview of the Hybrid Ensemble Strategy

Ensemble methods are widely recognized in machine learning for their ability to improve predictive performance by combining multiple models rather than relying on a single classifier. In this system:

- **AdaBoost** is used as the primary base learner aggregation method, focusing on **iterative error reduction** and **bias minimization**.
- **Majority voting** serves as a secondary layer that aggregates predictions from multiple AdaBoost ensembles to further reduce variance and enhance stability.

This two-tiered mechanism ensures that the model benefits from AdaBoost's **adaptive reweighting of misclassified samples** while also leveraging the **consensus strength** of majority voting to produce more consistent results.

2. AdaBoost Component

The AdaBoost (Adaptive Boosting) algorithm is implemented with **decision trees of shallow depth** (commonly referred to as *decision stumps* or weak learners). The steps include:

1. **Initial Training:**
   - The first weak learner is trained on the dataset with uniform weights assigned to all transactions (both fraudulent and legitimate).
2. **Weight Adjustment:**
   - After each iteration, misclassified transactions are given **higher weights**, increasing their influence in the next training cycle.
   - This forces subsequent learners to focus disproportionately on **hard-to-classify instances**, such as borderline cases or fraud attempts that closely mimic legitimate behavior.
3. **Iterative Model Generation:**

  - Multiple weak learners are sequentially generated, each correcting the mistakes of the previous one.
  - The contribution of each learner to the final model is weighted according to its classification accuracy.

This adaptive process **reduces classification bias** by incrementally refining the decision boundaries.

3. Majority Voting Integration

Once multiple AdaBoost-trained classifiers are created, their **individual predictions** for each transaction are collected. The final classification decision is made via **majority voting**:

- **Voting Mechanism:** The predicted labels (fraud or legitimate) from all classifiers are tallied, and the label with the **highest frequency** becomes the final prediction.
- **Bias–Variance Trade-off:**
  - AdaBoost primarily reduces **bias** by improving weak learners iteratively.
  - Majority voting reduces **variance** by stabilizing predictions against fluctuations caused by data noise or overfitting.

The combination creates a **balanced and resilient decision-making framework**.

4. Performance Evaluation Methodology

To ensure a comprehensive assessment, the reposed system was tested on:

- **Benchmark Datasets:** Publicly available, well-structured datasets used in prior research to allow comparative analysis.
- **Real-World Dataset:** Provided by a financial institution, containing transaction-level details from actual credit card operations.

Robustness Testing:
To simulate imperfect real-world data conditions, **Gaussian noise** was artificially injected into the datasets at varying intensities (10%, 20%, and 30%). This tested the model's ability to maintain performance despite data corruption or measurement errors.

5. Advantages of the Proposed Model

a. Rapid Detection:
The architecture is optimized for **low-latency classification**, enabling near-instantaneous fraud identification during transaction processing without causing delays to legitimate users.

b. Consensus-Based Reliability:
The **majority voting layer** ensures that sporadic misclassifications by individual AdaBoost ensembles have minimal impact on the final decision, increasing trustworthiness.

c. Adaptability to Evolving Fraud Patterns:

Because AdaBoost iteratively focuses on difficult-to-classify cases, the model inherently adapts to **emerging fraudulent behaviors** that differ from historical patterns.

d. Scalability:
The system's modular structure allows it to be deployed across **distributed processing environments**, supporting **real-time high-volume transaction analysis** in large-scale financial operations.

e. Financial Loss Mitigation:
By detecting fraud at early transaction stages, the model significantly reduces the **window of opportunity** for fraudulent withdrawals or purchases, minimizing overall losses.

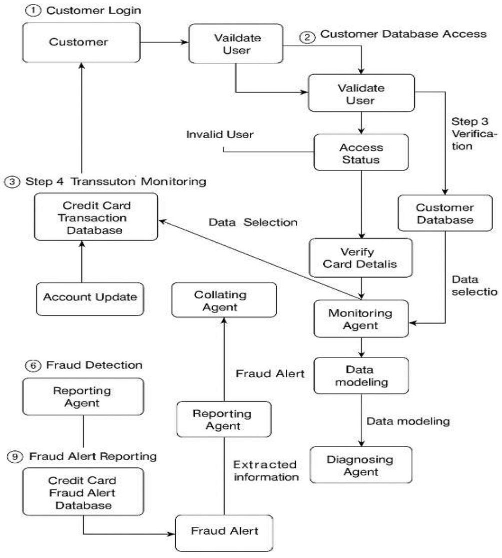

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Fig.1. Proposed Architecture Model

This Fig.1. Proposed Architecture Model represents the **workflow of a credit card fraud detection system**.

1. Customer Login

- **Customer → Login Request → Login**:

  The customer initiates the process by logging into the system with credentials.
- **Login Information → Validate User**:

  The system validates the credentials.
  - If **invalid**, access is denied (Invalid User path ends here).
  - If **valid**, the user is granted access (Valid User path continues).

2. Verification Stage

- **Request Account Information → Customer Database**:
  The system fetches customer details for verification.
- **Verify Card Details**:
  The card details are checked against stored data.

3. Transaction Monitoring

- **Credit Card Transaction Database**:
  The system pulls transaction records for analysis.
- **Monitoring Agent**:
  The monitoring agent receives selected transaction data from:
  - **Customer Database**
  - **Credit Card Transaction Database**

4. Fraud Detection Process

- **Data Mining (Monitoring Agent → Collating Agent)**:
  The monitoring agent applies data mining to detect unusual patterns.
- **Data Modeling (Collating Agent → Diagnosing Agent)**:
  The collating agent structures the data for the diagnosing agent.
- **Extracted Information**:
  The diagnosing agent analyzes patterns to decide whether the transaction is fraudulent.

5. Decision Path

- **If No Fraud Detected**:
  Transaction proceeds to:
  - **Fund Transfer** or
  - **Account Update**
    The records are updated in the **Credit Card Transaction Database**.
- **If Fraud Detected**:
  - The diagnosing agent triggers the **Reporting Agent**.
  - The **Reporting Agent** sends a **Fraud Alert**.
  - The fraud details are stored in the **Credit Card Fraud Alert Database**.

6. Outcome

- **Fraudulent transactions are blocked** and alerts are generated.
- **Legitimate transactions proceed** normally, updating customer account records.

IV. RESULTS & DISCUSSION

The proposed system implements a hybrid ensemble framework integrating AdaBoost with a majority voting scheme to enhance credit card fraud detection accuracy and robustness. Initially, multiple shallow decision trees are trained using AdaBoost, which iteratively assigns higher weights to misclassified transactions, thereby focusing subsequent learners on more challenging cases and reducing classification bias. The predictions from these classifiers are then aggregated via majority voting, wherein the final decision corresponds to the most frequent predicted label, effectively minimizing variance and stabilizing outputs.

Performance evaluation was conducted on both a publicly available credit card dataset and a proprietary dataset from a financial institution. Standard classifiers—Naive Bayes (NB), Support Vector Machines (SVM), and Deep Learning (DL)—were compared against the proposed hybrid model, with performance measured using the Matthews Correlation Coefficient (MCC). On the public dataset, the majority voting method achieved the highest MCC of 0.823, while the AdaBoost–majority voting hybrid attained a perfect MCC of 1 on the real-world dataset. Robustness testing, involving Gaussian noise levels from 10% to 30%, demonstrated that the proposed method maintained high stability, achieving an MCC of 0.942 at 30% noise.

The model offers multiple advantages, including rapid detection to minimize transaction delays, improved reliability through consensus-based classification, adaptability to evolving fraud patterns, scalability for real-time high-volume processing, and significant reduction of financial losses through timely identification of fraudulent activities.

V. CONCLUSION

This paper presents a comprehensive study on credit card fraud detection using various machine learning algorithms, including Naive Bayes (NB), Support Vector Machines (SVM), and Deep Learning (DL). The evaluation was conducted using both standard models and hybrid models that combined AdaBoost with majority voting techniques. A publicly available credit card dataset was used for initial testing, and the models' performance was measured using the Matthews Correlation Coefficient (MCC) metric, which accounts for all types of predicted outcomes—true positives, false positives, true negatives, and false negatives. The loftiest MCC score of 0.823 was achieved using the maturity voting system.

Additionally, a real-world credit card dataset provided by a financial institution was used for further evaluation. In this case, the AdaBoost and majority voting combination produced a perfect MCC score of 1. To test the robustness of the hybrid models, noise ranging from 10% to 30% was added to the dataset. The majority voting method performed exceptionally well, achieving an MCC score of 0.942 when 30% noise was introduced. This demonstrates the method's stability and reliability even when dealing with noisy data.

The results indicate that the hybrid approach using AdaBoost and majority voting is highly effective in detecting credit card fraud, even in complex and noisy environments. This research highlights the potential of machine learning techniques in enhancing fraud detection systems and providing more reliable, real-time solutions for financial institutions. Looking ahead, the methods explored in this study can be expanded to include online learning models, which could further improve fraud detection by enabling real-time detection of fraudulent transactions.

Additionally, exploring other online learning models could enhance the system's ability to adapt to new fraud patterns dynamically. This approach will help financial institutions detect and prevent fraudulent activities as they occur, significantly reducing financial losses daily.

At the end this This work presents a robust, accurate, and noise-resilient hybrid fraud detection framework that integrates AdaBoost with majority voting. Experimental evaluations on both benchmark and real-world datasets reveal that the proposed method achieves superior MCC scores—up to 1.0 in noise-free real-world scenarios and 0.942 under significant noise.

The findings suggest that combining boosting and ensemble aggregation offers substantial improvements over traditional detection systems, making it a strong candidate for large-scale, real-time deployment in financial institutions. Future research could focus on online learning models to dynamically adapt to emerging fraud patterns, thereby improving real-time detection accuracy and minimizing financial losses on a daily basis.

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