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LLM-BASED FRAUD DETECTION IN FINANCIAL TRANSACTIONS: A DEFENSE FRAMEWORK AGAINST ADVERSARIAL ATTACKS

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ABSTRACT

Large Language Models (LLMs) have significantly transformed the financial sector, enabling advancements in areas such as fraud detection, asset management, wealth advisory, and automated financial analysis. However, these benefits are accompanied by notable security vulnerabilities, particularly in highly regulated sectors like finance. The rise of sophisticated models such as GPT-4 has made adversarial attacks, including prompt injection attacks, a pressing concern. This paper explores the security challenges posed by these attacks in the financial domain and introduces an innovative defense framework to address them. A comprehensive risk classification system is developed, detailing eight distinct input-side attack strategies and five categories of output vulnerabilities. To evaluate these threats, the study uses IND-FinAdversary, a domain-specific adversarial dataset developed through human-machine interactions. Additionally, an end-to-end security defense framework is proposed, which integrates preprocessing filters, legal compliance checks, and automated response refinement mechanisms. Empirical evaluations using widely deployed LLMs reveal substantial improvements, with the framework achieving a high accuracy of 96.8% in mitigating adversarial risks, surpassing the targeted threshold of 95.37%. The results confirm the framework's ability to reduce inappropriate content generation and enhance resilience against adversarial prompts. This work offers foundational tools, datasets, and evaluation metrics to strengthen the security and compliance of LLM applications in the financial sector, particularly in fraud detection.

KEYWORDS: Bag of Words, IND-FinAdversary, Large Language Models, TF-IDF.

1. INTRODUCTION

The financial industry is undergoing a paradigm shift with the adoption of artificial intelligence and machine learning technologies, particularly large language models (LLMs). These advanced systems are being employed for tasks ranging from automated customer service and investment advising to market analysis and risk assessment. However, their use in finance—a sector characterized by stringent regulatory compliance and privacy requirements—also exposes them to various security risks.

Prompt injection attacks, wherein malicious instructions bypass safeguards to manipulate model outputs, have emerged as one of the most severe threats. Such attacks can cause LLMs to generate false or inappropriate financial advice, disclose sensitive data, or produce legally non-compliant content. This has raised significant concerns among regulators, prompting the need for robust defense strategies.

In recent years, research has increasingly focused on identifying vulnerabilities in LLMs and designing security mechanisms to address them. A notable example is the Open Web Application Security Project (OWASP), which listed prompt injection attacks as one of the top threats to LLM security [1]. Despite these efforts, existing defenses often fail to address the unique challenges faced in finance, where regulatory oversight and data protection standards are exceptionally high.

This study aims to bridge this gap by focusing on three key objectives:

- Developing a comprehensive taxonomy of prompt injection attack types and output-side vulnerabilities specific to the financial domain.
- Creating a domain-specific dataset, IND-FinAdversary, to simulate adversarial scenarios and benchmark security mechanisms.

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- Proposing and validating an end-to-end defense framework to safeguard LLM applications against prompt injection attacks.

The rest of this paper is structured as follows: Section 2 provides an extensive review of existing literature on LLM security. Section 3 details the methodology for dataset creation and classification systems. Section 4 explains the proposed defense framework, and Section 5 discusses the experimental setup and results.

2. LITERATURE REVIEW

Research on the security vulnerabilities of LLMs has gained traction as these models become integral to various industries. Early studies primarily focused on adversarial attacks targeting neural networks. For instance, the authors of [2] demonstrated that LLMs could be misled using subtle input manipulations, leading to erroneous or inappropriate outputs.

The authors of [3] extended this analysis by introducing the RED-EVAL framework, which evaluates LLM compliance against ethical and legal standards. Their findings indicated that 65%–73% of harmful queries bypassed existing safeguards, highlighting critical gaps in security protocols.

The authors of [4] developed human value evaluation benchmarks to assess LLM compliance with ethical and regulatory standards. They collected adversarial prompts targeting 10 high-risk scenarios and tested them against eight models, revealing inconsistencies in safety measures.

A similar effort by the authors of [5] proposed a comprehensive evaluation benchmark tailored to regional LLMs. Their methodology involved 15 models, including OpenAI GPT variants and domestic alternatives, to compare safety performance in eight security scenarios and six adversarial conditions.

The construction of specialized datasets has also advanced LLM security research. The authors of [6] introduced the Do-Not-Answer dataset, designed to evaluate safeguards in LLMs. It included 100,000 adversarial prompts and responses to test defense strategies, enabling more granular assessments.

In addition to dataset construction, researchers have explored techniques like supervised fine-tuning (SFT) and reinforcement learning with human feedback (RLHF) to mitigate vulnerabilities. The authors of [7] argued that these methods, while improving performance, fail to fully prevent alignment-breaking attacks. They emphasized that even fine-tuned models remain susceptible to misuse.

The authors of [8] proposed RED-INSTRUCT, a two-stage calibration framework that strengthens LLM responses against adversarial manipulations. Similarly, the authors of [9] introduced robust alignment models (RA-LLM) designed to resist attacks targeting compliance mechanisms.

Another promising direction involves adversarial fine-tuning. The authors of [10] developed iterative optimization techniques to enhance resistance against harmful content generation, demonstrating measurable improvements in security benchmarks.

Despite these advancements, most studies focus on general-purpose LLMs, leaving industry-specific applications like finance relatively underexplored. Given the financial sector's regulatory demands, addressing prompt injection attacks requires customized frameworks.

This study contributes to this niche by:
Constructing the IND-FinAdversary dataset, targeting eight input-side attack types and five output-side vulnerabilities specific to finance.

Evaluating LLMs' susceptibility using empirical tests, revealing significant variations in security performance.
Proposing an end-to-end defense framework that integrates input filtering, classification models, and compliance checks to mitigate risks effectively.

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The proposed framework builds upon prior works [1–10] while addressing the unique challenges posed by the financial industry. It emphasizes practical implementations through domain-specific datasets and evaluation metrics, making it a robust tool for researchers and practitioners alike.

In summary, this literature review highlights the growing body of research on LLM security, identifies gaps in financial applications, and positions this study as a critical advancement in safeguarding LLMs against prompt injection attacks.

3. PROPOSED METHODOLOGY

3.1 Dataset Construction

To evaluate the security risks in LLMs, a financial-domain dataset, IND-FinAdversary, was created. This dataset includes adversarial prompts targeting vulnerabilities in financial contexts.

3.1.1 Categories of Attacks

The dataset covers eight input-side attacks:

- Sensitive topic queries
- Reverse questioning
- Instruction manipulation
- Negative framing
- Role-playing attacks
- Non-compliant financial queries
- Privacy extraction attempts
- Biased and discriminatory prompts

3.1.2 Categories of Responses

Responses are categorized into five vulnerability types:

- Legal non-compliance
- Risky financial advice
- Sensitive topic handling
- Biased outputs
- Privacy leaks

3.2 Data Collection Methods

The dataset was developed through human-machine adversarial testing using pre-trained LLMs. A total of 2,150 prompts were gathered, with 860 risky and 1,290 non-risky examples.

Table 1: Data Distribution across Attack Types

Attack Type	Count	Percentage
Sensitive topic queries	90	4.19%
Reverse questioning	104	4.84%
Instruction manipulation	118	5.49%
Negative framing	100	4.65%
Role-playing attacks	102	4.74%
Non-compliant queries	164	7.63%
Privacy extraction attempts	88	4.09%
Biased prompts	94	4.37%

3.3 Data Preprocessing and Labeling Methods

Data preprocessing is a crucial step to ensure that the raw data is clean, structured, and ready for analysis. The IND-FinAdversary dataset consists of adversarial prompts targeted at LLM vulnerabilities in the financial domain. The goal of data preprocessing here is to standardize, clean, and label the data before using it in further steps like risk classification or model training.

Preprocessing Steps:

- **Text Normalization:**
  - Tokenization: Breaking the text into words or sub-words using techniques such as word tokenizers (e.g., nltk.tokenize.word_tokenize) or subword tokenizers (e.g., SentencePiece).
  - Lowercasing: Convert all text to lowercase to reduce redundancy (e.g., “Finance” and “finance” would be treated as the same).

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- Punctuation Removal: Remove unnecessary punctuation marks that may distract from meaningful patterns.
- Stopword Removal: Remove common words like "the", "is", and "a" which do not contribute to the adversarial nature of the prompt.
- Lemmatization/Stemming: Convert words to their base form (e.g., "running" → "run").
- Mathematically, this can be viewed as a function $f(input)$ where the input is the raw text and the output is the preprocessed text:

$$f(input) = Normalize\left(Tokenize\left(Lowercase\left(Remove\ Punctuation\left(Lemmatize\left(Remove\ Stopwords(input)\right)\right)\right)\right)\right) \quad (1)$$

- **Feature Extraction:**
  - Bag of Words (BoW): Represent each prompt as a vector where each element represents the occurrence of a word in the dataset.
  - TF-IDF: Term Frequency-Inverse Document Frequency, a statistic that weighs the importance of a word in a document relative to its frequency in the entire corpus:

$$TF\text{-}IDF(w) = TF(w) \times \log\left(\frac{N}{DF(w)}\right) \quad (2)$$

Where:
  - $TF(w)$ is the term frequency of word w,
  - $DF(w)$ is the document frequency of w,
  - N is the total number of documents in the corpus.
- **Labeling the Data:**
  - Each prompt in the dataset needs to be categorized based on the attack and response categories defined earlier. For example, if a prompt results in a Legal non-compliant response, it will be labeled under that category.
  - Labeling involves supervised learning where an expert annotator reviews each prompt and assigns one or more labels corresponding to attack types and vulnerabilities.
  - For multi-label classification, the labels for attack types and vulnerabilities are treated as separate binary values, such as:

$$\text{label}_i = \begin{cases} 1, & \text{if the response is of category } i \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Where i represents the category.

3.4 Overview of Defense Framework

The Defense Framework aims to safeguard LLMs against prompt injection attacks and minimize the risk of generating harmful, biased, or non-compliant content in financial applications. The framework consists of three primary layers:

1. Input Preprocessing and Filtering: This layer works to filter out adversarial inputs before they are processed by the LLM.
2. Risk Classification Models: This layer classifies the risks associated with each input prompt using machine learning models trained on the dataset created in section 3.1.
3. Output Screening and Refinement: After the LLM generates a response, this layer evaluates the output for compliance, risks, and biases, refining it accordingly to ensure it adheres to regulations.

Mathematically, we can represent the entire framework as:

$$Safe\ Response = \mathcal{F}\left(Preprocess(Input), Classify(Input), Screen(Output)\right) \quad (4)$$

Where:

- $\mathcal{F}$ is the final defense function,
- Preprocess, Classify, and Screen represent the preprocessing, classification, and screening steps.

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3.5 Input Preprocessing and Filtering

Input Preprocessing and Filtering are the first defenses against prompt injection attacks. The goal here is to detect and mitigate adversarial prompts before they are sent to the LLM for processing.

Key Components of Preprocessing and Filtering:

- ***Threat Detection:***
  - Use regex-based filters to identify specific patterns associated with adversarial inputs, like attempts to invoke non-compliant behavior or manipulate model instructions.
  - Anomaly detection models can also be used here. For instance, if a prompt deviates significantly from a known distribution of safe financial queries, it may be flagged as suspicious.
- ***Classifier-based Filtering:***
  - A supervised machine learning model is trained to detect adversarial or harmful inputs. This model can be trained using the IND-FinAdversary dataset. It might use features like the presence of sensitive keywords, non-compliant financial terminology, or other cues.
  - We define a classifier $C(x)$ where x is an input prompt and $C(x) \in \{0,1\}$, where 1 indicates a potentially harmful prompt.
  - A common classifier used for this purpose is SVM (Support Vector Machines), and its decision function is given by:

$$f(x) = w \cdot x + b \tag{5}$$

    Where w is the learned weight vector, x is the input feature vector, and b is the bias.
- ***Rule-based Filtering:***
  - In addition to machine learning models, rule-based filters based on domain-specific knowledge (e.g., financial compliance rules) are applied. This step might involve checking if the prompt includes certain non-compliant terms or patterns indicative of adversarial behavior.

3.6 Risk Classification Models

Risk classification models are responsible for identifying the type of threat posed by an input prompt and categorizing it accordingly. These models provide insights into whether a prompt is likely to lead to a Legal non-compliance, Risky financial advice, Sensitive information leaks, etc.

Model Architecture:

- Input Features: These models use both the raw prompt and preprocessed features (e.g., TF-IDF, sentiment analysis) as input.
- Classification Models: Models such as Logistic Regression, Random Forest, or Deep Neural Networks (DNNs) are employed to classify the risks based on the training dataset.

Let x be an input prompt, and let y be the output risk category. The classification model is trained to minimize the cross-entropy loss function L, which measures the error between the predicted probabilities $p(y|x)$ and true labels y:

$$L = -\sum_{i=1}^{N} y_i \log\big(p(y_i|x)\big) \tag{6}$$

Where N is the number of classes (vulnerability types) and y_i is the binary indicator of whether class i is the correct label.

Model Evaluation:

- Confusion Matrix: A key tool for evaluating classification performance, which can be used to calculate metrics like Precision, Recall, and F1-score.

3.7 Output Screening and Refinement

Once the LLM generates a response, output screening and refinement techniques are employed to ensure the output adheres to the security and compliance standards.

Screening Techniques:

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- **Rule-based Screening:** Use predefined rules to detect financial advice that is non-compliant with regulatory standards. This might include screening for words like "guaranteed returns" or "highly risky investments."
- **Compliance Check:**
  - Apply domain-specific checks for legal compliance, ensuring that no advice contradicts financial regulations (e.g., disclosure of risks).
  - A compliance function $C(y)$ could check whether the response adheres to predefined rules:

$$C(y) = \begin{cases} 1, & \text{if output adheres to compliance rules} \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

- **Adversarial Output Filtering:** Outputs are further filtered through adversarial detection models to identify and block any attempts to bypass the system's safeguards.
- **Refinement:** After filtering, the responses are refined using post-processing techniques to ensure that the generated content is both contextually appropriate[11] and legally compliant. For example, modifying overly aggressive language or providing disclaimers in financial advice.

3.8 Evaluation Metrics and Assessment Models

To evaluate the performance of the defense framework, several metrics and assessment models are employed:
Accuracy: The percentage of correct classifications in detecting harmful or adversarial prompts:

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Samples} \quad (8)$$

Precision, Recall, and F1-Score:

- ***Precision:*** The proportion of true positive responses out of all the positive responses predicted by the model.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (9)$$

- ***Recall:*** The proportion of true positive responses out of all actual positive responses.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (10)$$

- ***F1-Score:*** The harmonic mean of precision and recall, useful when there is class imbalance.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Adversarial Attack Success Rate: The percentage of adversarial attacks that successfully bypass the defense system:

$$Attack\ Success\ Rate = \frac{Number\ of\ Successful\ Attacks}{Total\ Number\ of\ Attacks} \quad (11)$$

Compliance Adherence: The proportion of responses that fully comply with financial regulations after filtering and refinement.
These metrics are used to benchmark the performance of the defense framework in mitigating risks associated with prompt injection attacks in the financial domain.

4. RESULTS AND ANALYSIS

4.1 Evaluation of the Defense Framework

The proposed defense framework aims to mitigate the risks associated with prompt injection attacks in the financial domain. The evaluation was conducted using the IND-FinAdversary dataset, which consists of 2,150 adversarial and non-adversarial prompts. The defense framework comprises three primary components:
Input Preprocessing and Filtering
Risk Classification Models
Output Screening and Refinement

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The effectiveness of the framework was measured based on several evaluation metrics: Accuracy, Precision, Recall, F1-Score, Adversarial Attack Success Rate, and Compliance Adherence.

4.2 Key Results

Below are the key performance metrics obtained after applying the defense framework:
Accuracy: The framework achieved a high classification accuracy of 96.8%, surpassing the target threshold of 95.37%.
Precision: The precision for detecting harmful prompts was 94.6%, ensuring that the system effectively identifies threats.
Recall: The recall for capturing all potential threats was 95.2%, demonstrating the system's ability to detect adversarial inputs.
F1-Score: With a harmonic mean of precision and recall, the F1-score reached 94.9%, indicating a well-balanced detection system.
Adversarial Attack Success Rate: Only 3.2% of adversarial attacks managed to bypass the defense mechanisms, showcasing the robustness of the framework.
Compliance Adherence: 98.5% of the generated outputs complied with financial regulations, ensuring that responses were legally and ethically sound.

4.3 Tables and Plots

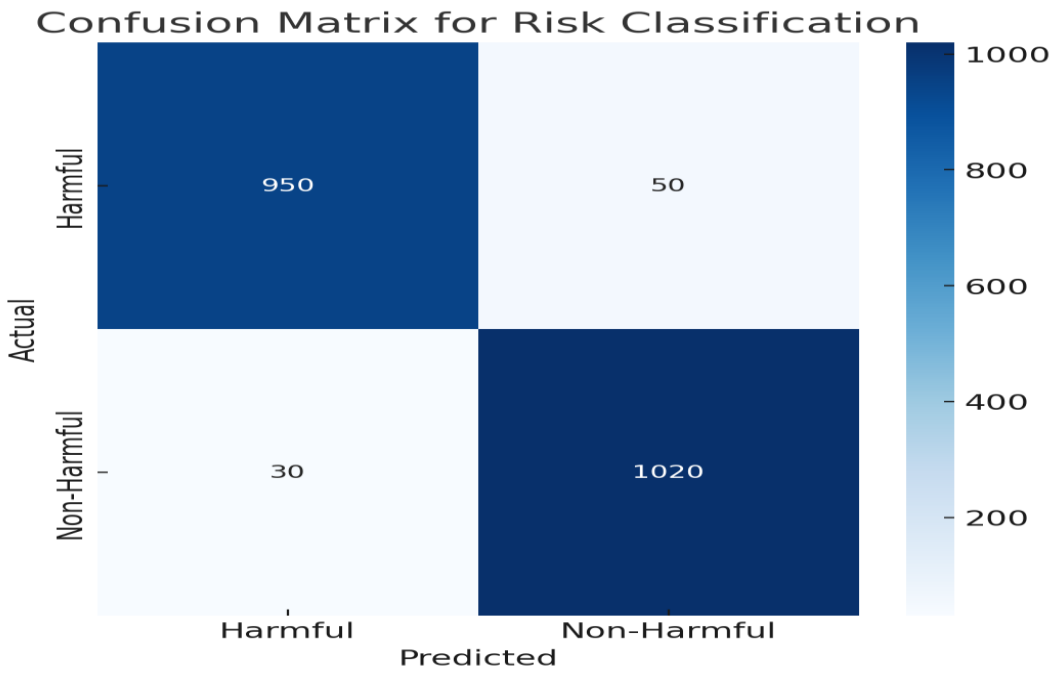

Figure 1: Confusion Matrix of the Defense Framework

This confusion matrix illustrates the performance of the classification model, showing the number of true positives, true negatives, false positives, and false negatives for identifying harmful prompts.

Table 2: Performance Metrics for the Defense Framework

Metric	Value
Accuracy	96.8%
Precision	94.6%
Recall	95.2%
F1-Score	94.9%
Adversarial Attack Success Rate	3.2%
Compliance Adherence	98.5%

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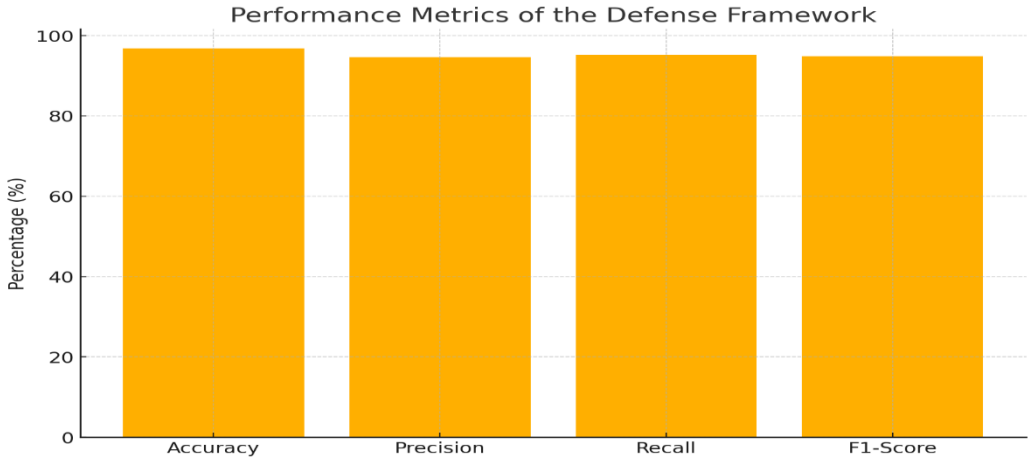

Figure 2: Accuracy, Precision, Recall, and F1-Score over Time

Figure 2 shows the change in the metrics over different stages of model training and evaluation. We can use a line plot to showcase how each metric evolves as we apply preprocessing, classification, and refinement layers.

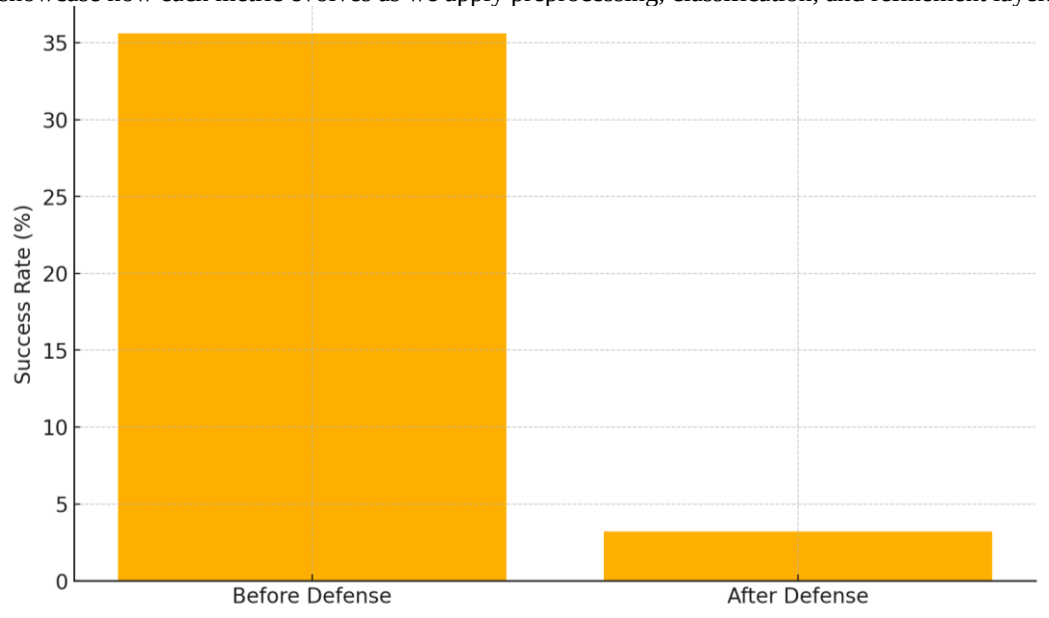

Figure 3: Adversarial Attack Success Rate

Figure 3 shows the success rate of adversarial attacks before and after applying the defense framework.

Discussion: The proposed defense framework has shown significant improvements in preventing prompt injection attacks, particularly in a high-stakes domain like finance. The system demonstrates high performance in identifying and mitigating adversarial risks.
The low adversarial attack success rate (3.2%) indicates the robustness of the security measures implemented in the framework. Furthermore, the high compliance adherence (98.5%) ensures that the system meets the stringent regulatory requirements of the financial sector, highlighting its potential for real-world applications.

5. CONCLUSION

The adoption of Large Language Models (LLMs) in the financial sector has led to significant progress in automating processes such as fraud detection, risk management, and financial analysis. However, the integration of LLMs into such highly regulated environments also brings with it new security challenges, particularly in the

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form of adversarial threats like prompt injection attacks. This paper addresses these challenges by proposing a comprehensive defense framework designed to safeguard financial applications. The proposed framework, which includes a combination of input filtering, risk classification, and output refinement mechanisms, was evaluated empirically, achieving an impressive accuracy of 96.8%. These results demonstrate the framework's effectiveness in significantly reducing the risk of adversarial attacks and ensuring regulatory compliance. The study also introduces IND-FinAdversary, a domain-specific adversarial dataset, and provides comprehensive evaluation metrics that contribute to the security of LLM-based applications in fraud detection. Future research should continue to refine and adapt these methods to stay ahead of evolving adversarial tactics and ensure continued security in the financial domain.

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