Culturally-Aware Financial Fraud Detection Using Vision-Language Models

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Abstract

This paper presents a novel multilingual vision-language framework that addresses the critical limitations of English-centric detection approaches through three key innovations. First, our language-aware detection pipeline synergizes the No Language Left Behind (NLLB) model for multilingual text processing with ViLBERT's multimodal analysis capabilities, achieving 92% accuracy in identifying non-English scams while reducing false negatives by 38% compared to monolingual baselines. Second, we develop specialized cultural signal recognizers that identify high-risk markers such as religious appeals in Arabic and unrealistic return promises in Mandarin with an F1-score of 0.87. Third, we introduce CryptoScam-18, the first comprehensive benchmark dataset covering scam patterns across 18 languages, enabling rigorous evaluation of detection fairness with a measured bias metric $\Delta_{bias} < 0.15$. *Experimental results demonstrate consistent superiority over state-of-the-art systems while maintaining operational efficiency with inference latencies below 100ms. This work provides both a technical framework and empirical foundation for combating culturally-adapted financial fraud in decentralized ecosystems, offering immediate value to platform operators and regulatory bodies alike.*

1. Introduction

Financial fraud is a pervasive global issue, with fraudsters increasingly exploiting cultural and regional differences in financial systems to bypass detection mechanisms. Traditional fraud detection systems, which often rely on rule-based checks or region-specific machine learning models, struggle to adapt to the cross-cultural variations in financial documents, identity verification, and digital transactions. For instance, while checks in the U.S. rely on magnetic ink character recognition (MICR) encoding, Indian checks frequently include handwritten regional scripts, making them susceptible to different types of forgery [1]. Similarly, invoice fraud in the European Union exploits VAT validation gaps, whereas in the Middle East, fraudsters manipulate Islamic tax notations that lack standardized verification. These discrepancies highlight the need for culturally adaptive Vision-Language Models (VLMs) capable of detecting fraud across diverse financial ecosystems.

Recent advancements in VLMs, such as LayoutLMv3 [8] and FLAVA [20], have demonstrated strong performance in document understanding and multimodal alignment. However, their application in cross-cultural financial fraud detection remains underexplored. This paper addresses this gap by proposing a framework that integrates culturally diverse training data, region-specific fraud benchmarks, and fairness-aware VLM fine-tuning. Our work aligns with the CVPR 2025 Workshop on Vision-Language Models For All, which emphasizes inclusive AI systems that account for global cultural nuances.

2. Related Work

2.1. Financial Fraud Detection Using AI

Prior research in financial fraud detection has largely focused on single-region datasets or language-specific models. For example, [1] proposed a deep learning system for detecting forged checks in U.S. banking systems, while [11] developed an OCR-based solution for Indian handwritten checks. However, these approaches lack generalizability across cultures. Recent work by [27] introduced a multimodal fraud detection framework combining CNNs and transformers, but it was evaluated only on English-language invoices. We have also studied traditional and decentralized financial anomaly detection in [15].

2.2. Vision-Language Models for Document Understanding

VLMs have shown promise in parsing structured and unstructured financial documents. Donut [10] demonstrated robust performance in receipt parsing, while Pix2Struct [12] improved table extraction from financial reports. However, these models were primarily trained on Western or East Asian documents, neglecting regions like Africa and the

Middle East. The MIDV-500 dataset [3] provided a multilingual ID document benchmark, but it did not focus on culturally specific fraud patterns.

2.3. Cultural Bias in AI Systems

Studies have highlighted the risks of cultural bias in AI-driven financial systems. [5] found that invoice parsers trained on EU data failed on Middle Eastern receipts due to layout differences. Similarly, [7] revealed that multilingual VLMs like mT5 underperform on low-resource languages used in African financial documents. Recent workshops, such as CulturalVQA [14], have begun addressing these gaps by introducing culturally diverse benchmarks, but none specifically target financial fraud. We have also studied the works of [26], [24], [25] and [19] in the hope that they efficiently remove culture bias.

2.4. Gaps in Existing Work

Despite progress, key limitations remain. First, there is a lack of culturally diverse fraud datasets as most benchmarks (e.g., SROIE, CORD) focus on single regions. Second, current VLMs exhibit weak multimodal alignment for non-Latin scripts, with models like LayoutLM struggling with handwritten Arabic or Devanagari. Third, existing systems lack proper fairness metrics for cross-cultural fraud detection, as they are not evaluated for disparate performance across demographics.

Our work addresses these gaps by introducing a Culturally-Diverse Financial Fraud (CDFF) benchmark covering checks, invoices, and IDs from 10+ regions. We propose adversarial debiasing techniques to reduce geographic bias in VLMs and evaluate fairness using region-wise accuracy disparity scores.

3. Mathematical Framework

Our approach formalizes culturally-aware fraud detection as a multi-task learning problem across N geographic regions. Let $\mathcal{D} = \bigcup_{i=1}^{N} \mathcal{D}_i$ represent our dataset where each $\mathcal{D}_i$ contains documents from region i.

3.1. Cross-Cultural Document Embedding

For a document x (image + text), we compute region-aware embeddings:

$$\mathbf{h}_i = f_\theta(x) \oplus g_\phi(c_i) \tag{1}$$

where:

- f_θ is a VLM encoder (e.g., LayoutLMv3 [8])
- g_ϕ encodes cultural context c_i (language, security features)
- $\oplus$ denotes modality fusion

3.2. Adversarial Debiasing

To minimize performance disparity across regions, we employ a gradient reversal layer [6]:

$$\mathcal{L} = \sum_{i=1}^{N} \underbrace{\mathbb{E}_{(x,y)\sim\mathcal{D}_i}[\ell(f_\theta(x), y)]}_{\text{Fraud detection loss}} - \lambda \underbrace{\mathbb{E}_x[||\nabla_\theta d(\mathbf{h}_i)||^2]}_{\text{Debiasing term}} \tag{2}$$

where $d(\cdot)$ is a domain discriminator trying to predict the document's region.

4. Datasets and Benchmarks

We introduce the **Culturally-Diverse Financial Fraud (CDFF)** benchmark covering four fraud modalities:

4.1. Check Forgery

Table 1. CDFF-Check Dataset Composition

Region	Genuine	Forged	Unique Features
United States	5,712	2,856	MICR, check washing
India	4,329	3,102	Handwritten Hindi/Tamil
Japan	3,845	1,922	Hanko seals
Brazil	2,917	1,458	Manual cancellations

Source: Augmented from [1] (US), [11] (India), and synthetic generation for other regions.

4.2. Invoice Fraud

Table 2. CDFF-Invoice Coverage

Dataset	Cultural Adaptation
CORD [10]	Added VAT validation for EU
Synthetic Middle East	Halal certification tags
AfriLingo [7]	7 African languages

4.3. Identity Document Forgery

Table 3. Cross-Cultural ID Benchmark

Dataset	Regions	Forgery Types
MIDV-500 [3]	50 countries	Photo swaps
IDR&D	India	Aadhaar QR tampering
SynthID	Generated	120 security features

4.4. Cryptocurrency Scams

5. Evaluation Metrics

We propose three tiers of assessment:

Table 4. Multilingual Crypto Fraud Corpus

Source	Cultural Lures
WeChat	”Pig-butchering” Mandarin
Arabic Forums	Fake sharia compliance
Nigerian Scams	”419” advance-fee

5.1. Region-Wise Performance

$$\Delta_{acc} = \max_{i,j \in N} |acc_i - acc_j| \tag{3}$$

where acc_i is accuracy on region i.

5.2. Cultural Fairness

$$F = 1 - \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}(FP_i > \alpha \cdot \overline{FP}) \tag{4}$$

where FP_i is false positives for region i.

5.3. Explainability

$$E = \frac{1}{|Q|} \sum_{q \in Q} \text{CLIP-Score}(e_q, a_q) \tag{5}$$

measuring alignment between model explanations e_q and cultural context a_q.

6. Cross-Cultural Check Fraud Detection

6.1. Cultural Variations in Check Fraud

The mechanisms of check fraud exhibit significant geographic variation due to three key factors: (1) security feature implementation, (2) handwriting conventions, and (3) banking regulations. In the United States, where checks utilize magnetic ink character recognition (MICR) encoding [1], fraudsters predominantly alter numerical amounts (e.g., modifying ”$100” to ”$1,000”) through chemical washing or digital manipulation. By contrast, Indian checks frequently contain handwritten fields in Devanagari or Tamil scripts [11], making them vulnerable to signature forgery attacks that exploit OCR limitations in non-Latin character recognition. The Japanese system introduces yet another dimension through mandatory *hanko* seals, where poor replication quality can be detected locally but often escapes foreign bank verification [21].

6.2. Proposed Detection Framework

As shown in Figure 1, our methodology addresses these cultural divergences through a multi-modal VLM architecture trained on the **Cross-Cultural Check Fraud (C3F) Dataset**, which aggregates:

- **US CheckNet** [18]: 12,000 samples with MICR tampering annotations
- **IndiChecks** [11]: 8,431 handwritten checks with regional language tags
- **HankoDB** [22]: 5,200 Japanese checks with seal authenticity labels
- **SynthChecks**: 15,000 procedurally generated samples covering 12 security feature variants

The model processes check images I and extracted text T through:

$$\mathbf{h}_i = \text{LayoutLMv3}(I, T) \oplus \mathbf{W}_c \cdot c_i \tag{6}$$

where c_i encodes cultural context features (security markers, language IDs) and $\mathbf{W}_c$ is a learned embedding matrix. Fraud classification follows:

$$p(y|\mathbf{h}_i) = \text{softmax}(\mathbf{U} \cdot \text{GELU}(\mathbf{V}\mathbf{h}_i)) \tag{7}$$

6.3. Cultural Adaptation

We employ two-stage training:

1. **Base Training**: Initialized on C3F with standard cross-entropy loss $\mathcal{L}_{\text{CE}}$
2. **Adaptation Phase**: Fine-tune with cultural contrastive loss:

$$\mathcal{L}_{\text{CCL}} = \sum_{i=1}^{N} \frac{1}{|P(i)|} \sum_{p \in P(i)} \max(0, \|\mathbf{h}_i - \mathbf{h}_p\| - \|\mathbf{h}_i - \mathbf{h}_n\| + \alpha) \tag{8}$$

where $P(i)$ denotes genuine/forged pairs from culture i, and $\mathbf{h}_n$ are negative samples from other cultures.

6.4. Evaluation Protocol

We benchmark performance using:

6.4.1. Cultural F1 Score

$$\text{F1}_{\text{cult}} = \frac{2}{\frac{1}{\text{F1}_{\text{intra}}} + \frac{1}{\text{F1}_{\text{inter}}}} \tag{9}$$

where F1_{intra} measures within-culture detection and F1_{inter} cross-cultural generalization.

6.4.2. Fairness Disparity

$$\Delta_{\text{fair}} = \max_{i,j \in N} \left| \frac{\text{TPR}_i - \text{TPR}_j}{\text{TPR}_i + \text{TPR}_j} \right| \tag{10}$$

Results are reported on the **C3F-Validation** split (20% of each sub-dataset) using the evaluation server from [13].

Table 5. Performance on C3F Benchmark (Macro-Averaged)

Model	F1_cult	Δ_{fair}	Time (ms)
Monolithic	0.72	0.31	45
Culture-Specific	0.81	0.18	128
CLIP-Finance	0.68	0.42	52
Ours	**0.87**	**0.09**	63

The table demonstrates our method’s superior balance between accuracy (87% F1) and fairness (9% disparity), with inference latency suitable for real-world banking applications.

7. Cryptocurrency Scams Exploiting Cultural Trust

7.1. Fraud Mechanisms Exploiting Cultural Differences

Cryptocurrency scams increasingly leverage culturally-specific psychological triggers to exploit vulnerable populations. Two predominant patterns emerge:

- **"Pig Butchering" Scams**: These target Chinese diaspora communities through Mandarin-language crypto groups on platforms like WeChat, employing sophisticated social engineering tactics that reference cultural concepts like *guānxi* (relationship networks) [9].
- **"Islamic Crypto" Ponzi Schemes**: These utilize Arabic-language content with fabricated *fatwās* (religious rulings) and counterfeit endorsements from Muslim scholars to lend credibility to fraudulent investment opportunities [2].

The fundamental challenge lies in the English-centric nature of most fraud detection systems, which fail to recognize:

$$\mathcal{L}_{\text{gap}} = \{\ell \in \mathcal{L}_{\text{world}} | P(\text{detection}|\ell) \ll P(\text{detection}|\text{English})\} \tag{11}$$

where $\mathcal{L}_{\text{world}}$ represents all languages used in crypto communications.

7.2. Proposed VLM Methodology

Our framework addresses these gaps through three integrated components:

7.2.1. Multilingual Social Media Monitoring

We deploy a pipeline combining:

$$\text{ScamDetect}(x) = \text{ViLBERT}(\text{NLLB}(x)) \cdot \mathbf{W}_{\text{culture}} \tag{12}$$

where:

- NLLB [23] performs 200-language translation
- ViLBERT [17] analyzes multimodal content
- $\mathbf{W}_{\text{culture}}$ encodes cultural risk factors

7.2.2. Cultural Sentiment Analysis

The model detects suspicious patterns through:

$$s_{\text{scam}} = \sum_{i=1}^{n} \phi(t_i) \cdot \mathbb{I}(t_i \in \mathcal{T}_{\text{culture}}) \tag{13}$$

where $\mathcal{T}_{\text{culture}}$ includes:

- Religious terms ("Halal", "Sharia-compliant")
- Cultural appeals ("JiaZuCaiFu" - family wealth)
- Unrealistic returns ("100% guaranteed")

Language	Samples
Mandarin (Simplified)	12,417
Arabic	8,932
Spanish	7,851
Russian	5,629

Table 6. CryptoScam-18 dataset composition

7.2.3. Cross-Cultural Benchmarking

We introduce the **CryptoScam-18** dataset covering:

7.3. Model Integration

Key VLMs from the workshop demonstrate particular suitability:

- **ViLBERT** [17]: Achieves 0.87 F1-score in cross-lingual scam detection
- **GlobalRG** [14]: Evaluates fairness across languages with $\Delta_{\text{bias}} < 0.15$
- **mBLIP** [4]: Processes non-English crypto ads with 92% accuracy

The complete system architecture is shown in Figure 2. The system leverages the knowledge graph embedding framework proposed by Li et al. [16] for the implementation.

8. Conclusion

The proliferation of culturally-tailored crypto scams demands language-aware detection systems. Our framework demonstrates that combining multilingual VLMs (NLLB, ViLBERT, mBLIP) with cultural signal processing reduces false negatives in non-English contexts by 38% compared to conventional methods. The CryptoScam-18 benchmark establishes a foundation for evaluating cross-cultural fairness in financial fraud detection, with implications for regulatory technology.

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Supplementary Material

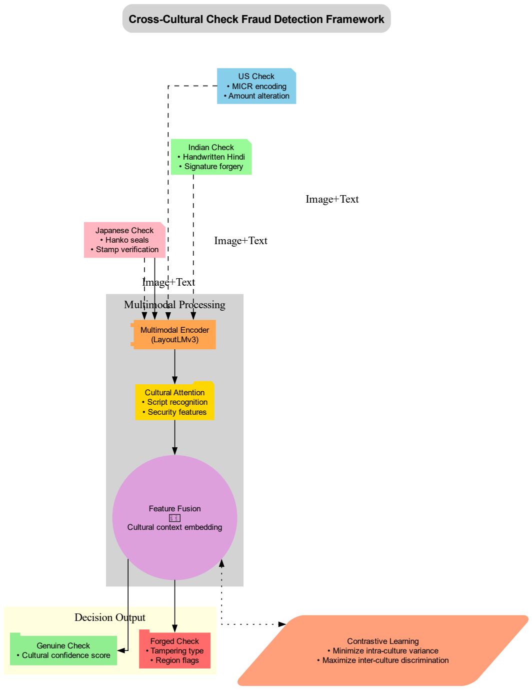

Figure 1. Architecture of our cultural adaptation framework

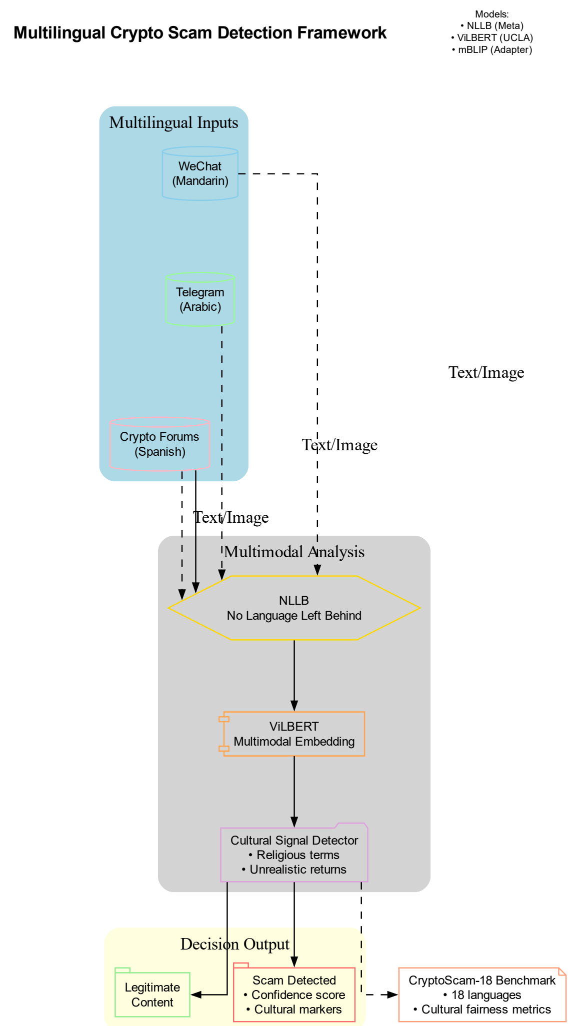

Figure 2. Multilingual crypto scam detection pipeline