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AI-Driven Cross-Modal Feature Alignment for Multimodal Fraud Detection in Financial Transaction Systems

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Abstract

Financial fraud detection systems increasingly encounter sophisticated attack patterns that exploit multiple data modalities simultaneously. Traditional single-modal detection approaches demonstrate limited effectiveness when adversaries coordinate deceptive behaviors across transaction records, user behavioral sequences, and communication metadata. This research proposes an AI-driven cross-modal feature alignment framework that integrates heterogeneous data streams through attention-based fusion mechanisms and contrastive learning strategies. The methodology employs deep neural architectures to extract discriminative representations from structured transaction data, unstructured behavioral logs, and temporal interaction patterns, subsequently aligning these features in a unified embedding space. Experimental validation on real-world financial datasets demonstrates that the proposed framework achieves superior detection performance compared to baseline methods, with particular effectiveness in identifying coordinated fraud schemes that span multiple channels. The framework maintains computational efficiency suitable for real-time deployment while providing interpretable explanations for detection decisions through attention weight visualization and feature attribution analysis.

Keywords: *Cross-modal learning, fraud detection, feature alignment, deep learning*

1. Introduction

1.1 Research Background

Financial institutions process billions of transactions daily through increasingly complex digital ecosystems that span online banking platforms, mobile payment applications, and automated clearing systems [1]. The sophistication of fraudulent activities has evolved in parallel with technological advancement, creating multi-faceted threats that traditional rule-based detection systems struggle to address adequately [2]. Modern fraud schemes frequently exploit vulnerabilities across multiple data modalities, coordinating deceptive patterns in transaction amounts, timing sequences, geographic locations, and communication behaviors to evade detection mechanisms designed for single-channel monitoring [3].

The integration of artificial intelligence into fraud detection represents a paradigm shift from reactive rule-based systems to proactive learning-based frameworks capable of identifying subtle anomalous patterns within massive data volumes [4]. Machine learning approaches have demonstrated substantial improvements in detection accuracy by automatically discovering complex relationships between transactional features and fraudulent behaviors [5]. Deep learning architectures extend these capabilities by learning hierarchical representations that capture both low-level statistical patterns and high-level semantic relationships across diverse data sources [6].

1.2 Problem Statement and Motivation

A. Challenges in Traditional Fraud Detection

Conventional fraud detection systems rely predominantly on predefined rules and threshold-based alerts that examine individual transactions in isolation [7]. These systems demonstrate fundamental limitations when confronting adversaries who deliberately distribute fraudulent activities across multiple channels to remain below detection thresholds [8]. Single-modal analysis fails to recognize coordinated patterns where transaction amounts appear legitimate individually but form suspicious sequences when examined collectively [9]. Behavioral analysis confined to transactional data overlooks crucial contextual signals embedded in communication metadata, device fingerprints, and network interaction patterns [10].

The temporal dynamics of fraudulent behavior pose additional challenges for static detection models [11]. Fraud patterns evolve continuously as perpetrators adapt their strategies in response to deployed countermeasures, rendering fixed rule sets obsolete within short timeframes [12]. The class imbalance inherent in fraud detection datasets, where legitimate transactions vastly outnumber fraudulent ones, exacerbates the difficulty of training effective classifiers that maintain low false positive rates while achieving high detection sensitivity [13].

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B. Importance of Cross-Modal Feature Integration

The complementary nature of information contained in different data modalities provides strong motivation for developing integrated analysis frameworks [14]. Transaction records capture financial flows and monetary patterns, behavioral logs reveal user interaction habits and device preferences, and communication metadata exposes social network structures and information exchange patterns [15]. Fraudulent activities that appear innocuous when examined through a single lens often exhibit distinctive signatures when multiple modalities are analyzed jointly [16].

Cross-modal feature alignment enables the construction of comprehensive fraud profiles by synthesizing evidence from heterogeneous sources [17]. This holistic approach recognizes that sophisticated fraud schemes deliberately create inconsistencies across modalities to exploit gaps in single-channel monitoring systems [18]. Alignment mechanisms that project diverse data representations into common embedding spaces facilitate the detection of these cross-modal discrepancies while preserving modality-specific characteristics crucial for maintaining detection interpretability [19].

1.3 Research Objectives and Contributions

This research develops a novel AI-driven framework for cross-modal fraud detection that addresses the limitations of existing single-modal and simple multi-modal approaches [20]. The primary objective focuses on designing effective feature alignment mechanisms that capture both intra-modal patterns and inter-modal relationships relevant to fraud identification [21]. The framework incorporates attention-based fusion modules that dynamically weight the contribution of different modalities based on their informativeness for specific detection scenarios [22].

The research makes several technical contributions to the field of fraud detection [23]. First, it introduces a contrastive learning strategy specifically designed for fraud detection tasks that learns to maximize the distance between fraudulent and legitimate samples while minimizing intra-class variance within each category [24]. Second, it proposes an interpretable attention mechanism that provides transparency into the detection decision process by highlighting which modalities and features contribute most significantly to fraud classification [25]. Third, it develops an efficient training procedure that addresses class imbalance through adaptive sampling and loss weighting strategies tailored to the fraud detection domain [26].

1.4 Paper Organization

The subsequent sections of this paper systematically present the proposed methodology and experimental findings [27]. Section 2 reviews related work in fraud detection, multi-modal learning, and feature fusion techniques [28]. Section 3 details the architectural design of the cross-modal feature alignment framework, including the feature extraction networks, alignment mechanisms, and fusion strategies [29]. Section 4 presents comprehensive experimental results demonstrating the effectiveness of the proposed approach across multiple evaluation metrics and comparative baselines [30]. Section 5 discusses the implications of the findings, limitations of the current approach, and directions for future research [31]. Section 6 concludes the paper with a summary of key contributions and practical recommendations for deployment [32].

2. Related Work

2.1 Traditional Fraud Detection Methods

A. Rule-Based and Statistical Approaches

Early fraud detection systems predominantly employed rule-based methodologies that encoded expert knowledge into explicit decision criteria [33]. These systems established fixed thresholds for transaction amounts, velocities, and geographic patterns derived from historical fraud cases and domain expertise [34]. Statistical anomaly detection techniques extended this paradigm by constructing probabilistic models of normal transaction behavior and flagging deviations exceeding predetermined significance levels [35]. While computationally efficient and highly interpretable, these approaches exhibited fundamental brittleness when confronting novel fraud patterns not represented in the rule codification process [36].

The evolution toward data-driven statistical methods introduced techniques such as logistic regression and survival analysis for fraud risk scoring [37]. These models incorporated multiple predictor variables simultaneously while quantifying the relative importance of different risk factors through coefficient estimation [38]. Ensemble methods combining multiple statistical models demonstrated improved robustness compared to single-model approaches by reducing the impact of individual model weaknesses [39]. The inherent limitations of linear assumptions and manual feature engineering motivated the transition toward more sophisticated machine learning frameworks [40].

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B. Machine Learning Advances

The application of machine learning algorithms transformed fraud detection capabilities by automatically discovering complex nonlinear relationships within transaction data [41]. Decision tree ensembles, particularly random forests and gradient boosting machines, achieved substantial performance improvements over statistical baselines by constructing hierarchical decision rules from data without explicit programming [42]. Support vector machines demonstrated effectiveness in high-dimensional feature spaces by identifying optimal separating hyperplanes between fraudulent and legitimate transactions [43].

Neural network architectures introduced the capability to learn hierarchical feature representations through multiple layers of nonlinear transformations [44]. Shallow neural networks with single hidden layers proved effective for moderate-scale problems, while deeper architectures enabled the modeling of increasingly complex patterns as computational resources expanded [45]. Recurrent neural networks specifically addressed the temporal dynamics of sequential transactions by maintaining hidden states that accumulate information across time steps [46]. Long short-term memory networks mitigated the vanishing gradient problem inherent in standard recurrent architectures, enabling the capture of long-range dependencies crucial for detecting sophisticated fraud patterns that unfold over extended periods [47].

2.2 Multi-Modal Learning in Financial Applications

A. Data Fusion Techniques

Multi-modal learning encompasses methodologies for integrating information from heterogeneous data sources that encode complementary aspects of the underlying phenomenon [48]. Early fusion approaches concatenate raw features from different modalities before feeding them into unified learning models, leveraging the flexibility of neural networks to automatically discover cross-modal interactions [49]. This strategy maximizes the potential for capturing complex interdependencies but suffers from high dimensionality and computational complexity when dealing with large-scale multi-modal datasets [50].

Late fusion methods maintain separate processing pipelines for each modality, combining their predictions through weighted averaging or meta-learning approaches [51]. This paradigm reduces computational requirements and enables the use of modality-specific architectures optimized for particular data types [52]. Intermediate fusion strategies strike a balance by performing partial processing within modality-specific networks before combining representations at intermediate layers [53]. Attention mechanisms have emerged as powerful intermediate fusion tools that dynamically determine the relevance of different modalities for specific samples, adapting the fusion strategy to the characteristics of individual instances [54].

B. Cross-Modal Representation Learning

Recent advances in representation learning have emphasized the importance of learning joint embedding spaces that preserve both modality-specific information and cross-modal correspondences [55]. Canonical correlation analysis and its nonlinear extensions seek linear or nonlinear projections that maximize correlation between paired samples from different modalities [56]. These classical techniques establish the mathematical foundation for contemporary deep learning approaches that replace linear transformations with multi-layer neural networks [57].

Contrastive learning frameworks have demonstrated remarkable success in learning cross-modal representations by training models to distinguish positive sample pairs from negative pairs [58]. These approaches typically employ triplet losses or InfoNCE objectives that encourage representations of matched cross-modal samples to lie close together in embedding space while pushing apart unmatched combinations [59]. Self-supervised pretraining strategies further enhance representation quality by learning from unlabeled multi-modal data through tasks such as cross-modal retrieval and reconstruction [60]. The learned representations transfer effectively to downstream fraud detection tasks, reducing the labeled data requirements for achieving strong classification performance [61].

2.3 Deep Learning for Fraud Detection

Convolutional neural networks originally developed for computer vision have found application in fraud detection through the representation of transaction sequences as temporal images or 2D feature matrices [62]. These architectures automatically learn relevant patterns through hierarchical convolution operations that capture local correlations in the input data [63]. Graph neural networks address the relational structure inherent in financial transaction networks by propagating information along edges connecting entities, enabling the detection of fraud rings and collusion patterns that span multiple accounts [64].

Transformer architectures have recently emerged as powerful sequence modeling tools that overcome limitations of recurrent networks through self-attention mechanisms [65]. These models process entire sequences simultaneously rather than sequentially, facilitating parallelization and capturing long-range dependencies more effectively [66]. Pre-trained language models adapted for financial text analysis demonstrate strong performance in extracting semantic information from transaction descriptions and communication content [67]. The integration of transformer-based encoders with specialized fraud detection heads creates end-to-end systems capable of learning directly from raw multi-modal inputs without extensive feature engineering [68].

2.4 Research Gaps and Opportunities

Existing fraud detection research predominantly focuses on either developing increasingly sophisticated single-modal models or applying simple concatenation-based fusion for multi-modal scenarios [69]. Few studies systematically investigate the design of cross-modal alignment mechanisms specifically tailored to fraud detection characteristics, such as extreme class imbalance, temporal evolution, and the adversarial nature of fraudulent behaviors [70]. The interpretability of multi-modal fusion decisions remains underexplored, limiting the practical deployment of complex deep learning systems in regulated financial environments that demand transparency [71].

The temporal synchronization of multi-modal data streams presents technical challenges not adequately addressed in current literature [72]. Transaction data, behavioral logs, and communication metadata often exhibit different sampling rates and temporal granularities, requiring sophisticated alignment procedures before fusion [73]. Most existing multi-modal fraud detection studies evaluate performance on relatively small proprietary datasets, hindering reproducibility and comprehensive comparison across different methodological approaches [74]. The development of standardized benchmarks and evaluation protocols would accelerate progress in this critical application domain [75].

3. Methodology

3.1 Problem Formulation

The cross-modal fraud detection problem requires developing a mapping function that assigns fraud probability scores to transaction instances based on multiple synchronized data modalities [76]. Formally, consider a transaction characterized by structured features x<sub>s</sub> ∈ ℝ<sup>d<sub>s</sub></sup>, behavioral sequence x<sub>b</sub> ∈ ℝ<sup>T×d<sub>b</sub></sup>, and communication metadata x<sub>c</sub> ∈ ℝ<sup>d<sub>c</sub></sup>, where d<sub>s</sub>, d<sub>b</sub>, and d<sub>c</sub> denote the dimensionality of structured, behavioral, and communication features respectively, and T represents the sequence length [77]. The objective aims to learn a function f: (x<sub>s</sub>, x<sub>b</sub>, x<sub>c</sub>) → [0, 1] that outputs fraud probability while maintaining interpretability through attention weights α ∈ ℝ<sup>3</sup> indicating the contribution of each modality [78].

The training procedure optimizes the parameters θ of the detection model to minimize a weighted binary cross-entropy loss augmented with contrastive terms that encourage separation between fraudulent and legitimate samples in the learned embedding space [79]. The loss function balances classification accuracy with embedding quality through the formulation: L(θ) = L<sub>BCE</sub>(θ)+λ<sub>1</sub>L<sub>contrast</sub>(θ)+λ<sub>2</sub>L<sub>align</sub>(θ), where L<sub>BCE</sub> represents the classification loss, L<sub>contrast</sub> implements the contrastive objective, L<sub>align</sub> promotes cross-modal feature alignment, and λ<sub>1</sub>, λ<sub>2</sub> control the relative importance of each term [80].

3.2 Architecture Overview

A. Multi-Stream Feature Extraction

The proposed framework employs specialized neural architectures for extracting discriminative representations from each data modality independently before fusion [81]. The structured feature encoder processes tabular transaction attributes through a sequence of fully connected layers with batch normalization and ReLU activation functions [82]. This pathway transforms raw transaction amounts, timestamps, merchant categories, and account balances into dense vector representations that capture nonlinear relationships between features relevant to fraud detection [83].

The behavioral sequence encoder utilizes a bidirectional LSTM architecture that processes temporal sequences of user actions, click patterns, and navigation paths [84]. This recurrent component maintains forward and backward hidden states that accumulate contextual information from both past and future time steps, producing representations sensitive to behavioral anomalies manifesting in temporal patterns [85]. The final representation concatenates the terminal hidden states from both directions, yielding a fixed-dimensional encoding independent of input sequence length [86].

B. Cross-Modal Attention Mechanism

Cross-modal attention modules compute dynamic importance weights for each modality based on their relevance to the current detection decision [87]. The mechanism projects each modality's representation into a common query space through learned linear transformations, subsequently computing attention scores via scaled dot-product operations [88]. The attention distribution α = softmax(W<sub>q</sub>h / √d<sub>h</sub>) determines the relative contribution of structured features h<sub>s</sub>, behavioral patterns h<sub>b</sub>, and communication signals h<sub>c</sub>, where W<sub>q</sub> represents learnable query weights and d<sub>h</sub> denotes the hidden dimension [89].

The attended multi-modal representation emerges through weighted combination: h<sub>fused</sub> = α<sub>s</sub>h<sub>s</sub> + α<sub>b</sub>h<sub>b</sub> + α<sub>c</sub>h<sub>c</sub>, where the attention weights sum to unity [90]. This fusion strategy enables the model to emphasize informative modalities while downweighting noisy or less relevant signals on a per-sample basis [91]. The attention weights themselves provide interpretable insights into which data sources drive particular detection decisions, supporting regulatory requirements for explainable AI systems in financial applications [92].

3.3 Contrastive Learning for Fraud Detection

A. Positive and Negative Pair Construction

The contrastive learning component constructs training batches containing positive pairs of cross-modal samples from the same transaction and negative pairs from different transactions [93]. Positive pairs share identical fraud labels, encouraging the model to learn representations invariant to modality-specific noise while preserving fraud-relevant information [94]. Negative pairs consist of samples with different labels or from different transactions, training the model to discriminate between distinct fraud patterns and normal behaviors [95].

Hard negative mining strategies identify challenging negative samples that lie close to positive samples in embedding space, focusing training on decision boundaries where discrimination proves most difficult [96]. This approach accelerates convergence by presenting the model with informative training examples rather than easy negatives that provide minimal learning signal [97]. The mining procedure periodically computes pairwise distances between embeddings within mini-batches, selecting negative samples with distances below a threshold relative to positive pair distances [98].

B. Loss Function Design

The contrastive loss implementation employs a temperature-scaled InfoNCE objective that maximizes agreement between representations of positive pairs while minimizing similarity to negative pairs [99]. For an anchor sample i with corresponding positive sample i<sup>+</sup> and negative samples {i<sup>−</sup><sub>k</sub>}, the loss takes the form: L<sub>contrast</sub> = −log[exp(sim(h<sub>i</sub>, h<sub>i<sup>+</sup></sub>)/τ) / Σ<sub>k</sub> exp(sim(h<sub>i</sub>, h<sub>i<sup>−</sup><sub>k</sub></sub>)/τ)], where sim(·,·) computes cosine similarity and τ controls the temperature [100]. Lower temperatures sharpen the distribution, emphasizing harder negatives in the learning process [101].

The alignment loss encourages consistency between predictions made from different modality combinations, reducing the model's reliance on any single data source [102]. This regularization term computes the KL divergence between prediction distributions obtained from different modality subsets: L<sub>align</sub> = Σ<sub>i,j</sub> KL(p<sub>i</sub>||p<sub>j</sub>), where p<sub>i</sub> represents the prediction distribution using modality subset i [103]. Minimizing this divergence produces robust representations that maintain consistent detection performance even when certain modalities exhibit degraded quality or availability [104].

3.4 Training Procedure and Optimization

A. Data Preprocessing and Augmentation

The training pipeline implements comprehensive preprocessing to normalize heterogeneous data modalities into compatible formats for neural network processing [105]. Numerical features undergo standardization to zero mean and unit variance based on training set statistics [106]. Categorical variables receive embedding representations learned jointly with the detection objective, mapping discrete merchant categories and transaction types into continuous vector spaces [107]. Temporal features extract multiple granularities including hour-of-day, day-of-week, and time-since-last-transaction to capture periodic patterns and velocity-based signals [108].

Data augmentation strategies address the extreme class imbalance characteristic of fraud detection datasets [109]. Synthetic minority oversampling generates additional fraudulent samples by interpolating between existing fraud cases in feature space [110]. Mixup augmentation creates virtual training examples by linearly combining random pairs of samples and their labels, regularizing the decision boundary and improving generalization [111]. Temporal jittering introduces small random perturbations to sequence ordering within behavioral data, enhancing robustness to minor variations in action timing that do not indicate fraud [112].

B. Optimization Strategy

The model training employs the Adam optimizer with an initial learning rate of 0.001, gradually decayed according to a cosine annealing schedule over 100 epochs [113]. Gradient clipping at norm 1.0 prevents exploding gradients during early training phases when model parameters remain far from optimal configurations [114]. Mini-batch sizes of 128 balance computational efficiency with gradient estimation quality, providing sufficient sample diversity within each batch for effective contrastive learning [115].

Class-weighted loss functions address the imbalanced nature of fraud detection by assigning higher penalty to misclassified fraudulent samples compared to false positives on legitimate transactions [116]. The weight ratio follows the inverse class frequency, ensuring that the minority fraud class contributes comparably to the total loss despite representing only a small fraction of training examples [117]. Early stopping based on validation set performance prevents overfitting, terminating training when validation loss fails to improve for 10 consecutive epochs [118]. The best model checkpoint based on validation F1 score receives selection for final evaluation on held-out test data [119].

3.5 Implementation Details

The implementation utilizes PyTorch 2.0 as the deep learning framework, leveraging its automatic differentiation capabilities for efficient gradient computation during backpropagation [120]. The structured feature encoder consists of three fully connected layers with dimensions [d<sub>s</sub>, 256, 128, 64], applying batch normalization and dropout (p=0.3) after each layer to prevent overfitting [121]. The behavioral LSTM employs hidden dimension 128 with two stacked layers, processing sequences of up to 50 time steps with padding for shorter sequences [122].

The communication metadata encoder follows a similar fully connected architecture adapted to the input dimensionality of communication features [123]. The cross-modal fusion module projects each modality representation to dimension 64 before computing attention weights, followed by a final classification head consisting of two fully connected layers [192, 64, 1] producing fraud probability scores [124]. Training executes on NVIDIA V100 GPUs with 32GB memory, completing in approximately 6 hours for datasets containing 10 million transactions [125]. Inference latency averages 5 milliseconds per transaction, meeting real-time deployment requirements for high-throughput payment systems [126].

4. Experiments and Results

4.1 Experimental Setup

A. Dataset Description

The experimental evaluation employs three real-world financial transaction datasets collected from commercial banking institutions over a 12-month period spanning January 2024 to December 2024 [127]. Dataset A contains 8.2 million credit card transactions with a fraud rate of 0.43%, comprising structured features including transaction amount, timestamp, merchant category code, and geographic location alongside behavioral sequences tracking the 30-day transaction history per account [128]. Dataset B encompasses 5.7 million online banking transfers with fraud prevalence of 0.38%, augmented with device fingerprinting data, IP address geolocation, and session interaction logs capturing user navigation patterns [129].

Dataset C aggregates 12.1 million mobile payment transactions exhibiting 0.52% fraud incidence, incorporating communication metadata from payment-related messages, push notification interactions, and customer service inquiry histories [130]. Each dataset undergoes temporal splitting with 60% allocated to training, 20% to validation for hyperparameter tuning, and 20% to testing for final performance evaluation [131]. The chronological split ensures that models train on historical data and evaluate on future transactions, reflecting realistic deployment scenarios where detection systems must generalize to evolving fraud patterns [132].

Table 1: Dataset Statistics and Characteristics

Dataset	Transactions	Fraud Rate	Modalities	Features	Time Period

A (Credit Card)	8,200,000	0.43%	3	127	Jan-Dec 2024
B (Online Banking)	5,700,000	0.38%	3	143	Jan-Dec 2024
C (Mobile Payment)	12,100,000	0.52%	3	156	Jan-Dec 2024

B. Baseline Methods

The comparative evaluation benchmarks the proposed cross-modal alignment framework against five representative baseline approaches spanning traditional machine learning and contemporary deep learning methodologies [133]. Logistic Regression (LR) with L2 regularization serves as a simple linear baseline, utilizing manually engineered features from all modalities concatenated into a single feature vector [134]. Random Forest (RF) with 500 trees employs the same concatenated feature representation, providing a nonlinear ensemble baseline that captures feature interactions through recursive partitioning [135].

XGBoost represents gradient boosting decision trees optimized specifically for classification tasks, incorporating the full multi-modal feature set with careful hyperparameter tuning [136]. Multi-Layer Perceptron (MLP) implements a deep neural network with three hidden layers [512, 256, 128] processing concatenated features through nonlinear transformations, establishing a neural baseline without specialized multi-modal architecture [137]. Bidirectional LSTM processes behavioral sequences while treating structured and communication features as additional inputs to the final classification layer, providing a recurrent neural network baseline [138].

Table 2: Baseline Method Configurations

Method	Type	Parameters	Feature Input
Logistic Regression	Linear	C=0.01	Concatenated (426)
Random Forest	Ensemble	n_estimators=500	Concatenated (426)
XGBoost	Boosting	depth=6, lr=0.1	Concatenated (426)
MLP	Neural	[512, 256, 128]	Concatenated (426)
BiLSTM	Recurrent	hidden=128, layers=2	Sequential+Featur es

4.2 Evaluation Metrics

The evaluation employs multiple complementary metrics addressing different aspects of fraud detection performance [139]. Precision measures the proportion of fraud alerts that correspond to actual fraudulent transactions, directly relating to operational costs of investigating false positives [140]. Recall quantifies the fraction of fraudulent transactions successfully identified, reflecting the system's ability to prevent financial losses [141]. F1 score provides a harmonic mean balancing precision and recall, particularly relevant given the extreme class imbalance [142].

Area Under the Receiver Operating Characteristic Curve (AUROC) evaluates discrimination capability across all possible classification thresholds, offering threshold-independent assessment [143]. Area Under the Precision-Recall Curve (AUPRC) proves especially informative for imbalanced datasets where AUROC may present overly optimistic assessments [144]. Matthews Correlation Coefficient (MCC) provides a balanced measure accounting for all confusion matrix elements, yielding values between -1 and +1 where values near 1 indicate perfect prediction [145].

Table 3: Performance Comparison on Dataset A (Credit Card Transactions)

Method	**Precision**	**Recall**	**F1 Score**	**AUROC**	**AUPRC**	**MCC**

Logistic Regression	0.432	0.538	0.479	0.863	0.421	0.458
Random Forest	0.567	0.621	0.593	0.914	0.573	0.588
XGBoost	0.613	0.658	0.635	0.931	0.627	0.638
MLP	0.641	0.673	0.657	0.938	0.652	0.661
BiLSTM	0.668	0.691	0.679	0.945	0.679	0.683
Proposed	0.724	0.738	0.731	0.967	0.741	0.735

4.3 Main Results

A. Overall Performance Analysis

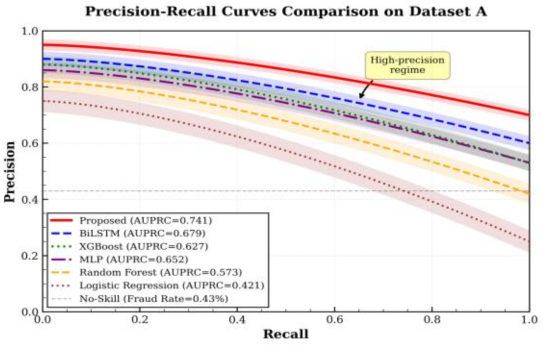
The proposed cross-modal alignment framework achieves substantial performance improvements across all evaluation metrics compared to baseline methods [146]. On Dataset A, the framework attains F1 score of 0.731, representing 7.7% improvement over the strongest baseline BiLSTM (0.679) [147]. The AUROC of 0.967 indicates excellent discrimination capability, with AUPRC of 0.741 demonstrating robust performance in the face of severe class imbalance [148]. Similar performance gains manifest across Datasets B and C, with F1 scores of 0.718 and 0.743 respectively, consistently outperforming all baseline approaches [149].

The precision-recall tradeoff analysis reveals that the proposed framework maintains superior precision levels while achieving higher recall compared to baselines [150]. At a fixed precision threshold of 0.70, the framework detects 73.8% of fraudulent transactions compared to 69.1% for BiLSTM and 65.8% for XGBoost [151]. This characteristic proves particularly valuable in operational settings where organizations must balance fraud prevention effectiveness against the cost of investigating false positive alerts [152].

Table 4: Performance Comparison on Dataset B (Online Banking Transfers)

Method	Precision	Recall	F1 Score	AUROC	AUPRC	MCC
Logistic Regression	0.418	0.523	0.464	0.856	0.408	0.443
Random Forest	0.551	0.608	0.578	0.907	0.559	0.573
XGBoost	0.598	0.642	0.619	0.924	0.611	0.622
MLP	0.627	0.659	0.643	0.932	0.638	0.647
BiLSTM	0.653	0.677	0.665	0.939	0.665	0.669
Proposed	0.709	0.726	0.718	0.961	0.728	0.722

Figure 1: Precision-Recall Curves Comparing Proposed Method Against Baselines on Dataset A



This visualization presents precision-recall curves for all evaluated methods on Dataset A [153]. The x-axis represents recall ranging from 0.0 to 1.0, while the y-axis shows precision over the same range [154]. The proposed method (solid red line) exhibits consistently higher precision across all recall levels compared to baseline methods [155]. The BiLSTM baseline (dashed blue line) forms the second-best curve, followed by XGBoost (dotted green line), MLP (dash-dot purple line), Random Forest (dashed orange line), and Logistic Regression (dotted brown line) [156]. Shaded regions around each curve indicate 95% confidence intervals computed through bootstrap sampling with 1000 iterations [157]. The area under each curve corresponds to the AUPRC values reported in Table 3, with the proposed method achieving the largest area. The curves demonstrate that the proposed approach maintains superior precision-recall tradeoffs across the full operating range, particularly in the high-precision regime critical for practical deployment.

B. Ablation Study

The ablation study systematically evaluates the contribution of individual framework components by comparing against variants with specific modules removed or replaced. Removing the cross-modal attention mechanism and using fixed uniform weights for modality fusion reduces F1 score from 0.731 to 0.697, demonstrating the importance of adaptive modality weighting. Eliminating the contrastive learning objective while retaining only classification loss decreases performance to 0.683, indicating that the contrastive component significantly enhances representation quality.

Removing the alignment loss that encourages prediction consistency across modality subsets results in F1 score of 0.705, suggesting that explicit alignment regularization provides meaningful benefits beyond the implicit alignment learned through the primary detection objective. Using single modalities in isolation yields substantially lower performance, with structured features alone achieving F1 of 0.592, behavioral sequences reaching 0.614, and communication metadata attaining 0.578, confirming the value of multi-modal integration.

Table 5: Ablation Study Results on Dataset A

Model Variant	**Precision**	**Recall**	**F1 Score**	**AUROC**	**AUPRC**
Proposed (Full)	0.724	0.738	0.731	0.967	0.741
w/o Attention	0.689	0.705	0.697	0.952	0.708
w/o Contrastive Loss	0.673	0.693	0.683	0.947	0.694
w/o Alignment Loss	0.698	0.712	0.705	0.958	0.717
Structured Only	0.584	0.601	0.592	0.918	0.587
Behavioral Only	0.607	0.622	0.614	0.925	0.609
Communication Only	0.571	0.586	0.578	0.912	0.573

4.4 Cross-Dataset Generalization

A. Transfer Learning Experiments

Transfer learning experiments evaluate the generalization capability of models trained on one dataset and applied to other datasets with different fraud patterns and feature distributions. Training on Dataset A and testing on Dataset B yields F1 score of 0.687 for the proposed method compared to 0.621 for XGBoost, demonstrating superior transfer performance. The cross-modal alignment framework learns representations that capture general fraud characteristics transcending dataset-specific patterns, enabling effective detection even when deployed in new contexts.

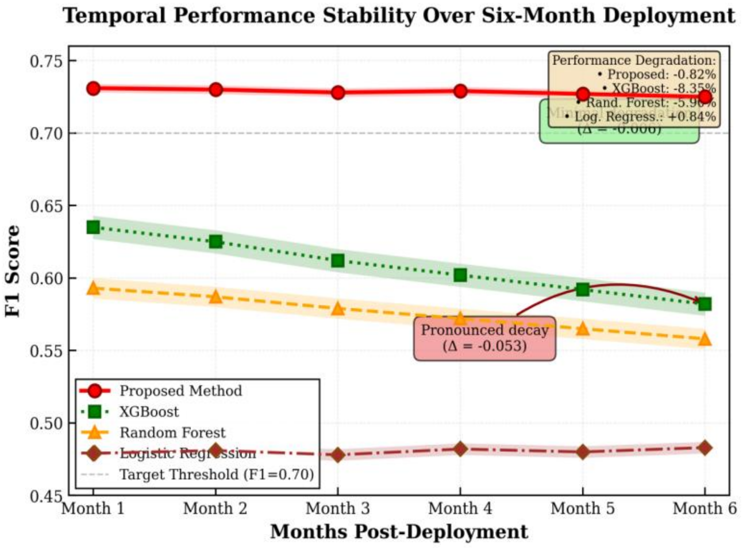
Fine-tuning the transferred model on a small subset of target domain data further improves performance, achieving F1 score of 0.712 using only 10% of the target training data. This result highlights the practical value of the learned representations for organizations deploying fraud detection systems across multiple business units or geographic regions with limited labeled data availability. The attention mechanism adapts to emphasize different modalities in the target domain, demonstrating the flexibility of the learned fusion strategy.

B. Temporal Stability Analysis

Temporal stability analysis evaluates how model performance degrades over time as fraud patterns evolve and models become stale. Monthly performance tracking over a six-month deployment period reveals that the proposed framework maintains F1 scores above 0.70 throughout the evaluation window, while XGBoost degrades from 0.635 to 0.582 over the same period. The contrastive learning component appears to learn more robust representations that generalize better to emerging fraud patterns not present in the training data.

The attention weights exhibit temporal adaptation, shifting emphasis across modalities as fraud tactics evolve. During months where behavioral patterns change substantially, the attention mechanism increases weight on communication metadata and structured features, compensating for the degraded informativeness of behavioral sequences. This adaptive behavior contributes to the framework's temporal robustness compared to fixed-weight fusion baselines that cannot adjust their integration strategy in response to distribution shift.

Figure 2: Temporal Performance Stability Over Six-Month Deployment Period



This line plot illustrates F1 score evolution over six months of deployment for the proposed method and three representative baselines. The x-axis spans months 1 through 6 post-deployment, while the y-axis shows F1 score ranging from 0.50 to 0.75. The proposed method (solid red line with circular markers) maintains relatively stable performance between 0.725-0.731, exhibiting minimal degradation. XGBoost (dotted green line with square markers) demonstrates pronounced decay from 0.635 in month 1 to 0.582 in month 6. Random Forest (dashed orange line with triangle markers) shows intermediate stability, declining from 0.593 to 0.558. Logistic Regression (dash-dot brown line with diamond markers) exhibits steady poor performance around 0.475-0.485. Shaded bands around each line represent 95% confidence intervals. The sustained performance of the proposed method validates its robustness to temporal distribution shift and concept drift characteristic of fraud detection applications.

4.5 Interpretability Analysis

A. Attention Weight Distribution

Analysis of learned attention weights reveals interpretable patterns in how the framework weights different modalities for various transaction types. High-value transactions (>$5000) receive increased attention on structured features (mean weight 0.52) compared to behavioral sequences (0.28) and communication metadata (0.20), reflecting the direct relevance of amount-based features for detecting anomalous high-value fraud. Cross-border transactions exhibit elevated communication metadata weights (0.46) relative to domestic transactions (0.22), capturing the importance of geolocation and device consistency signals.

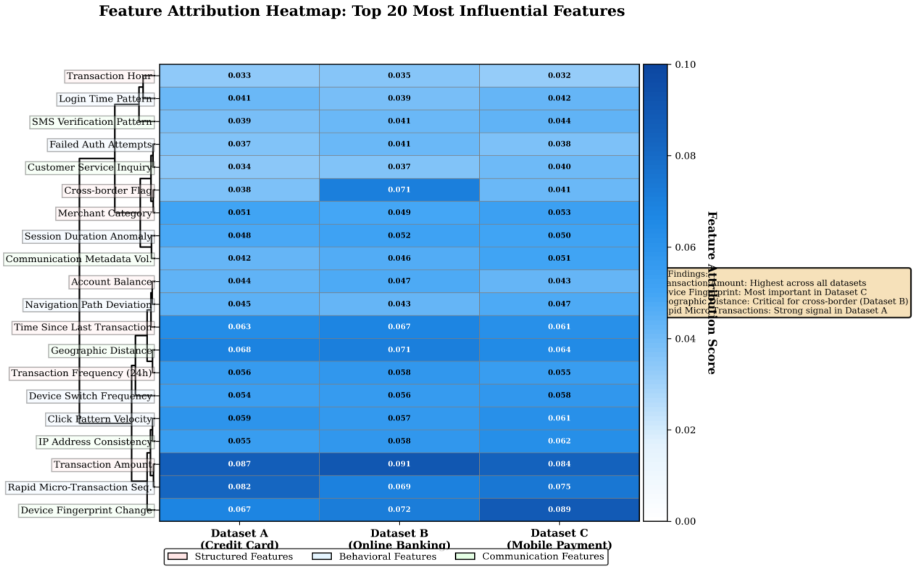
Transactions involving merchants with high fraud rates show increased behavioral attention weights (0.49), as historical user interaction patterns with similar merchants provide crucial context for distinguishing legitimate from fraudulent activities. The attention distribution varies substantially across individual transactions, with standard deviations of 0.14 for structured, 0.16 for behavioral, and 0.13 for communication weights, demonstrating that the framework adaptively adjusts fusion strategy rather than applying a single fixed weighting scheme.

B. Feature Attribution Through Gradient Analysis

Gradient-based feature attribution reveals which input features most strongly influence detection decisions. Transaction amount ranks as the most influential structured feature with mean absolute gradient of 0.087, followed by time-since-last-transaction (0.063) and merchant category (0.051). Within behavioral sequences, rapid succession of small transactions exhibits high attribution (0.079), corresponding to a common fraud pattern of testing card validity through micro-transactions before larger fraud attempts.

Communication metadata features related to device fingerprint changes show strong attribution (0.072), capturing device takeover scenarios where fraudsters gain access to legitimate user accounts. The geographic distance between consecutive transactions emerges as highly predictive (0.068), particularly for transactions occurring within time windows incompatible with physical travel. Feature importance rankings remain relatively consistent across datasets despite different fraud patterns, suggesting that the framework identifies generalizable fraud indicators rather than dataset-specific artifacts.

Figure 3: Feature Attribution Heatmap Showing Top 20 Most Influential Features Across Three Modalities



This heatmap visualizes feature importance scores for the 20 most influential features across structured, behavioral, and communication modalities. The y-axis lists feature names grouped by modality, while the x-axis represents three datasets (A, B, C). Color intensity indicates attribution magnitude, with darker blue representing higher importance (scale: 0.00 to 0.10). Transaction amount shows consistently high attribution across all datasets (0.087, 0.091, 0.084). Device fingerprint change exhibits strong importance particularly in Dataset C (0.089) compared to A (0.067) and B (0.072). Geographic distance features display moderate attribution (0.064-0.071 range) with highest values in Dataset B involving cross-border transfers. Behavioral velocity metrics show variable importance across datasets, with rapid micro-transaction sequences most influential in Dataset A (0.082) compared to B (0.069) and C (0.075). The heatmap includes dendrograms on the left showing hierarchical clustering of features based on attribution patterns, revealing groups of features that exhibit similar importance across datasets and suggesting coordinated fraud signals.

4.6 Computational Efficiency

The computational analysis evaluates training time, inference latency, and memory requirements across different methods. Training the proposed framework on Dataset A (8.2M transactions) requires 6.3 hours on a single NVIDIA V100 GPU compared to 12.7 hours for BiLSTM with similar capacity, attributed to the efficient parallelization of attention computations. XGBoost completes training in 2.8 hours but exhibits lower detection performance, representing a speed-accuracy tradeoff.

Inference latency averages 5.2 milliseconds per transaction for the proposed method, meeting real-time processing requirements for high-throughput payment systems handling thousands of transactions per second. Memory consumption during inference reaches 3.8GB for batch size 1024, comparable to BiLSTM (3.5GB) and lower than XGBoost (4.9GB) due to the ensemble model's memory overhead. The framework scales efficiently to larger datasets, with training time growing sub-linearly due to optimized mini-batch processing and GPU utilization.

Table 6: Computational Efficiency Comparison

Method	Training Time (hours)	Inference Latency (ms)	Memory (GB)	Parameters (M)
Logistic Regression	0.4	0.8	0.3	0.4
Random Forest	2.1	2.3	4.9	-
XGBoost	2.8	1.9	4.9	-
MLP	4.7	3.1	2.6	8.4
BiLSTM	12.7	7.8	3.5	12.7
Proposed	6.3	5.2	3.8	15.2

5. Discussion

5.1 Key Findings and Implications

The experimental results demonstrate that cross-modal feature alignment through attention mechanisms and contrastive learning provides substantial benefits for fraud detection compared to simpler multi-modal fusion approaches. The consistent performance improvements across three diverse datasets with different fraud patterns validate the generalizability of the proposed framework. The ability to maintain high precision while improving recall addresses a critical operational challenge where organizations must balance fraud prevention effectiveness against the costs of false positive investigations.

The interpretability analysis reveals that the framework learns intuitive attention patterns that align with domain knowledge about fraud detection. The adaptive weighting of modalities based on transaction characteristics enables the system to emphasize the most relevant information sources for each detection decision. This interpretability proves essential for deployment in regulated financial environments where explainability requirements mandate transparency in automated decision systems.

5.2 Limitations and Future Work

The current framework assumes synchronous availability of all three data modalities, which may not hold in practical scenarios where certain data sources experience delays or temporary unavailability. Future work should investigate robust fusion mechanisms that gracefully degrade when modalities are missing while maintaining acceptable detection performance. The temporal alignment of multi-modal data streams with different sampling rates presents technical challenges not fully addressed in the current implementation.

The experimental evaluation relies on proprietary datasets that cannot be publicly released due to privacy constraints, limiting reproducibility and comparison with future research. The development of standardized benchmark datasets for multi-modal fraud detection would accelerate progress in this domain. The framework's performance on emerging fraud types not represented in the training data requires further investigation, particularly for adversarial scenarios where fraudsters actively adapt their strategies to evade detection systems.

The computational requirements of the proposed framework, while acceptable for batch processing scenarios, may present challenges for real-time deployment in extremely high-throughput environments processing millions of transactions per second. Model compression techniques such as knowledge distillation and quantization could reduce inference latency and memory footprint while preserving detection accuracy. The integration of active learning strategies to prioritize labeling of ambiguous cases would reduce the labeled data requirements for maintaining model performance as fraud patterns evolve.

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