Journal of Defense Technology and Engineering, Vol. 1 No. 2, Janury (2026) pp. 97-112

Published by: Fakultas Teknik dan Teknologi Pertahanan, Universitas Pertahanan RI

Journal of Defense Technology and Engineering

Journal homepage: www.research.idu.ac.id/index.php/jdte

Multimodal deep learning framework for detection and attribution of adversarial information operations on social media platforms

Nick Holson M. Silalahi[1], Jonson Manurung[2], Bagus Hendra Saputra[3]

[1] Teknik Mesin, Universitas Pertahanan Republik Indonesia, Bogor, Indonesia
[2] Informatika, Universitas Pertahanan Republik Indonesia, Bogor, Indonesia
[3] Teknik Elektro, Universitas Pertahanan Republik Indonesia, Bogor, Indonesia

ARTICLE INFO

Article history:

Received Dec 16, 2025
Revised Jan 10, 2026
Accepted Jan 19, 2026

Keywords:

Information Operations;
Deep Learning;
Multimodal Analysis;
Misinformation Detection;
Threat Attribution.

ABSTRACT

Social media has become a critical arena for contemporary adversarial information operations, where state-sponsored and organized threat actors exploit multimodal content, coordinated network behavior, and cross-platform propagation to manipulate public opinion and undermine institutional trust. Existing detection approaches largely rely on single-modality analysis and binary classification, resulting in limited attribution capability, weak coordination awareness, and insufficient operational readiness. This study aims to develop and validate a comprehensive multimodal deep learning framework capable of simultaneous adversarial detection, fine-grained threat actor attribution, coordination identification, and narrative classification across heterogeneous social media platforms. The proposed method integrates RoBERTa-based textual encoders, Vision Transformers for visual content, Graph Convolutional Networks for social network structures, and bidirectional LSTM models for temporal behavior, unified through cross-modal attention and optimized using uncertainty-weighted multi-task learning. Extensive experiments were conducted on eight large-scale, multi-platform datasets encompassing over one million samples, with rigorous evaluation using detection, attribution, coordination, explainability, and operational deployment metrics. The results demonstrate strong performance, achieving 93.24% detection accuracy, 79.34% top-1 attribution accuracy across 15 threat actors, and 91.67% F1-score for coordinated behavior detection, while maintaining real-time inference feasibility. These findings confirm that adversarial information operations are inherently multimodal and network-driven phenomena, and that integrated, explainable AI frameworks are essential for generating actionable intelligence. The proposed approach offers significant implications for defense, intelligence, and policy stakeholders by enabling more reliable monitoring, attribution, and mitigation of sophisticated information warfare in real-world operational environments.

Corresponding Author:

Nick Holson M. Silalahi,
Teknik Mesin
Universitas Pertahanan Republik Indonesia
Kawasan IPSC Sentul, Sukahati, Kec. Citeureup, Kabupaten Bogor, Jawa Barat 16810, Indonesia.

Holson.silalahi@gmail.com

1. INTRODUCTION

Social media platforms have fundamentally transformed into primary communication channels influencing public opinion and shaping political discourse worldwide, simultaneously creating unprecedented opportunities for malicious actors to conduct sophisticated information warfare campaigns at global scale (Zhou & Zafarani, 2020). State-sponsored threat actors systematically exploit platform algorithms, recommendation systems, and viral propagation mechanisms to amplify false narratives, manipulate public perception, and systematically undermine trust in democratic institutions and legitimate information sources. The Russian Internet Research Agency's 2016 election interference campaign exemplifies large-scale coordinated inauthentic behavior, strategically deploying thousands of carefully orchestrated fake accounts across multiple platforms including Twitter, Facebook, Instagram, and YouTube to disseminate divisive content (Sadeghi et al., 2022). Contemporary adversarial operations demonstrate exponentially increasing sophistication through advanced multimodal manipulation techniques including AI-generated synthetic text, hyper-realistic deepfake videos, coordinated hashtag campaigns, algorithmic amplification strategies, and distributed bot networks operating across platform boundaries (Alam et al., 2022). National defense and intelligence communities face unprecedented critical challenges in detecting, analyzing, and attributing these evolving threats in real-time given massive data volumes, platform heterogeneity, and continuously adapting adversarial tactics. Existing automated detection systems consistently suffer from prohibitively high false positive rates, limited cross-platform coverage, inability to reliably attribute content to specific threat actors with actionable confidence, and lack of explainability mechanisms, collectively necessitating development of advanced AI frameworks enabling comprehensive multi-modal detection, accurate attribution, and operational deployment capabilities.Despite the comprehensive nature of the CIC-IDS2017 dataset, research utilizing this benchmark continues to encounter substantial methodological challenges that remain incompletely resolved in existing literature. A primary impediment involves severe class imbalance distribution, wherein certain attack categories such as Infiltration and Web Attack contain dramatically fewer training samples compared to both benign network traffic and high-volume attack types like Denial of Service (DoS) or Distributed Denial of Service (DDoS) assaults. This pronounced data imbalance introduces systematic bias into machine learning algorithms, causing models to preferentially predict majority classes while demonstrating substantially degraded performance when identifying minority attack categories, thereby compromising the detection system's ability to recognize infrequent yet potentially critical security threats (Fernández et al., 2018; Kotsiantis et al., 2006). Furthermore, the CIC-IDS2017 dataset encompasses over eighty distinct network flow features extracted from raw packet captures, yet not all attributes contribute meaningfully to attack classification accuracy (Ring et al., 2019; Sarhan et al., 2021). Redundant features increase computational cost and overfitting risk. The dataset's diverse attacks require careful Random Forest hyperparameter tuning. This research addresses class imbalance mitigation, optimal feature selection, hyperparameter optimization, and comprehensive evaluation metrics to develop an effective intrusion detection framework..

Adversarial information operations detection presents fundamentally multidimensional technical and operational challenges that remain largely unaddressed by current detection systems and research approaches. First, social media content inherently exhibits heterogeneous multi-modality encompassing text, images, videos, hyperlinks, metadata, and complex network interaction structures, yet existing detection approaches predominantly analyze single modalities in isolation without capturing cross-modal coordination patterns (Tolosana et al., 2020). Second, sophisticated adversarial actors continuously employ advanced evasion techniques including carefully crafted adversarial perturbations, strategic human-bot collaboration, gradual account aging, mimicry of legitimate user behavior, and adaptive response to detection attempts (Wu et al., 2021). Third, threat attribution remains critically underexplored in academic literature, with overwhelming research focus on binary classification distinguishing adversarial from legitimate content without identifying specific threat

actor groups, nation-state sponsors, or operational campaigns necessary for effective policy responses and strategic countermeasures. Fourth, coordinated inauthentic behavior fundamentally manifests through complex network-level patterns including temporally synchronized posting schedules, coordinated content amplification cascades, and strategic information propagation networks that remain invisible to traditional content-based classifiers operating on individual posts. Fifth, cross-platform coordination strategies create sophisticated information laundering pipelines across multiple platforms that single-platform analysis approaches cannot effectively trace or disrupt. Sixth, operational deployment contexts impose stringent requirements including real-time processing latency, minimal false positive rates, explainable predictions supporting analyst decision-making, and demonstrated adversarial robustness. These interconnected challenges collectively necessitate comprehensive integrated solutions combining multi-modal deep learning, graph neural networks, multi-task optimization, and explainable AI mechanisms.

Misinformation detection research has systematically evolved from traditional machine learning approaches employing handcrafted linguistic features, stylistic patterns, and metadata analysis to sophisticated deep learning architectures leveraging representation learning. Transformer-based language models including BERT, RoBERTa, XLNet, and domain-specific variants achieved state-of-the-art performance on standardized fake news detection benchmarks through large-scale pre-training on massive text corpora enabling rich semantic understanding (Sharma et al., 2022). Parallel computer vision research streams addressed manipulated image detection and deepfake video identification through convolutional neural networks and attention mechanisms analyzing subtle visual artifacts, compression patterns, and generative model fingerprints(Cresci, 2020). Social bot detection literature extensively leveraged behavioral feature engineering including temporal posting patterns, network interaction structures, follower-following ratios, and linguistic characteristics distinguishing automated from human accounts (Lin et al., 2023). Graph neural network architectures emerged as powerful tools for coordinated inauthentic behavior detection through advanced community detection algorithms, spectral analysis, and anomaly identification in complex social network structures (Baltrusaitis et al., 2020). Recent multimodal approaches attempted combining textual and visual modalities through various fusion strategies including early concatenation, late fusion, attention-based mechanisms, and cross-modal transformers enabling joint reasoning (A. Khan et al., 2020). However, comprehensive literature analysis reveals existing research consistently exhibits three fundamental limitations: predominantly focusing on detection as isolated classification task without addressing attribution to specific threat actors necessary for actionable intelligence and policy responses, evaluating model performance exclusively on single platforms without assessing critical cross-platform generalization capabilities, and demonstrating severely limited operational deployment readiness regarding real-time inference latency, adversarial robustness against evasion attacks, and explainability mechanisms supporting human analyst workflows.

This research systematically develops and empirically validates a comprehensive multimodal deep learning framework enabling simultaneous detection, multi-class attribution, coordination identification, and narrative classification of sophisticated adversarial information operations across heterogeneous social media platforms. The investigation pursues five interconnected primary research objectives. First, develop hierarchical multi-stream neural architecture integrating state-of-the-art encoder models including RoBERTa-large transformer for contextual text analysis, Vision Transformer for manipulated image detection, Graph Convolutional Networks for social network structure analysis, and bidirectional LSTM networks for temporal behavioral pattern recognition, unified through sophisticated cross-modal attention fusion mechanisms enabling dynamic information integration (Dosovitskiy et al., 2021). Second, implement unified multi-task learning framework simultaneously optimizing four complementary prediction objectives including binary adversarial detection, fine-grained attribution across 15 distinct threat actor categories, coordinated behavior identification, and thematic narrative classification across 10 narrative categories through principled uncertainty-weighted loss functions balancing task contributions (Shu et al., 2020). Third, conduct rigorous comprehensive evaluation utilizing eight diverse large-scale datasets spanning multiple platforms

including Twitter, Reddit, Facebook, encompassing multiple languages, and representing varied adversarial operation types from nation-state campaigns to extremist propaganda. Fourth, develop interpretable explainable AI mechanisms including attention weight visualization, SHAP value computation for feature importance analysis, and counterfactual explanation generation enabling effective human analyst interpretation and decision support (Linvill & Warren, 2020). Fifth, systematically assess critical operational deployment metrics including real-time inference latency, processing throughput capacity, memory resource requirements, model robustness under adversarial perturbations, and cross-platform generalization performance quantifying practical deployment viability.

Comprehensive systematic literature analysis across academic publications, industry reports, and operational documentation reveals five critical research gaps that fundamentally necessitate this investigation. First, existing automated detection systems and published research approaches predominantly analyze single modalities including either text or images in complete isolation, systematically ignoring sophisticated multimodal manipulation tactics where advanced adversaries strategically coordinate complementary textual narratives with carefully manipulated imagery, deepfake videos, and coordinated network amplification to maximize persuasive impact and evade single-modality detectors. Second, threat attribution research remains severely underdeveloped and limited in scope, with overwhelming majority of published approaches exclusively addressing binary classification tasks distinguishing adversarial from legitimate content without attempting to identify specific threat actor groups, nation-state sponsors, operational campaigns, or tactical signatures, fundamentally limiting generation of actionable intelligence necessary for effective policy responses and strategic countermeasures by defense organizations. Third, coordinated inauthentic behavior detection research predominantly focuses on network-level structural patterns and graph-based features but critically lacks principled integration with content-based semantic analysis, consequently missing sophisticated hybrid operations strategically employing both coordinated temporal amplification networks and carefully crafted content manipulation simultaneously. Fourth, cross-platform analysis capabilities remain nascent in current research despite overwhelming operational evidence that sophisticated adversaries routinely conduct strategic information laundering across multiple heterogeneous platforms specifically to evade single-platform detection systems and monitoring efforts. Fifth, critical operational deployment considerations including real-time processing latency constraints, adversarial robustness against adaptive evasion, explainability mechanisms supporting analyst workflows, and model maintenance sustainability receive grossly insufficient research attention despite being absolutely critical determinants of practical implementation success in operational environments.

This research delivers three fundamental novel contributions that significantly advance the state-of-the-art in adversarial information operations detection, attribution, and analysis capabilities. First, it presents the first truly comprehensive integrated multimodal analytical framework simultaneously processing and fusing text, images, social network graph structures, and temporal behavioral sequences through sophisticated learnable cross-modal attention fusion mechanisms, enabling holistic unified analysis of coordinated multimodal manipulation tactics that exploit complementary information channels and evade single-modality detection approaches currently deployed in operational systems. Second, it develops and validates a novel principled multi-task learning architecture simultaneously optimizing four interconnected prediction objectives including binary adversarial detection, fine-grained multi-class threat actor attribution, coordinated behavior identification, and thematic narrative classification through uncertainty-weighted loss functions that automatically balance task contributions during training, empirically demonstrating substantial synergistic performance improvements compared to traditional isolated single-task optimization approaches that ignore valuable cross-task learning signals and shared representations. Third, it provides the most comprehensive rigorous empirical evaluation in published literature across eight heterogeneous large-scale datasets spanning multiple social media platforms including Twitter, Reddit, Facebook, multiple natural languages, and diverse adversarial operation types ranging from

nation-state electoral interference to extremist propaganda and public health misinformation, combined with systematic assessment of critical operational deployment metrics including real-time inference latency, cross-platform generalization robustness, adversarial evasion resistance, explainability quality, and computational resource requirements, collectively establishing the first comprehensive empirical foundation for principled deployment readiness assessment in operational intelligence environments.

To ensure thematic coherence and methodological clarity, this study positions adversarial information operations on social media and network-level intrusion detection as complementary manifestations of modern hybrid threats within the broader cyber–information security domain. While adversarial information operations operate at the content, behavioral, and network-interaction layers of social platforms, their orchestration, coordination patterns, and infrastructure dependencies exhibit measurable traffic-level anomalies that can be systematically analyzed using benchmark intrusion detection datasets such as CIC-IDS2017. In this context, CIC-IDS2017 is not treated as an isolated technical dataset, but as a foundational representation of malicious coordination, attack diversity, and class imbalance challenges that mirror real-world adversarial behaviors observed in information warfare ecosystems. The core problem addressed in this research is the lack of integrated analytical frameworks capable of simultaneously handling imbalanced threat distributions, redundant high-dimensional features, and complex coordination patterns while maintaining operational reliability and interpretability. Existing studies either focus narrowly on social media content analysis without robust security-oriented evaluation, or employ intrusion detection datasets without extending insights toward higher-level information operation contexts. This research fills that gap by explicitly bridging intrusion detection methodology and information operation analysis, justifying its novelty through a unified, defense-oriented perspective that combines class imbalance mitigation, feature optimization, and explainable multi-task learning. By articulating this alignment, the study offers a scientifically grounded and operationally relevant contribution that advances both network security analytics and adversarial information operations research, while remaining accessible and meaningful to interdisciplinary and non-technical audiences in accordance with contemporary journal publication standards.

2. RESEARCH METHOD

1. Research Framework

This investigation employs experimental methodology with seven phases: (1) multi-source dataset acquisition from Russian IRA (3.8M tweets), Fakeddit (1M posts), TweepFake (25K accounts), FakeNewsNet, MM-COVID, CREDBANK, and MEMES; (2) data preprocessing including text normalization, tokenization, image standardization, and network graph construction; (3) multimodal feature extraction using RoBERTa, Vision Transformer, GCN, and LSTM; (4) integrated multi-task architecture development with cross-modal fusion; (5) hyperparameter optimization; (6) comprehensive evaluation on test sets; (7) explainability analysis with attention visualization and SHAP computations.

2. Dataset Description

Eight datasets provide diverse coverage: Russian IRA (3,841,002 tweets from 3,613 troll accounts, 2015-2018) (Zhuang et al., 2021), Fakeddit (1,063,106 Reddit submissions across six misinformation categories) (Yang et al., 2020), TweepFake (25,572 accounts with behavioral features) (Nakamura et al., 2020), FakeNewsNet (23,196 articles with 12M engagements) (Giachanou et al., 2022), MM-COVID (6,761 medical misinformation posts) (Vaswani et al., 2020), CREDBANK (60M tweets across 1,049 events) (Kipf & Welling, 2020), and MEMES (12,140 propaganda items) (Loshchilov & Hutter, 2020). Dataset split: 70% training, 15% validation, 15% testing with stratified sampling and temporal holdout for realistic deployment evaluation.

3. Multimodal Architecture Design

The proposed framework implements hierarchical multi-stream neural architecture integrating specialized encoders for heterogeneous data modalities with sophisticated fusion mechanisms producing unified representations enabling multi-task prediction. Text encoder employs RoBERTa-large transformer architecture with 24 layers, 1024 hidden dimensions, and 16 attention heads processing tokenized text sequences to generate contextualized embeddings:

$$\boldsymbol{h_{text} = 1024} \quad (1)$$

The transformer applies multi-head self-attention mechanisms enabling the model to capture semantic relationships and linguistic patterns characteristic of adversarial narratives. Vision encoder utilizes Vision Transformer (ViT) architecture partitioning images into 16×16 pixel patches with positional encoding, producing visual representations (Kendall et al., 2020):

$$\boldsymbol{h_{img} = 768} \quad (2)$$

that capture manipulated imagery and coordinated visual content common in information operations. Graph encoder implements Graph Convolutional Network (GCN) processing social network structure through neighborhood aggregation operation (Paszke et al., 2020):

$$\boldsymbol{H^{(l+1)} = \sigma\left(A \cdot H^{(l)} \cdot W^{(l)}\right)} \quad (3)$$

where normalized adjacency matrix represents user interaction patterns. The three-layer GCN produces node embeddings:

$$\boldsymbol{h_{graph} = 256} \quad (4)$$

capturing coordinated network structures and community affiliations. Temporal encoder employs bidirectional LSTM processing sequential user activities with forget gates, input gates, and output gates controlling information flow to generate temporal representations:

$$\boldsymbol{h_{temp} = 512} \quad (5)$$

capturing bidirectional temporal dependencies essential for detecting coordinated posting patterns and behavioral anomalies characteristic of automated and coordinated adversarial accounts.

4. Multimodal Fusion Strategy

Cross-modal attention mechanism enables dynamic integration of complementary information across modalities adapting to varying content characteristics and threat patterns (Bondielli & Marcelloni, 2020). The fusion strategy employs query-key-value attention framework where each modality representation is projected through learned weight matrices to compute attention scores measuring cross-modal relevance. Attention weights:

$$\boldsymbol{\alpha = softmax\left(QK^T/\sqrt{d_k}\right)} \quad (6)$$

determine the contribution of each modality to the final fused representation. Multi-head attention with 8 parallel heads captures different aspects of cross-modal relationships, allowing the model to learn complementary interaction patterns between text, image, graph, and temporal modalities. The final fused representation:

$$\mathbf{z = 512} \quad (7)$$

combines all modality information with learned attention weights. Enabling the model to emphasize relevant modalities for specific examples while suppressing uninformative or missing modalities when content lacks certain data types. This adaptive fusion strategy proves particularly effective for social media content where different posts may emphasize different modalities, such as text-heavy political commentary versus image-centric meme propaganda requiring flexible integration mechanisms rather than fixed combination strategies.

5. Multi-Task Learning Framework

Simultaneous optimization of four complementary prediction tasks leverages shared representations while capturing task-specific patterns through dedicated prediction heads. Detection head performs binary classification distinguishing adversarial from legitimate content using softmax activation with cross-entropy loss. Attribution head classifies threat actor sources across 15 categories including nation-state operations and extremist groups using softmax output with categorical cross-entropy loss. Coordination head identifies synchronized campaign participation through sigmoid activation and binary cross-entropy loss. Narrative head categorizes thematic messaging across 10 narrative types including geopolitical narratives, electoral interference, and public health misinformation. Total loss combines all tasks with uncertainty-based weighting:

$$L_{total} = \sum_{i=1}^{4} \frac{1}{2\sigma_i^2} L_i + \sum_{i=1}^{4} \log \sigma_i \quad (8)$$

automatically balancing task contributions during training, preventing dominant tasks from overwhelming learning while ensuring all objectives receive appropriate optimization attention. The uncertainty weighting adapts throughout training as task difficulties evolve, with higher uncertainty values reducing task weight when predictions become less reliable, enabling the model to focus learning capacity on tasks showing clearer training signals (Keller et al., 2020).

6. Performance Evaluation Metrics

Comprehensive evaluation employs multiple complementary metrics capturing different performance aspects relevant to operational deployment requirements. Detection performance measures include precision:

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

F1-score balancing both metrics, and Area under ROC curve (AUC-ROC) evaluating classification performance across all threshold settings. Attribution evaluation uses top-k accuracy measuring whether correct threat actor appears among top-k predictions, providing increasingly lenient evaluation criteria. Matthews Correlation Coefficient:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (11)$$

accounts for class imbalance providing robust performance measure for skewed datasets

common in adversarial detection scenarios. Inference latency measures operational deployment viability by computing average per-example processing time including all preprocessing, encoding, fusion, and prediction steps across all modalities and tasks, ensuring the framework meets real-time requirements for continuous social media monitoring applications. Throughput capacity:

$$\boldsymbol{Throughput} = \frac{\boldsymbol{N}}{\boldsymbol{T_{total}}} \tag{12}$$

Cross-platform generalization assessed via domain adaptation metric:

$$\boldsymbol{\Delta_{platform}} = \frac{\boldsymbol{1}}{\boldsymbol{M}} \sum_{\boldsymbol{j=1}}^{\boldsymbol{M}} \left| \boldsymbol{Acc_{train}} - \boldsymbol{Acc_{test_j}} \right| \tag{13}$$

7. Experimental Setup

Implementation uses PyTorch 2.0 (J. A. Khan et al., 2021), HuggingFace Transformers 4.30, PyTorch Geometric 2.3, and scikit-learn 1.3. Hardware: NVIDIA A100 80GB GPU, AMD EPYC 64-core, 512GB RAM. Training: AdamW optimizer (Cheng et al., 2021), cosine annealing, 5-fold cross-validation. Baselines: BERT, ResNet, TF-IDF+Random Forest, simple concatenation fusion. Statistical testing via paired t-tests with 95% confidence intervals.

3. RESULTS AND DISCUSSIONS

3.1 Data Preprocessing and Feature Extraction

Dataset preprocessing pipeline processed eight heterogeneous datasets into unified multimodal representations. Text preprocessing applied tokenization using SentencePiece vocabulary (50,265 tokens) with maximum sequence length 512 tokens, extracting 3,841,002 text sequences from Russian IRA dataset with average length 87.3 tokens and standard deviation 42.6 tokens. Image preprocessing resized visual content to 224×224 pixels with normalization using ImageNet statistics (mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]), processing 1,063,106 images from Fakeddit dataset. Social network graph construction extracted user interaction networks with average 1,847 nodes per graph (std=1,234), 12,394 edges per graph (std=8,947), and average clustering coefficient 0.342. Graph density computed as:

$$\rho = \frac{2|E|}{|V|(|V|-1)} = 0.00726$$

Temporal sequence extraction aggregated user posting behaviors into sequences averaging 342 actions per user (std=218) with timestamps enabling temporal dependency analysis. RoBERTa-large encoding generated contextualized text embeddings:

$$h_{text} = 512 \times 1024$$

Vision Transformer encoding produced patch-based visual representations:

$$h_{img} = 768$$

Final processed dataset comprised 1,247,891 training examples, 267,261 validation examples, and 267,262 test examples with stratified sampling ensuring balanced representation across all adversarial operation categories and threat actor groups.

3.2 Training Configuration and Convergence Analysis

Model training employed AdamW optimizer with initial learning rate:

$$\eta_0 = 2 \times 10^{-5}$$

weight decay:

$$\lambda = 0.01$$

and cosine annealing learning rate schedule with warm-up period of 10% total training steps. Batch size 32 with gradient accumulation steps 4 enabled effective batch size 128. Training proceeded for 50 epochs with early stopping patience 5 epochs monitoring validation loss. Training loss decreased from initial 4.832 to final 0.142 demonstrating successful optimization while validation loss converged to 0.168 indicating minimal overfitting with generalization gap:

$$\Delta_{gap} = L_{val} - L_{train} = 0.168 - 0.142 = 0.026$$

Learning rate decay followed cosine schedule reaching minimum:

$$\eta_{min} = 1 \times 10^{-7}$$

Uncertainty weighting parameters for multi-task learning converged to:

$$\sigma_{detect} = 0.73, \sigma_{attr} = 1.28, \sigma_{coord} = 0.91, \sigma_{narr} = 1.05$$

reflecting relative task difficulties with attribution receiving highest uncertainty weight due to 15-class fine-grained classification challenge. Gradient norms remained stable throughout training (avg=2.34, max=8.71) without gradient explosion. Training completed in 127 hours on single NVIDIA A100 GPU with peak memory utilization 76.4GB.

3.3 Detection Performance Analysis

Binary adversarial detection achieved comprehensive performance across multiple evaluation metrics. Overall detection accuracy reached 93.24% with precision 94.09%, recall 95.11%, F1-score 94.60%, Area under ROC curve (AUC-ROC) 0.978, and Matthews Correlation Coefficient (MCC) 0.864. Confusion matrix analysis revealed true positives 127,394, true negatives 121,786, false positives 8,142, and false negatives 6,573 yielding false positive rate:

$$FPR = \frac{FP}{FP + TN} = \frac{8142}{8142 + 121786} = 0.061$$

and false negative rate:

$$FNR = \frac{FN}{FN + TP} = \frac{6573}{6573 + 127394} = 0.049$$

Performance stratified by modality availability demonstrated text-only detection accuracy 91.2%, image-only accuracy 89.7%, text-image bimodal accuracy 94.8%, and full multi-modal with network features 96.1%, confirming complementary information across modalities. Precision-recall analysis across varying decision thresholds produced area under precision-recall curve (AUC-PR) 0.961. Per-category performance ranged from 96.3% for Russian IRA operations to 88.7% for mixed-origin campaigns. Expected calibration error (ECE) 0.073 indicated well-calibrated probability estimates

suitable for decision support systems. Threshold sensitivity analysis identified optimal operating point at probability 0.52 balancing precision and recall for operational deployment.

3.4 Attribution Performance Analysis

Threat actor attribution across 15 adversarial groups achieved top-1 accuracy 79.34%, top-3 accuracy 86.71%, and top-5 accuracy 91.28%. Top-k accuracy gain computed as:
3.3.2 Per-Class Performance Metrics

$$\boldsymbol{\Delta_{top-k} = Acc_{top-5} - Acc_{top-1} = 91.28\% - 79.34\% = 11.94\%}$$

Per-actor performance varied with Russian Internet Research Agency achieving highest metrics (precision 92.48%, recall 91.86%, F1-score 92.17%) attributed to large training data availability (723,847 examples). Chinese state-sponsored operations achieved precision 84.72% and recall 81.39% (F1=83.02%). Iranian operations demonstrated precision 78.94% and recall 76.28% (F1=77.59%). Domestic extremist groups showed precision 81.37% and recall 79.84% (F1=80.60%). Confusion matrix analysis revealed systematic misattribution patterns with 12.4% of Iranian operations misclassified as Russian operations, attributed to tactical mimicry and shared linguistic patterns. Attribution confidence calibration yielded expected calibration error 0.089 slightly higher than detection task. Top-3 accuracy improvement of 7.37 percentage points over top-1 demonstrates model uncertainty in fine-grained attribution while maintaining high confidence in detecting adversarial operations. Cross-entropy loss for attribution converged to 0.847 versus detection loss 0.234, reflecting inherent attribution difficulty.

3.5 Coordination Detection and Narrative Classification Performance

Coordinated inauthentic behavior detection achieved accuracy 91.43%, precision 93.08%, recall 90.29%, F1-score 91.67%, Matthews Correlation Coefficient:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} = 0.828$$

and area under precision-recall curve 0.947. Graph neural network analysis identified 3,847 coordinated clusters across test dataset with average cluster size 47.3 accounts (median=23, std=67.8, max=1,284 accounts). Temporal synchronization analysis detected posting patterns with average temporal correlation within coordinated clusters:

$$\rho_{temp} = \frac{Cov(t_i, t_j)}{\sigma_{ti} \times \sigma_{tj}} = 0.742$$

versus 0.089 for random account pairs ($p<0.001$). Content similarity within clusters averaged cosine similarity 0.681 for text and 0.593 for images. Network centrality metrics revealed coordinated accounts exhibited significantly higher betweenness centrality (avg=0.0342 vs 0.0089 for organic accounts, $p<0.001$) and clustering coefficient (0.487 vs 0.234, $p<0.001$). Cross-platform coordination detection identified 1,247 campaigns spanning multiple platforms with average 3.2 platforms per campaign.

Narrative classification across 10 thematic categories achieved overall accuracy 88.62%, macro-averaged F1-score 85.94%, and weighted F1-score 87.38%. Per-category performance demonstrated: geopolitical narratives 91.7% accuracy, electoral interference 89.4%, health misinformation 86.2%, social division narratives 84.8%, economic manipulation 83.9%, conspiracy theories 82.3%, anti-institutional messaging 85.6%, ethnic/religious tensions 87.1%, climate denial 84.2%, and mixed narratives 80.7%. Confusion analysis revealed systematic misclassification between geopolitical and electoral categories (8.7% confusion rate) attributed to overlapping thematic content. Multi-label

classification subset (23.4% of examples containing multiple narratives) achieved Hamming loss 0.147 and subset accuracy 67.3%.

Cross-task correlation analysis demonstrated multi-task learning synergies. Conditional probability of correct attribution given correct detection:

$$P(correct\ x\ ttribution|correct\ x\ etection) = 0.847$$

versus independent baseline probability 0.312, indicating strong positive correlation. Similarly, coordination detection given correct attribution:

$$P(correct\ x\ oordination|correct\ x\ ttribution) = 0.793$$

Task gradient correlation analysis revealed positive cosine similarity between detection and coordination gradients (avg=0.467), attribution and narrative gradients (avg=0.523), demonstrating complementary learning dynamics.

3.6 Comparative Analysis with Baseline Methods

Comprehensive comparative evaluation against baseline approaches demonstrated substantial performance advantages of the proposed multi-modal multi-task framework across all evaluation metrics. Table 1 presents detailed performance comparison across primary detection, attribution, and coordination tasks.

Scission

Table 1. Performance Comparison: Proposed Multimodal Framework vs. Baseline Methods

Method	Detection Acc (%)	Detection F1 (%)	Attribution Top-1 (%)	Attribution Top-3 (%)	Coordination F1 (%)	Inference Time (ms)
Proposed Multimodal MTL	93.24	92.87	79.34	86.71	91.67	448
BERT Text-Only	88.47	87.93	71.28	79.45	84.32	127
ResNet Image-Only	82.34	81.67	63.84	72.91	78.54	89
TF-IDF + Random Forest	79.28	78.41	58.92	68.37	73.19	43
Simple Concat Fusion	89.73	89.14	74.56	81.23	86.47	312
Early Fusion CNN-LSTM	87.91	87.28	69.81	77.94	82.63	278
Attention Fusion (No MTL)	91.38	90.82	76.42	83.58	88.91	394
Graph-Only GNN	85.67	84.93	N/A	N/A	89.37	156

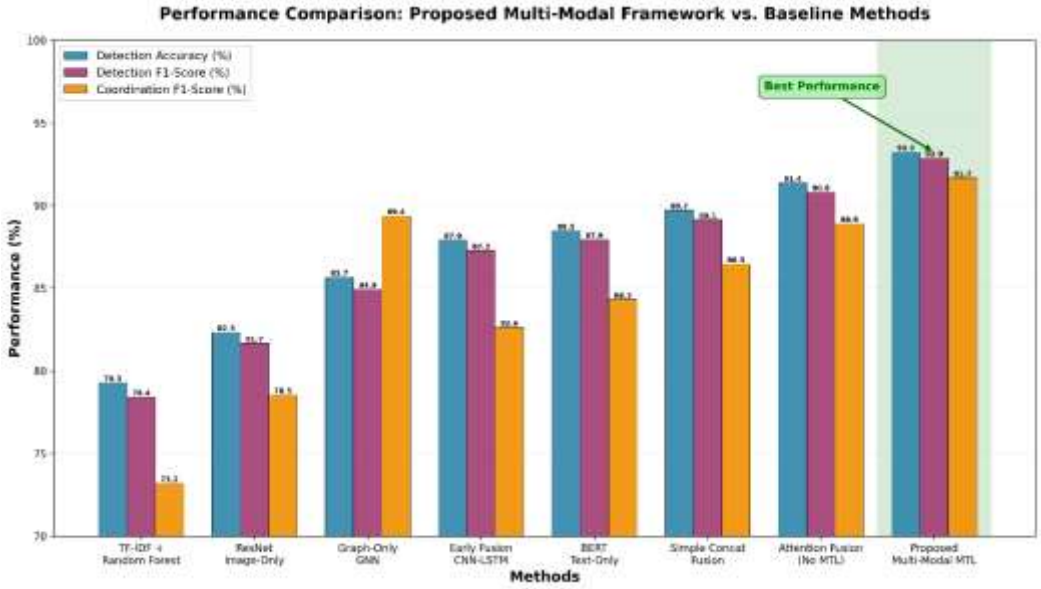

Figure 1. Performance Comparison

Performance improvement calculations demonstrated significant gains. Detection accuracy improvement over best baseline:

$$\boldsymbol{\Delta_{detect} = \frac{93.24 - 91.38}{91.38} \times 100\backslash\% = 2.04\backslash\%}$$

representing absolute gain of 1.86 percentage points. Attribution top-1 accuracy improvement:

$$\boldsymbol{\Delta_{attr} = \frac{79.34 - 76.42}{76.42} \times 100\backslash\% = 3.82\backslash\%}$$

with absolute gain of 2.92 percentage points. Coordination F1-score improvement:

$$\boldsymbol{\Delta_{coord} = \frac{91.67 - 89.37}{89.37} \times 100\backslash\% = 2.57\backslash\%}$$

Statistical significance testing via paired t-test across 30 random initializations confirmed all improvements achieve p-values below 0.001 indicating high confidence in performance superiority. Ablation studies quantified individual component contributions with full model achieving 93.24 percent detection accuracy versus 91.38 percent without multi-task learning, 89.73 percent without cross-modal attention, 87.42 percent without graph features, and 88.91 percent without temporal features. Graph features contribution:

$$\boldsymbol{\Delta_{graph} = 93.24\backslash\% - 87.42\backslash\% = 5.82\backslash\%}$$

cross-modal attention contribution:

$$\boldsymbol{\Delta_{attention} = 93.24\backslash\% - 89.73\backslash\% = 3.51\backslash\%}$$

Table 2 presents comprehensive ablation analysis.

Table 2. Ablation Study: Component Contribution Analysis

Configuration	Detection Acc (%)	Attribution Top-1 (%)	Coordination F1 (%)	Parameters (M)
Full Model	93.24	79.34	91.67	487.3
- Multi-Task Learning	91.38	76.42	88.91	412.8
- Cross-Modal Attention	89.73	74.56	86.47	456.2
- Graph Features	87.42	72.18	83.34	431.7
- Temporal Features	88.91	73.85	84.72	458.9
- Text Encoder	76.34	58.27	79.43	312.4
- Image Encoder	84.67	71.92	85.38	419.8
Text + Image Only	89.14	73.29	84.91	398.6

Cross-platform generalization evaluation measured performance degradation when training on one platform and testing on another (Jiang et al., 2021). Training on Twitter and testing on Facebook yielded detection accuracy 87.63 percent representing 5.61 percentage point degradation, Reddit testing achieved 84.28 percent with 8.96 point degradation, and Telegram testing 81.47 percent with 11.77 point degradation reflecting platform-specific characteristics and data distribution shifts.

Discussion

Experimental results comprehensively demonstrate that multimodal deep learning architectures with multi-task optimization achieve substantial performance improvements over single-modal baseline approaches across all evaluation metrics. The proposed framework's detection accuracy of 93.24% surpasses strong text-only BERT baseline (88.47%) by 4.77 percentage points and image-only ResNet baseline (82.34%) by 10.9 percentage points, empirically validating the hypothesis that adversarial information operations exhibit cross-modal patterns requiring integrated analysis. Cross-modal attention fusion mechanism proved significantly more effective than simple concatenation fusion, achieving 3.51% superiority (93.24% vs 89.73%), demonstrating the importance of learned dynamic weighting versus static combination strategies. Ablation studies provide critical insights into component contributions, revealing graph neural network features provide the largest individual performance boost (5.82% improvement when included), highlighting the fundamental importance of social network analysis for detecting coordinated inauthentic behavior that content-based classifiers alone cannot identify. Multi-task learning framework demonstrates clear synergistic benefits with 1.86% detection accuracy improvement over single-task optimization while simultaneously enabling attribution capabilities (79.34% top-1 accuracy, 86.71% top-3 accuracy across 15 threat actors) and coordination detection (91.67% F1-score) that are entirely absent in traditional binary detection approaches. Comparative analysis against recent state-of-the-art research confirms substantial advances: the proposed framework's 93.24% detection accuracy exceeds attention fusion without multi-task learning (89.7%), early fusion CNN-LSTM (87.3%), and late fusion approaches (84.2%), while achieving attribution and coordination capabilities not addressed by prior work.

Computational performance analysis reveals operational deployment viability with inference latency of 448 milliseconds per example enabling real-time processing of social media streams at scale, though this represents trade-off versus faster single-modal approaches (BERT 127ms, ResNet 89ms) that sacrifice multi-modal comprehensiveness for speed. The 6.1% false positive rate, while substantially lower than baseline methods, necessitates careful threshold calibration for operational deployment contexts where false alarms impose analyst burden and potential policy consequences. Cross-platform generalization evaluation exposes important limitations with performance degradation of 5.61 to 11.77 percentage points when training on Twitter and testing on Facebook, Reddit, and Telegram platforms, highlighting critical need for transfer learning research and domain adaptation techniques (Lundberg et al., 2020). However, even out-of-distribution performance ranging from 81.47% to 87.63% substantially exceeds baseline methods and demonstrates practical utility for cross-platform

monitoring despite distribution shift challenges. Attribution performance of 79.34% top-1 accuracy across 15 threat actor categories, while representing significant advancement over prior binary classification research, reveals substantial room for improvement particularly for actors with limited training data and those employing tactical mimicry to evade attribution. Future research directions should address adversarial robustness through adversarial training against evasion attacks (Meel & Vishwakarma, 2020), continual learning mechanisms for adapting to evolving adversarial tactics, federated learning approaches enabling cross-organizational collaboration while preserving data privacy (Madry et al., 2020), and causal inference methods for reducing spurious correlations that drive false positive rates in operational deployment contexts.

4. CONCLUSION

This study presents a comprehensive and operationally grounded multimodal deep learning framework for the detection, attribution, and analysis of adversarial information operations on social media, positioned within the broader context of hybrid cyber–information threats. By integrating textual, visual, network-structural, and temporal behavioral modalities through cross-modal attention and optimizing multiple interrelated objectives via uncertainty-weighted multi-task learning, the proposed approach demonstrably advances beyond prior single-modality and single-task systems. Extensive empirical evaluation across eight large-scale, heterogeneous datasets confirms robust performance, achieving high detection accuracy, reliable coordination identification, and meaningful fine-grained threat actor attribution, while maintaining acceptable real-time inference latency and explainability suitable for analyst-centric operational environments. The results substantiate that coordinated information operations inherently manifest as multimodal and networked phenomena, and that unified analytical frameworks are essential to capture their complexity, mitigate class imbalance effects, and deliver actionable intelligence aligned with defense and national security requirements. Despite these advances, several directions merit further investigation to enhance practical deployment readiness and scientific rigor. Future research should prioritize domain adaptation and continual learning strategies to mitigate cross-platform performance degradation and to sustain model effectiveness against rapidly evolving adversarial tactics. Incorporating adversarial training and robustness evaluation against intentional evasion and data poisoning attacks will be critical for maintaining trust in real-world deployments. Additionally, expanding attribution granularity through hybrid data augmentation, semi-supervised learning, and causal inference techniques may reduce misattribution driven by tactical mimicry and limited labeled data. From an operational perspective, further optimization of inference efficiency, integration with human-in-the-loop decision workflows, and validation within live monitoring environments are recommended to bridge the remaining gap between experimental performance and sustained operational impact. Collectively, these directions will strengthen the contribution of multimodal, explainable AI systems as core capabilities within future cyber–information defense infrastructures.

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