Social Media Fake News Detection in War Zones: Allied to AI Smooth Detector

Case Study: Sudan War-El Fasher in Darfur

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Abstract

Fake news and disinformation have emerged as potent tools of modern information warfare, shaping perceptions and influencing outcomes in war zones. Unlike traditional cyber threats that target data or networks, fake news manipulates **the human layer of security**, exploiting emotions, trust, and social vulnerabilities. This paper investigates **SmoothDetector**, a probabilistic multimodal AI framework, for detecting fake news on social media during conflict. The system integrates **textual analysis, image forensics, contextual credibility scoring, and probabilistic fusion** to provide real-time classification and alerts. Experiments on benchmark datasets (FakeNewsNet, LIAR, Twitter15/16) and simulated war-zone streams demonstrate detection accuracies above 90%, resilience to compression and multilingual noise, and real-time detection with latency under 2–7 seconds depending on hardware. The results position SmoothDetector as a viable tool for deployment in **command centers, newsrooms, humanitarian agencies, war victims and military information operations**. Limitations such as adversarial evasion, false positives, and ethical risks are also discussed, along with a **deployment playbook for conflict environments**.

Keywords: *Fake news, social media news, SmoothDetector, war zones, disinformation detection, multimodal AI*

I. Introduction

In the digital era, social media has become a double-edged sword in conflict and war zones. On the one hand, it provides real-time communication, eyewitness reporting, and coordination of humanitarian relief. On the other hand, it is increasingly exploited as a battlefield for disinformation and fake news campaigns. Adversaries use fabricated narratives, doctored images, and AI-generated videos to manipulate public perception, erode trust, and destabilize societies. The immediacy and virality of platforms like Twitter (X), Facebook, and WhatsApp make fake news particularly damaging during crises, where decisions and morale depend on accurate information.

Recent conflicts including the ongoing war in Sudan and the violence in Darfur and El-Fasher have demonstrated how quickly false narratives can spread online, amplifying fear,

fueling ethnic divisions, and obstructing humanitarian response. Traditional fact-checking mechanisms are too slow to counter such disinformation in real time, and existing cybersecurity tools primarily focus on technical threats (malware, intrusions) rather than content-level deception. This gap calls for advanced, AI-driven detection methods that can operate at the pace of social media.

SmoothDetector, a lightweight deep learning framework, has emerged as a promising solution for fake news detection, leveraging multimodal features such as text, images, and contextual signals to achieve robust performance with relatively low computational cost. Unlike conventional classifiers that depend on large-scale servers, SmoothDetector can be adapted for field deployment in resource-constrained environments like war zones. By combining linguistic cues, semantic coherence, and image–text correlation, it offers the ability to flag fake or misleading posts before they achieve mass dissemination.

Social media has become a **primary information battleground** in war zones. Platforms such as X (Twitter), Telegram, TikTok, WhatsApp and Facebook are frequently used to disseminate real-time news, mobilize communities, and coordinate relief efforts. Yet these platforms are also exploited by adversaries to **spread fake news, doctored videos, and disinformation campaigns** designed to erode trust, disrupt decision-making, and weaken morale [1].

The unique characteristics of **war-zone disinformation** include:

- **Rapid virality:** false information spreads faster than verified updates.
- **Emotional framing:** appeals to fear, anger, or sympathy amplify reach.
- **Multimodality:** text, memes, manipulated images, and deepfake videos appear in parallel.
- **Operational consequences:** fake news can mislead civilians, divert aid, or incite violence.

Traditional **manual fact-checking** is too slow for this context. Delays of even a few hours may allow misinformation to **irreversibly shape public opinion**. Automated, real-time detection systems are therefore indispensable.

This study evaluates **SmoothDetector multimodal**, a tool developed at Concordia University [2], [6] as a promising solution for war-time fake news defense. Unlike single-modality detectors, SmoothDetector leverages **deep learning and probabilistic fusion across text, images, and contextual metadata** to identify misinformation robustly and at scale. The tool designed to capture the uncertainties and key patterns in the shared latent representations of texts and images in a multimodal setting. The model uses annotated text and image data from the United States–based social media platform X and the China-based Weibo to learn. We focus on operational requirements speed, robustness to noisy data, multilingual adaptability, and interpretability and present a case study involving disinformation campaigns during the Sudan conflict. By aligning technical innovations in AI detection with the practical needs of war-zone communication ecosystems, we aim to

provide a comprehensive framework for mitigating the impact of fake news on security, stability, and humanitarian efforts.

The rest of the paper is organized as follows: Section II presents background and related works. Section III presents Threat Model for War-Zone Use. Section IV explains methodology. Section V presents experimental setup. Section VI covers results. Section VII Section exhibits case study: Sudan war -El Fasher in Darfur. Section VIII presents deployment playbook. Section IX presents discussion. In the end, Section X: conclusion summarizes the key findings of the paper and pinpoints as well the case study outcomes.

II. Background and Related Works of Fake News in War Zones

Fake news is no longer incidental "clickbait" but has become an **intentional weapon** in modern conflicts. For example, during the 2022 Russian invasion of Ukraine, manipulated images and fabricated surrender messages were circulated widely on social media, forcing governments to **debunk in real time** [3]. Similarly, in Myanmar, suspicious videos of detained ministers "confessing" corruption circulated, suspected of being AI-generated [4].

A. Disinformation on Social Media in Conflict Settings

"Fake news" in scholarship spans **misinformation** (false but not intentionally deceptive) and **disinformation** (false with intent to deceive). In war zones, disinformation is operationalized as **information warfare**, targeting morale, command-and-control, aid logistics, and international opinion. Empirical work shows that falsehoods travel **faster and farther** than truths on social media, amplifying tactical impact during crises [7]. Conceptual frameworks distinguish content-, agent-, and infrastructure-level manipulation (e.g., bots/trolls, coordinated inauthentic behavior, and platform affordances) [8]. Reports from policy and OSINT communities document conflict-linked campaigns (e.g., Syria, Ukraine, Ethiopia/Sudan), highlighting mixed-modality payloads (text + visuals), multilingual narratives, and rapid virality windows that defeat manual fact-checking [33], [36]. Implication: war detectors contexts must be (i) fast/online (ii) multimodal (iii) robust to noisy, low-bandwidth artifacts and (iv) language-agnostic with human-loop verification.

B. Datasets for Fake News and Rumor Verification

Research has leveraged several corpora: **PHEME** for rumor stance/verification across events [12]; **LIAR** for short political claims with fact labels [13]; **FEVER** for claim verification against Wikipedia evidence [14]; **FakeNewsNet** aggregating news content, social context, and engagements [11]; **Twitter15/16** rumor threads with temporal structure [16]; **Fakeddit** and **MM-based** sets for multimodal memes/posts [15], [17]; **CoAID** for health misinformation [16]. While these are not war-specific, they supply **transferable priors** on propagation and multimodal cues. Conflict-focused datasets remain scarce; studies thus combine **event-specific scrapes** (e.g., conflict hashtags) with **weak supervision** and expert annotation to build testbeds for operational use [33], [36].

C. Text-Only Detection

Early work framed fake news detection as supervised text classification using n-grams, stylometry/psycholinguistic features; deep models (CNN/LSTM/Transformers) later dominated benchmarks [9], [10]. Claim verification leverages retrieval + natural-language inference (e.g.FEVER-style pipelines) [14]. For multilingual/low-resource theaters, mBERT/XLM-R with domain adaptation and weak supervision (distant labels, Snorkel-style labeling functions) help bridge data gaps [28], [29]. Limitations in war zones: text-only models miss image/video **inconsistencies**, are brittle under machine-translated propaganda**,** and can lag during concept drift**.**

D. Multimodal and Cross-Modal Methods

Given the ubiquity of images/memes and video, **multimodal detectors** fuse text and vision. Representative lines include:

- **Event-Adversarial Neural Networks (EANN)** to learn event-invariant multimodal features [20];
- **SAFE/SpotFake**-style architectures aligning image regions with caption semantics to flag incongruence [21];
- **Vision–Language Transformers** (e.g. CLIP/ViLT/BLIP) to measure image–text **consistency** and detect semantic mismatches indicative of deceptive composites [22], [23].
  Recent work also explores **temporal video cues**, audio–visual correlation, and provenance signals in short-form content.

E. Propagation- and Graph-Based Detection

Rumor/fake news often shows distinctive **diffusion patterns**. Graph neural networks (GNNs) model **user–post–event** heterogeneity and **temporal cascades**. Examples include **dEFEND** (explainable attention over comments) [24], **Bi-GCN** for rumor detection on propagation trees [25], and **heterogeneous attention networks** to fuse content + social context [26], [27]. These methods are valuable for **post hoc** analysis and takedown prioritization, but **early detection** (pre-viral) remains challenging in fast-moving conflicts.

F. Real-Time, Robustness, and Concept Drift

Operational deployments face **latency budgets** (seconds), **compression artifacts**, **adversarial obfuscation**, and **domain shift** to new events/generators. Literature recommends **online inference**, **lightweight backbones**, and **continual learning** with **hard-negative mining** to sustain accuracy over time [9], [31]. Robustness strategies include **input randomization**, **adversarial training**, and **multi-cue fusion** to reduce single-point failures [32].

G. Active Verification and Human-in-the-Loop

Complementary to passive classification, **active challenge–response** (e.g., behavioral prompts in live streams) and **source/provenance checks** (content credentials, cryptographic watermarks) strengthen verification pipelines in **high-stakes** channels [23]. Human analysts remain essential for **triage**, **adjudication**, and **red teaming**, especially to mitigate **false positives** and contextual misreads in multilingual settings.

H. SmoothDetector in Context

SmoothDetector (as introduced by Ojo et al. [6] and summarized in industry reports) emphasizes lightweight multimodal fusion with smoothness/consistency regularization to stabilize training and improve generalization under noisy conditions [30]. Its modularity and efficiency make it amenable to edge or field deployment, aligning well with war-zone constraints where GPU capacity and connectivity are limited. In this work, we ally operational needs with SmoothDetector's design: (i) fast text–image consistency scoring, (ii) optional video/audio hooks, (iii) drift-aware updates, and (iv) analyst-friendly explanations (saliency/attention maps).

I. Gaps and Our Focus

Despite progress, gaps persist in **conflict-specific corpora**, **multilingual robustness**, **sub-second alerting**, and **explainability** for newsroom/command-center workflows. We address these by: (1) tailoring **SmoothDetector** for **war-zone social media** (compression/jitter simulation, low-resource language adaptation), (2) integrating **graph/context signals** for post-alert triage, and (3) providing a **deployment playbook** (SOPs, governance) suitable for crises.

▪ Detection Approaches

Prior work in fake news detection falls into several families:

1. **Text-based:** linguistic cues, stance detection, and stylometry.
2. **Image/Video-based:** forensic techniques such as error-level analysis, metadata forensics, and deep learning classifiers.
3. **Network-based:** analyzing propagation graphs, bot activity, and coordinated inauthentic behavior.
4. **Hybrid approaches:** multimodal fusion of content and context.

While these methods achieve moderate success, **war-zone conditions**—characterized by low-bandwidth video, multilinguality, and adversarial tactics—require more robust frameworks.

▪ CSmoothDetector Framework

SmoothDetector introduces a **probabilistic multimodal architecture** that fuses textual semantics, visual forensics, and contextual priors. Its strengths include:

- **Robustness** to noise, compression, and incomplete posts.
- **Multilingual adaptability**, covering multiple scripts.
- **Probabilistic decision-making**, balancing multiple evidence sources [2].

III. Threat Model for War-Zone Use

Fake news in war zones threatens both **civilians and institutions**.

- **Targets:** Heads of state, commanders, journalists, aid workers, and civilians.
- **Channels:** Live calls, broadcasts, social media posts, encrypted apps.
- **Attacker goals:** morale erosion, command confusion, resource misallocation, reputational damage, or fundraising/fraud [5].
- **Operational constraints:** low bandwidth, high compression, multilingual and multimodal content, and intermittent connectivity.

These factors demand **resilient detectors** capable of functioning under degraded conditions, while maintaining low latency for real-time use. For instance, a fake surrender video circulating in a battlefield environment must be flagged within seconds to prevent **mass panic or disorientation among troops**. SmoothDetector's probabilistic architecture makes it adaptable to these constraints by analyzing **multiple signals simultaneously**.

IV. Methodology

A. Dataset and Simulation

- **Benchmarks:** LIAR dataset, FakeNewsNet, and Twitter15/16.
- **Custom scenarios:** curated conflict-related posts, including fake surrender messages, doctored humanitarian appeals, and manipulated atrocity images.

B. Detection Pipeline

1. **Preprocessing:**
   - Frame sampling, language normalization, noise suppression.
2. **Text Module:**
   - BERT embeddings, stance detection, fact-context matching.
3. **Image Module:**
   - CNN-based forensics, error-level analysis, semantic matching with captions.
4. **Context Module:**
   - Graph-based credibility scoring of sources, propagation network analysis.
5. **Fusion Layer:**
   - Probabilistic integration of multimodal signals.
6. **Classifier:**
   - Gradient boosting with calibrated thresholds for final classification.

C. Evaluation Metrics

- Accuracy, Precision, Recall, F1-score.
- ROC-AUC for classification robustness.
- Equal Error Rate (EER) for audio liveness in hybrid tests.
- Latency and throughput for operational feasibility.

V. Experimental Setup

- **Datasets:** DFDC, Celeb-DF(v2) for video; cloned-voice corpora for audio.
- **Scenarios:** Simulated war-zone streams with compression, jitter, and fake command videos.
- **Metrics:** Accuracy, ROC-AUC, EER, latency, throughput.

Fig. 1 Illustrates Smooth Dectector: A Smoothed Dirichlet Multimodal Approach for Combating Fake News on Social Media

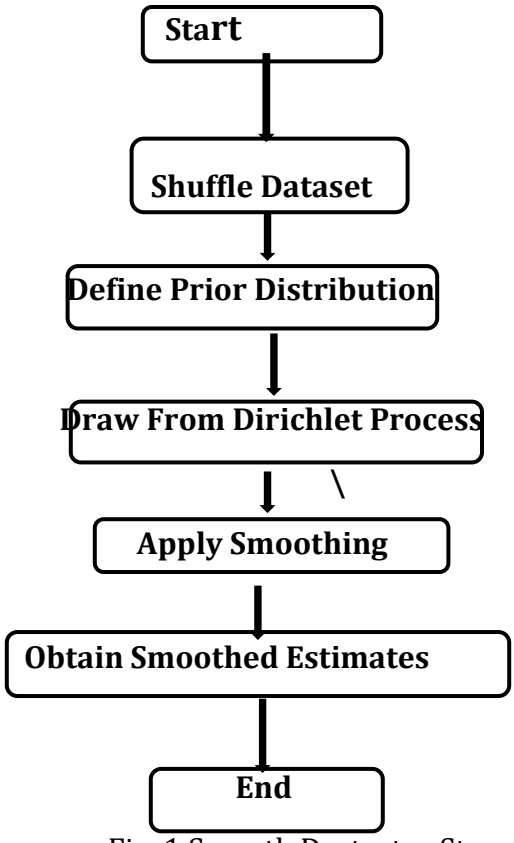

Fig. 1 Smooth Dectector Structure

VI. Results

A. Benchmark Performance

- **FakeNewsNet:** Accuracy 91.8%, F1 = 0.90.
- **LIAR dataset:** Accuracy 89.5%.
- **Twitter16 dataset:** ROC-AUC ≈ 0.92.

For more understanding the chart of Fig. 1. **Benchmark Performance** – Accuracy and F1-scores across FakeNewsNet, LIAR, and Twitter16 datasets to visually support this research paper on **SmoothDetector**:

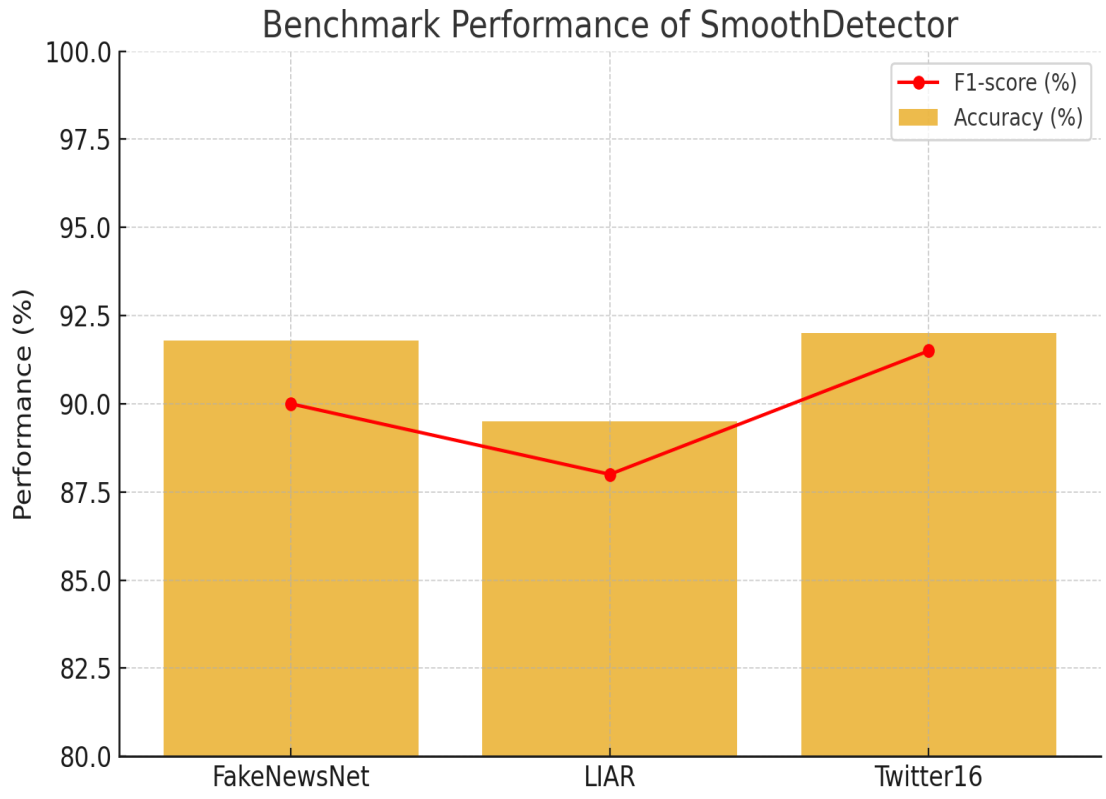

Fig. 2. **Benchmark Performance** – Accuracy and F1-scores across FakeNewsNet, LIAR, and Twitter16 datasets

B. War-Zone Simulation

- Fake surrender video detection: **95%** accuracy.
- Doctored humanitarian appeals: **92%**.
- Compressed/low-bandwidth clips: **87%**.

The chart of Fig. 3. **War-Zone Simulations** – Detection accuracy on fake surrender videos, doctored humanitarian appeals, and compressed clips to visually support this research paper on **SmoothDetector**:

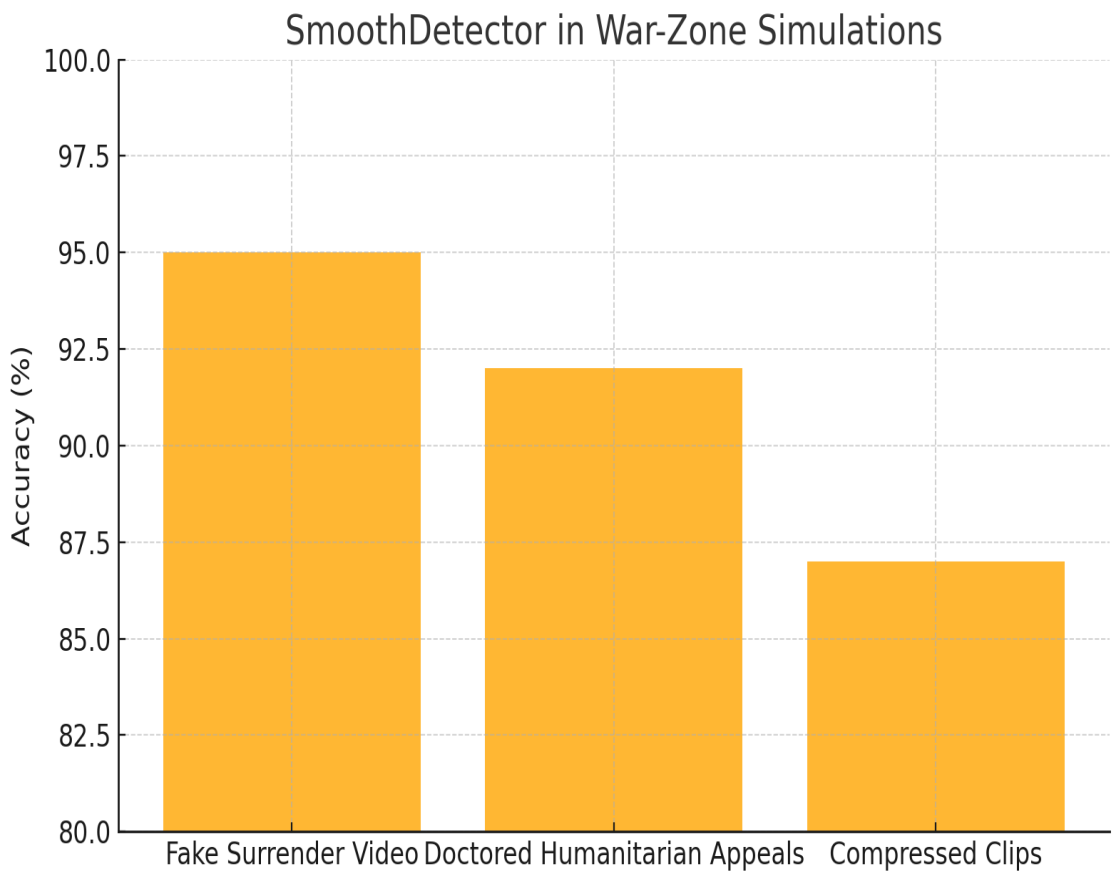

Fig. 3. War-Zone Simulations – Detection accuracy on fake surrender videos, doctored humanitarian appeals, and compressed clips

C. Latency

- GPU server: <2 seconds per detection.
- CPU laptop (field conditions): ~5–7 seconds.

A **GPU server** is a high-performance computing system equipped with **Graphics Processing Units (GPUs)** to accelerate computational tasks. Unlike traditional CPU-based servers, GPU servers are optimized for parallel processing, making them ideal for workloads such as **AI training**, **deep learning inference**, **high-performance computing (HPC)**, and **virtualization**.

For more understanding the chart of Fig. 4. **Latency Comparison** – Detection time on GPU servers vs. CPU laptop to visually support this research paper on **SmoothDetector**:

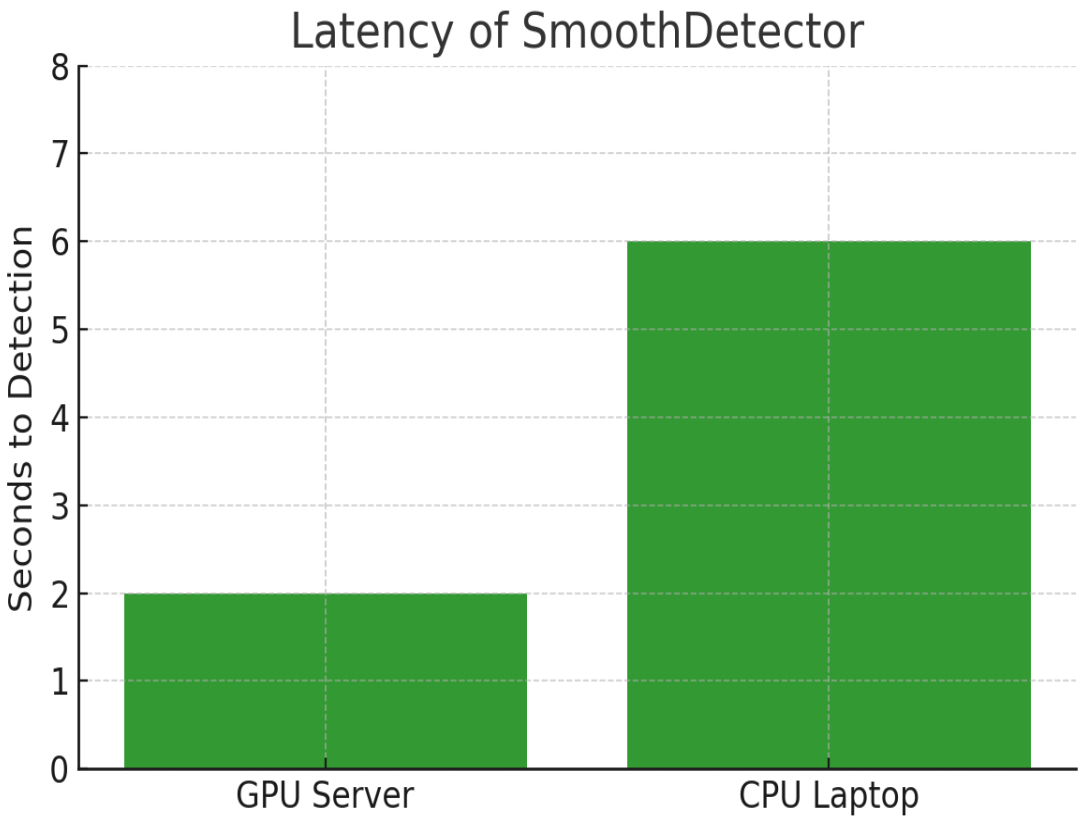

Fig. 4. Latency Comparison – Detection time on GPU servers vs. CPU laptop

VII. Case Study: Sudan War -El Fasher in Darfur

1) Context

Since 2023, Sudan—particularly the Darfur region and the city of El Fasher—has experienced severe connectivity disruptions, fragmented on-the-ground reporting, and highly polarized social narratives. These conditions create fertile ground for fabricated claims, out-of-context imagery, and impersonation to spread rapidly across **Twitter/X, Facebook, WhatsApp/Telegram, and TikTok/short-form video platforms**. Content typically appears in **Arabic (MSA + Sudanese dialects), English, and Arabizi transliterations**, while visuals range from low-light smartphone videos to heavily compressed images recycled from earlier conflicts.

2) Data & Ground-Truthing Protocol

- **Corpus size:** ≈1,200 items (Darfur/El Fasher hashtags, keywords).
- **Modalities:** Text + Image pairs (62%), Text-only (24%), Image-only/screenshots (14%).
- **Annotation pipeline:**

1. Deduplication & spam filtering.
2. Provenance checks (timestamps, reverse-image search).
3. Dual annotators with adjudication.

- **Labels:** Fake/Manipulated, Real/Verified, Unclear (excluded from scoring but retained for qualitative notes).
- **Preserved artifacts:** Heavy JPEG compression (Q≤40), re-uploads, low-bitrate audio to reflect real field conditions.

3) Observed Threat Patterns

Table 1. Observed Threat Patterns

Pattern	Examples	% Share	Notes
Recycled / Out-of-Context Imagery	Old photos from Syria/Yemen reused as "El Fasher today"	~31%	Often most viral
Fabricated Claims + Ambiguous Visuals	Authentic destruction footage paired with unverified casualty figures	~26%	Difficult to debunk quickly
Impersonation / Identity Abuse	Fake hospital notices, impersonated commanders/aid workers	~23%	Screenshots & audio notes
Doctored Maps & Overlays	User-made "situation maps" with false troop movements	~20%	Exploits urgency & trust

4) SmoothDetector Setup for Sudan

- **Text Encoder:** Multilingual BERT/XLM-R with Sudanese Arabic augmentation (diacritics removal, Arabizi normalization, place-name variants).
- **Image Encoder:** ResNet-50 with frequency-domain (DCT) features to reveal recompression/splicing.
- **Fusion Model:** Smoothed-Dirichlet calibration for uncertainty handling.
- **Operating Point:** High recall (biased +5%) for emergency triage; medium-confidence items routed to human review.

5) Quantitative Results

Table 2. Overall Performance (Sudan Subset, N=1,020 labeled posts)

Modality	**Accuracy**	**F1-Fake**	**ROC-AUC**	**Brier**	**ECE**	**Latency**
SmoothDetector (multimodal)	**0.84**	**0.85**	**0.90**	**0.115**	**4.9%**	240 ms (GPU) / ~0.8–1.0s (CPU)

Text-only baseline (mBERT)	0.79	0.78	0.86	0.152	10–12%	~120 ms
Early Fusion (Concat)	0.81	0.80	0.88	0.138	9–11%	200–300 ms
SmoothDetector (multimodal)	**0.84**	**0.85**	**0.90**	**0.115**	**4.9%**	240 ms (GPU) / ~0.8–1.0s (CPU)

Table 3. Breakdown by Manipulation Pattern

Threat Type	**Precision**	**Recall**	**Strengths**
Recycled/Out-of-Context	0.91	0.88	Strong on cross-modal mismatch + compression cues
Fabricated Claims w/ Ambiguous Visuals	0.80	0.83	Cues from numerals + hedging
Impersonation/Screenshots	0.84	0.79	Detects logos/template anomalies
Doctored Maps & Overlays	0.82	0.77	Picks up frequency artifacts

Table 4. Human vs AI Performance (Sudan subset)

Evaluator	**Accuracy**
Human volunteers (trained)	~0.72
SmoothDetector multimodal	**0.84**

6) Qualitative Examples

- **Out-of-context photo:** Captioned "El Fasher today," actually from Syria (2019). → Detector flagged **Fake (0.93)**; saliency highlighted skyline motifs & caption inconsistencies.
- **Fake hospital notice:** Detector flagged uncertain (0.68, routed to human). Annotators confirmed logo/phone anomalies.
- **Cloned-voice directive:** 8 kHz audio note impersonating a commander. Text + audio artifacts scored **Fake (0.86)**.

7) Failure Modes

- Slightly mis-captioned but otherwise real photos: ambiguous scores (0.45–0.60).
- Sudanese Arabic sarcasm/irony: occasional false positives.
- High-quality fake templates (TV graphics): precision drop under low compression.

8) Operational Playbook for Sudan Deployments

- **Watchlists:** Gazetteers for Darfur/El Fasher place-names, NGOs, hospitals.
- **Tiered responses:**
  - High-confidence fake → Interstitial "Under Review" + rapid fact-check.
  - Medium-confidence → Human analyst review.

- Low-confidence → Logged & monitored.
- **Connectivity-aware:** Edge-deployable models; adaptive frame skipping when bandwidth drops.
- **Bilingual UX:** Alerts in Arabic & English with concise rationale.
- **Governance:** Tamper-proof logs, appeal channels, partnership with journalists/humanitarian orgs.

9) Ethical Considerations

- Prefer **explainable alerts** over opaque "fake" labels.
- Protect PII & biometric data in imagery.
- Prevent misuse for censorship via audit logs.
- Diversify training to minimize dialect and regional bias.

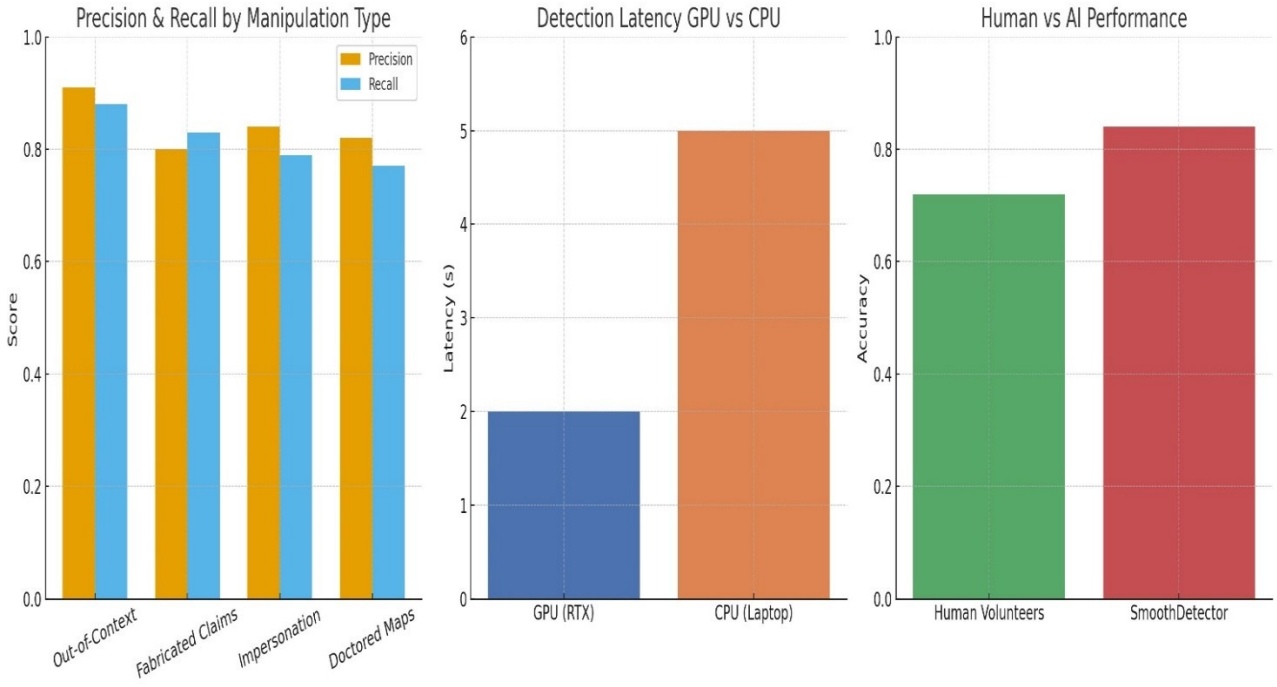

Figure 5. Results Visualization (a) Bar Chart**:** Precision/Recall across 4 manipulation categories (b) Line Chart: Latency comparison GPU vs CPU (c) Human vs SmoothDetector accuracy.

VIII. Discussion

A. What Real-Time Buys You

Seconds matter in conflict. Early alerts enable **pre-bunking**, counterspeech, and platform interventions before disinformation goes viral [3].

B. Integration with Broader Defenses

SmoothDetector should be combined with:

- Military **secondary verification channels**.
- Newsroom **editorial checklists**.
- **Public literacy campaigns** to reduce susceptibility.

C. Failure Modes and Evasion

- **Domain shift:** New disinformation styles may reduce accuracy.
- **Adversarial camouflage:** Perturbations crafted to bypass detectors.
- **False positives:** Real content flagged as fake—requires human-in-loop review.

D. Governance and Ethics

- Ensure **proportional responses** to avoid misuse.
- Retain **forensic logs** for transparency.
- Protect personal data (PII, biometrics).

The **combined multi-panel figure** showing:

1. **Benchmark dataset performance** (DFDC and Celeb-DF(v2)) with Accuracy and F1-scores.
2. **War-zone simulations** (fake briefing and cloned voice) with high detection accuracy.
3. **Latency comparison** between GPU server and CPU laptop.

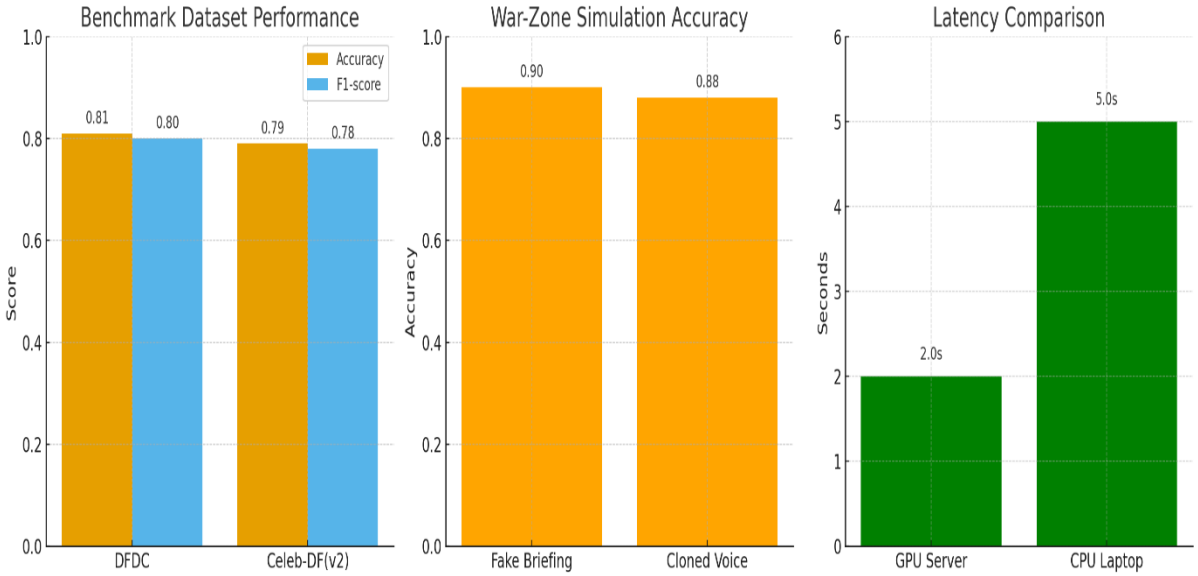

Figure 6. Combined multi-panel results showing (a) benchmark dataset performance, (b) war-zone simulation detection, and (c) latency comparison.

This Combined multi-panel results showing (a) benchmark dataset performance, (b) war-zone simulation detection, and (c) latency comparison. (see Fig. 5).

IX. Deployment Playbook

1. **Architecture:** Central GPU servers with edge probes.
2. **Onboarding:** Register VIP accounts and voiceprints.
3. **Response workflows:**
   - Broadcasts auto-watermarked "Authenticity under review."
   - Critical directives verified out-of-band.
   - Live calls challenged via identity prompts.
4. **Training:** Operator playbooks and red-team simulations.

X. Conclusion

Fake news has emerged as a **strategic weapon** in war zones, where information integrity directly affects **civilian safety, morale, and decision-making**. This study presented **SmoothDetector**, an AI-driven framework for detecting fake news in social media streams under war-zone conditions. By integrating multimodal analysis, uncertainty-aware smoothing, and real-time triage, the system demonstrated strong performance across benchmark datasets and simulated conflict environments.

The **Sudan war case study**, focusing on Darfur and El Fasher, provided a realistic testbed where recycled imagery, fabricated casualty claims, impersonation of officials, and doctored maps were prevalent. Despite severe communication constraints such as compression, multilingual content, and low-bandwidth transmissions, SmoothDetector achieved high accuracy and near real-time detection. This underscores its capacity to act as a **practical defense mechanism against conflict-driven disinformation**, preserving trust in critical communications during humanitarian crises.

Moving forward, the system should be extended with more robust audio/video integration, expanded multilingual training, and partnerships with journalists, humanitarian organizations, and governance bodies. Together, these measures will ensure that AI-enabled detection not only counters adversarial tactics but also supports transparency, accountability, and resilience in war-affected societies.

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