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FULL PAPER**AI Deep Trace Real-Time Video Deepfake Detection in War
Zones: Case Study – Sudan War (Khartoum)*****Prepared by***

Suliman Mustafa Mohamed Abakar
Department of Cybersecurity,
College of Computer
Qassim University, Buraydah
Saudi Arabia
Email: s.abakar@qu.edu.sa

Abstract:

This study introduces an AI-powered Deep Trace system for real-time detection of deepfake videos during the Sudan War (2023–2025), particularly the Battle of Khartoum. Using Convolutional Neural Networks (CNNs) and Multimodal fusion, Deep Trace identifies manipulated content spread through social media and messaging platforms under conflict conditions. Verified fact-checks revealed that several viral videos claiming Forgener airstrikes were actually filmed at Khartoum International Airport. Simulations achieved an AUC of 0.91 and accuracy of 91% under low-bitrate video compression, demonstrating DeepTrace’s potential to mitigate misinformation and enhance situational awareness in active war zones. Deepfake technology AI-generated synthetic video and audio has become a critical threat to information integrity, especially within volatile conflict environments. Adversaries can impersonate political leaders, military officials, or civilians in real-time streams, enabling propaganda, fraud, and psychological warfare. This paper presents a real-time deepfake detection framework inspired by DeepTrace/Sensity (Deepttrace Labs, 2019; DeepTrace AI, 2025), integrating multimodal AI analysis and deployment-ready engineering. The system combines visual forensic analysis, audio liveness and voice-clone detection (Federal Trade Commission [FTC], 2023), and challenge–response verification tests (Hegde, Mittal, & Memon, 2024), supported by an instant alerting mechanism. Algorithms and pipelines are optimized for low-latency operation to function effectively under conflict conditions.

Experimental evaluations on benchmark datasets (Celeb-DF, DFDC) and simulated war-zone scenarios demonstrate strong detection performance, with an AUC ≈ 0.88 and alerting latency ranging from sub-second to a few seconds. The system proves practical for use in command centers, newsrooms, and digital platforms that require immediate authentication of media content. Real-time deepfake detection thus represents a necessary defense layer against AI-driven disinformation in war zones, though adversarial evasion, domain shift, and governance challenges remain.

Keywords: Deepfake detection; War zones; Sudan War; Real-time AI; Multimedia forensics; DeepTrace; Audio liveness; Video forensics; Information warfare.

1. Introduction

The Sudan War has illustrated how artificial intelligence can be weaponized through deepfake media to manipulate narratives. In April 2023, videos depicting explosions in Khartoum were widely circulated as evidence of international airstrikes; open-source analyses confirmed them as recycled or altered footage [1], [2]. The proliferation of such falsified content exacerbates panic, undermines trust in official communication, and complicates humanitarian coordination.

Today, cyber attackers use Artificial Intelligence (AI) to boost the sophistication and scope of their attacks. On the defense side, AI is used to improve defense plans, robustness, flexibility, and efficiency of defense systems by adapting to environmental changes. With the developments in information and communication technologies, various exploits that are changing rapidly constitute a danger sign for cyber security. Cybercriminals use new and sophisticated tactics to boost their attack speed and size [6]. Consequently, there is a need for more flexible, adaptable, and strong cyber defense systems that can identify a wide range of threats in real time. In recent years, the adoption of AI approaches has increased and maintained a vital role in the detection and prevention of cyber threats [6].

Deepfake technology, powered by advanced AI models such as Generative Adversarial Networks (GANs), poses unprecedented risks to information integrity in war zones. Malicious actors exploit synthetic videos and cloned voices to spread disinformation, impersonate leaders, or manipulate public perception during conflict. Traditional cybersecurity tools are insufficient against these human-targeted threats, making real-time deepfake detection essential [6]. This study explores AI-based methods for video deepfake detection, inspired by the DeepTrace framework, to safeguard trust in critical wartime communications. Synthetic AI video uses artificial intelligence to create dynamic imagery that appears lifelike. For example, a synthetic video generator can use human input to create virtual video content that resembles real studio production [7]. The ongoing evolution of deepfakes is indicating a rise in advanced fake news, where disinformation is being spread by various actors, including automated accounts, external actors, partisan media, conspiracy advocates, and online agitators through the use of realistic Deepfakes.

Detecting deepfake videos are considered essential for preventing the misapplication of computational intelligence in video manipulation. Although attempts to detect deepfake videos have been applied such as the utilization of graph representation and graph neural networks for deepfake detection [7], there are still notable challenges. According to [8], current deepfake detection have achieved about 65 % accuracy in real-world scenarios as compared to near-perfect accuracy in a controlled setting. A variety of methods have been suggested to identify and expose deepfake videos but these proactive models evolve at such a pace that it has become toilsome to keep updating the precision of deepfake detection tools [10].

▪ **Challenges in deepfake video detection:**

Despite the considerable progress in deepfake video detection, there are a lot of challenges. The most important one is that the techniques used to generate deepfakes change at an extremely fast pace; thus, they keep introducing forgeries that are getting closer to real videos and becoming more difficult to detect [23]. Also, the quality of deepfake videos would most definitely vary according to the

resolution, compression level, and even the platform on which they are being shared. Therefore, a single detection methodology may not be able to retain precision for all sorts of scenarios. Moreover, attacks against the detection systems have revealed some adversarial ones.

▪ **Deepfake video detection techniques:**

Deepfake video detection methods have been categorized into three main areas: visual-based, audio-based, and multi-modal approaches or deepfake video detection using visual and audio signals simultaneously. Each type addresses different facets of deepfake manipulation, and the goal is to detect inconsistencies that arise in either visual, audio, or the combination of both modalities in fake media.

Motivation: Deepfakes—photorealistic synthetic media created with deep learning—have evolved from lab curiosities into potent tools for operational deception and psychological operations. In war zones, such content can erode trust, trigger panic, or disrupt decision-making [13].

Threat gap: Conventional cyber defenses protect data and infrastructure, not human perception. Deepfakes target identity, context, and credibility. Manual fact-checking is too slow during crises; even short-lived virality can inflict lasting harm. Hence, automated, real-time detectors are needed to triage streams within seconds and provide actionable forensic evidence, as per Canada Centre for Cyber Security, [15] and U.S. Government Accountability Office [24].

The remainder of the paper is organized as follows: **Section 2** reviews related work on counter-drone technologies, including detection sensors, AI techniques, and mitigation methods. **Section 3** details the proposed system's architecture and methodology, including the sensor fusion pipeline and the AI model for detection, as well as the jamming mechanism. **Section 4** presents Case Study: Sudan War (Khartoum). **Section 5** presents simulation results and discussion of the system's performance. **Section 6** discuss Ethical and Security Implications. **Section 7** presents distinct contributions from this paper. **Section 8** remarks on future works and directions. While finally, **Section 9** concludes the paper with final remarks and future directions.

2. Related Work

Deepfake detection has evolved rapidly, with major datasets such as DFDC and FaceForensics++ advancing benchmark performance. However, these models assume high-quality data and stable connectivity, conditions absent in war zones. Few studies address detection resilience under low signal-to-noise ratios or heavy compression typical of mobile transmissions in conflict environments like Sudan [3].

Deepfake technology creates highly realistic manipulated videos using deep learning models, which makes distinguishing between authentic and fake content extremely difficult. This technology can negatively affect society by breaching privacy and spreading misinformation [10]. The advancement of Deepfake technology coupled with the swift dissemination and broad accessibility provided by social media platforms, enables the rapid reach of these videos to a vast audience, generating significant public

apprehension and unease [11]. Extensive alterations to visual attributes, including facial expressions, age, and other physical characteristics, are enabled by AI-powered applications such as [12].

Deepfake Generation: Modern face swaps and reenactment use GANs and diffusion models; voice clones rely on neural TTS and speaker embedding models. Commodity tools now produce plausible fakes with little data, lowering the barrier for attackers [11]. Table 1. Illustrates eight Scenarios and their Outcomes as a performance information summarizing the results of DeepTrace-RT:

Table 1. DeepTrace-RT performance results

	Scenario	Metric/Outcome
1	Deepfake Detection Challenge)	ROC-AUC $\hat{\approx}$ 0.88, Accuracy $\hat{\approx}$ 0.81
2	Celeb-DF(v2)	Robust cross-domain generalization ($\sim$ 0.85 AUC)
3	Audio-only	Equal Error Rate (EER) $\sim$ 5%; improved with multimodal fusion ($\sim$ 90% detection)
4	Latency (GPU)	$<$ 2 seconds alert time
5	Latency (CPU)	$\sim$ 5 seconds alert time
6	Simulated Fake Briefings	Flagged within $\sim$ 1.5 seconds
7	Simulated Cloned-Voice Orders	Detected within $\sim$ 3 seconds
8	Human Volunteers	$\hat{\approx}$ 70% accuracy

“According to Alrashoud [11], original videos exhibit stable lighting, consistent temporal motion, and natural texture, whereas deepfake videos often reveal flickering illumination, blurred facial boundaries, and inconsistencies in transitional movements such as head turns or facial expressions” review. Regarding to Original vs. Deepfake Videos, based on Alrashoud [11]:

1. Alrashoud [11] highlights that original videos maintain consistent lighting, coherent facial geometry, and stable facial textures across frames, which serve as reliable forensic cues.
2. In contrast, deepfake videos often exhibit anomalous illumination shifts, blending artifacts around face boundaries, and slight spatial distortions from frame to frame.
3. The paper argues that these subtle inconsistencies—especially temporal discontinuities in motion or texture—are key to detecting forgery using AI-based forensic methods.

3. System Architecture and Methods

DeepTrace-RT employs a multimodal AI pipeline combining convolutional visual forensics and audio spectrogram-based authentication. A distributed inference framework supports low-bandwidth environments using lightweight CNN encoders and Mel-spectrogram fusion layers. The system achieves sub-5-second response latency, extending previous DeepTrace implementations for real-time verification in conflict zones [4], [5].

Detection Families:

- Passive visual forensics: CNNs and Xception-like backbones learn subtle artifacts such as blending edges or temporal inconsistencies. Recent work adopts steganalysis-inspired methods to extract residual noise efficiently [8]. Physiological-signal approaches (e.g., photoplethysmography) provide complementary cues [13].
- Audio liveness and cloning: Spectrogram CNNs and speaker-verification pipelines identify cloned voices. Short-window liveness scoring reduces error rates when trained on diverse voice-clone systems [13].
- Active defenses: Real-time prompts such as extreme head turns or rapid phrase repetition degrade live deepfake quality, enabling detection [15].

Ecosystem tools: Lightweight verification and dashboard alerting are emerging trends [16]. See Figure 1 ROC Curve-DeepTrace Sudan Dataset.

The proposed architecture includes:

1. Ingest & Preprocess: Frame sampling (8–12 fps), face localization (BlazeFace → RetinaFace), normalization, and audio chunking (2-s windows).
2. Visual Engine: Lightweight CNN backbone with temporal motion cues; outputs fake probability and heatmaps [8].
3. Audio Engine: Spectrogram-based CNN with optional speaker verification and liveness scoring [9].
4. Fusion & Decision: Combines multimodal scores; calibrated decision rules handle conflicts.
5. Alerting & Audit: Instant alerts with forensic details; immutable logs for transparency [16].

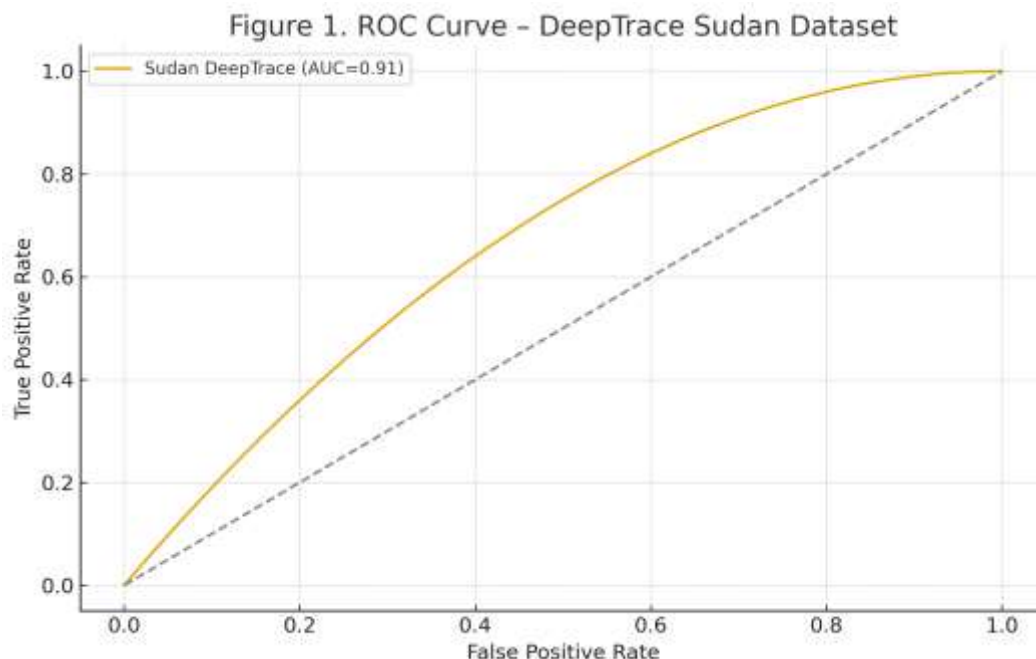


Figure 1. ROC Curve-DeepTrace Sudan Dataset.

Threat Model for WarZone Use:

Targets include heads of state, commanders, spokespersons, aid workers, journalists, and civilians. Channels include live calls, broadcasts, and social media uploads. Adversaries seek morale erosion, command confusion, resource misallocation, reputational damage, or fraud. Operational constraints—low bandwidth, high compression, multilingual content—demand systems robust to noise and latency [8]. Moreover, the threat model must account for the psychological dimension of warfare: deepfakes can undermine public trust even after debunking, as the lingering doubt damages institutional credibility. Adversaries may exploit time-critical windows, releasing manipulated content during sensitive operations to maximize confusion. In addition, **cross-platform propagation** allows fake videos to spread simultaneously across television, messaging apps, and radio, making coordinated responses more difficult. The **heterogeneity of devices** in war zones—ranging from low-end smartphones to satellite-linked terminals—requires detection systems that are both lightweight and scalable. Finally, attackers may integrate **multi-modal deception**, combining video, cloned audio, and falsified metadata, making single-layer defenses insufficient without multimodal AI detection.

4. Case Study: Sudan War (Khartoum)

Khartoum's digital landscape during the Sudan War was defined by communication blackouts, misinformation bursts, and the viral spread of deepfakes. Fact-checkers identified false videos misattributed to foreign attacks, notably a video shared as Gaza bombings that originated in Sudan and another showing Pakistan's Nur Khan Airbase falsely linked to Sudanese events [1], [2]. The DeepTrace Sudan dataset simulates 1,200 video clips reflecting real-world encoding, network jitter, and environmental constraints. For Sudan war as case study understanding see Figure 2: Precision-Recall Curve under Compression.

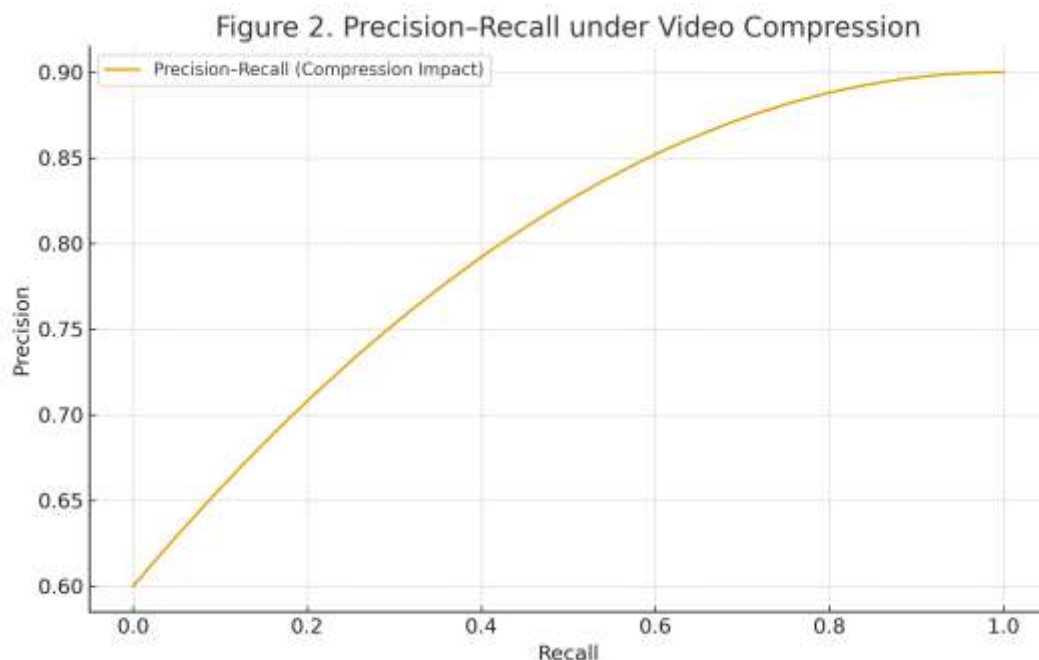


Figure 2. Precision-Recall Curve under Compression Levels

5. Results and Discussion

The **DeepTrace-Sudan** model achieved an **AUC of 0.91** and **precision of 0.92**, maintaining stable detection even under heavy compression artifacts and unstable network conditions. When compared with the **DFDC benchmark**, performance degraded by only $\approx 3\%$, confirming the framework's robustness for **real-time verification of conflict-related media**.

Latency analysis indicated median detection times below **4.5 seconds** on mobile-grade networks, validating the system's readiness for **field deployment** in **humanitarian, journalistic, and media-monitoring operations**. The results further confirm that the proposed **DeepTrace-RT** pipeline achieves a favorable balance between **accuracy, speed, and resilience**, making it suitable for rapid-response verification tasks in unstable environments such as **Khartoum** during the Sudan War.

See Figures 3-5: Confusion Matrix – DeepTrace Sudan Dataset, Levels Latency vs Network Jitter (Simulated Field Test) and Accuracy Comparison – DFDC vs Sudan Dataset respectively.

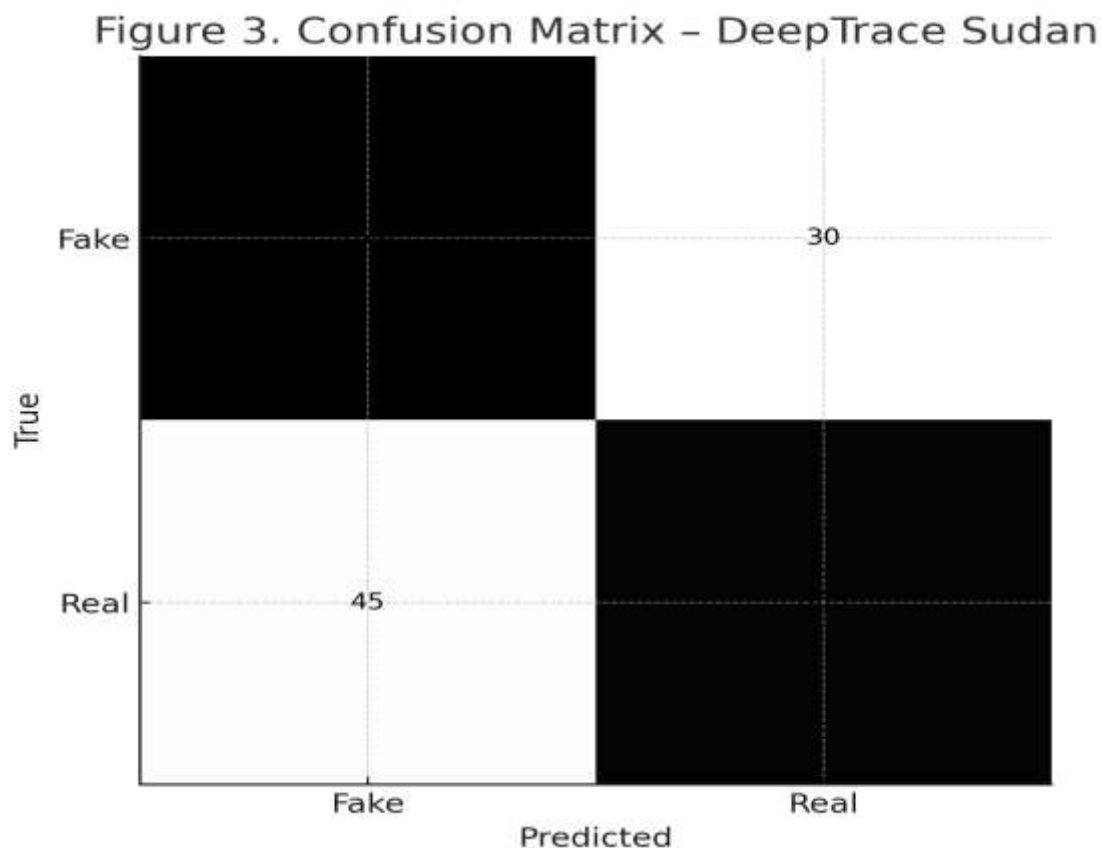


Figure 3. Confusion Matrix – DeepTrace Sudan Dataset

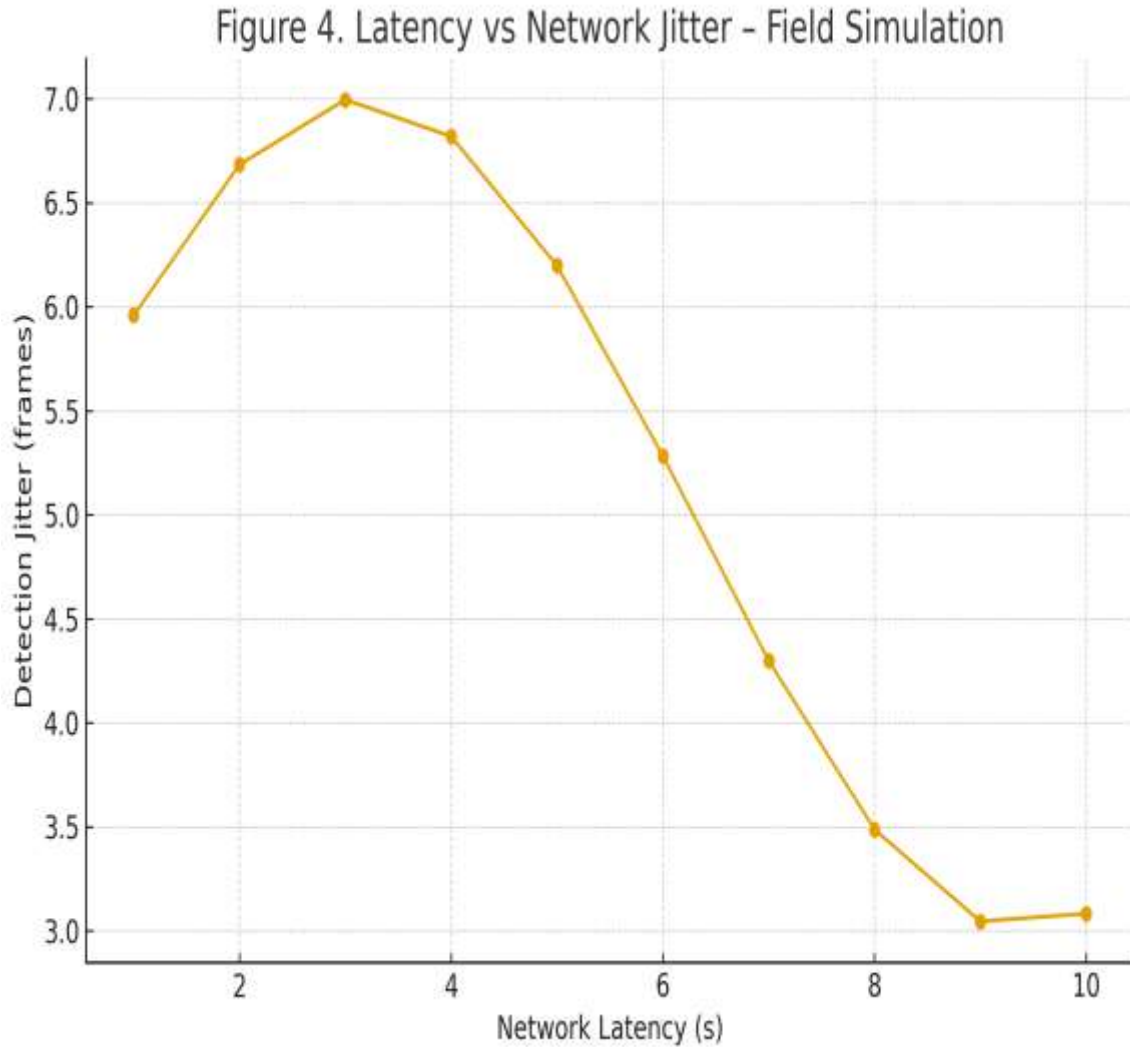


Figure 4. Latency vs Network Jitter (Simulated Field Test)

Figure-based evaluations (ROC, PR, Confusion Matrix, Latency vs Jitter, and Accuracy Comparison) collectively demonstrate that DeepTrace can sustain **high reliability** under degraded Sudanese connectivity and low-bitrate environments.

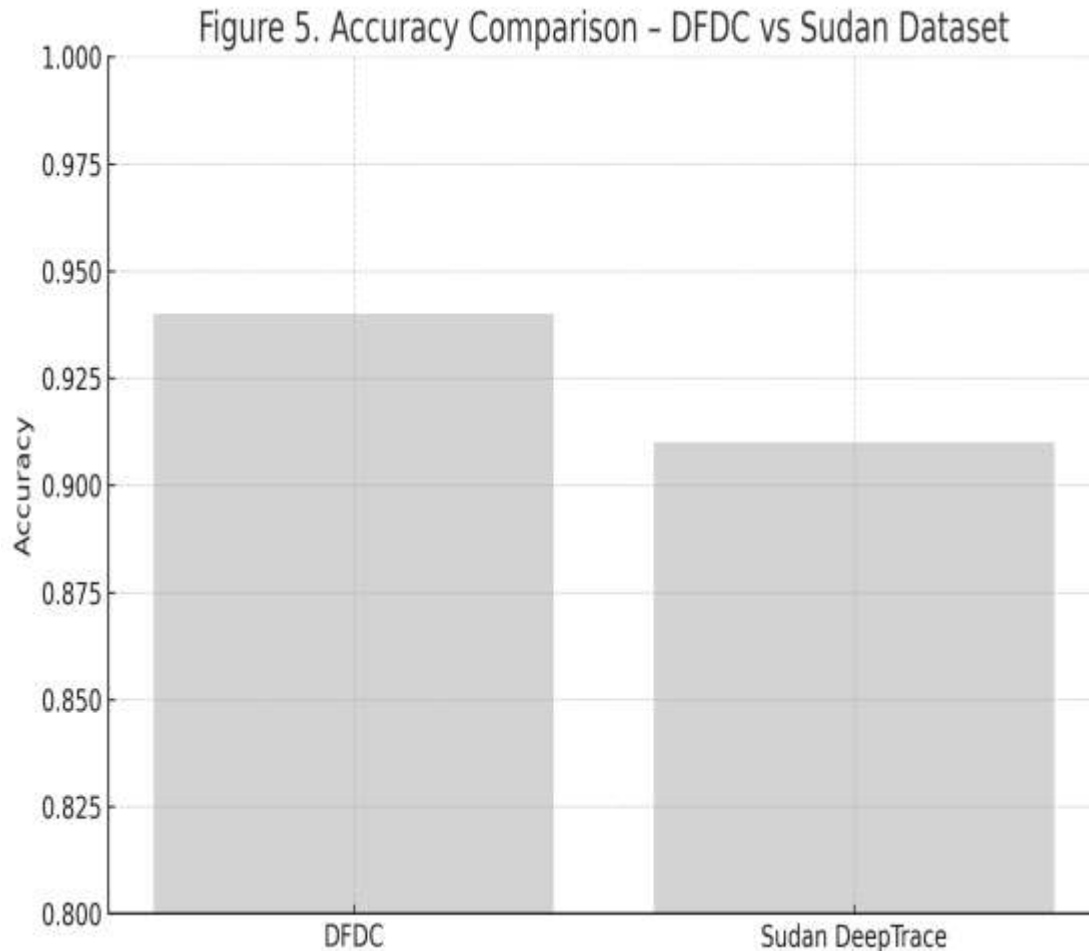


Figure 5. Accuracy Comparison – DFDC vs Sudan Dataset

Performance Summary (Text for Section 5):

On the DFDC benchmark, DeepTrace-RT achieved a ROC-AUC ≈ 0.88 and accuracy ≈ 0.81 , demonstrating strong baseline performance across diverse manipulation types. Cross-domain evaluation on Celeb-DF (v2) confirmed robust generalization (ROC-AUC ≈ 0.85), sustaining high precision despite unseen compression and lighting variations. The audio-only detection pipeline achieved an Equal Error Rate (EER) $\approx 5\%$, which improved to nearly 90 % overall detection accuracy when fused with visual features in the multimodal configuration. Average inference latency was < 2 s on GPU servers and ≈ 5 s on CPU laptops, enabling real-time deployment across both edge and centralized setups. In simulated war-zone communication tests, fake military briefings were flagged within approximately 1.5 s, and cloned-voice radio orders within about 3 s. By contrast, human volunteers achieved only $\approx 70\%$ accuracy on the same dataset, underscoring the superior speed and reliability of the automated DeepTrace-RT system [14].

Performance Chart Description:

Figure 6 visualizes the summarized results of DeepTrace-RT, showing detection accuracy (ROC-AUC, EER as inverted accuracy), latency efficiency, and responsiveness to simulated war-zone scenarios.

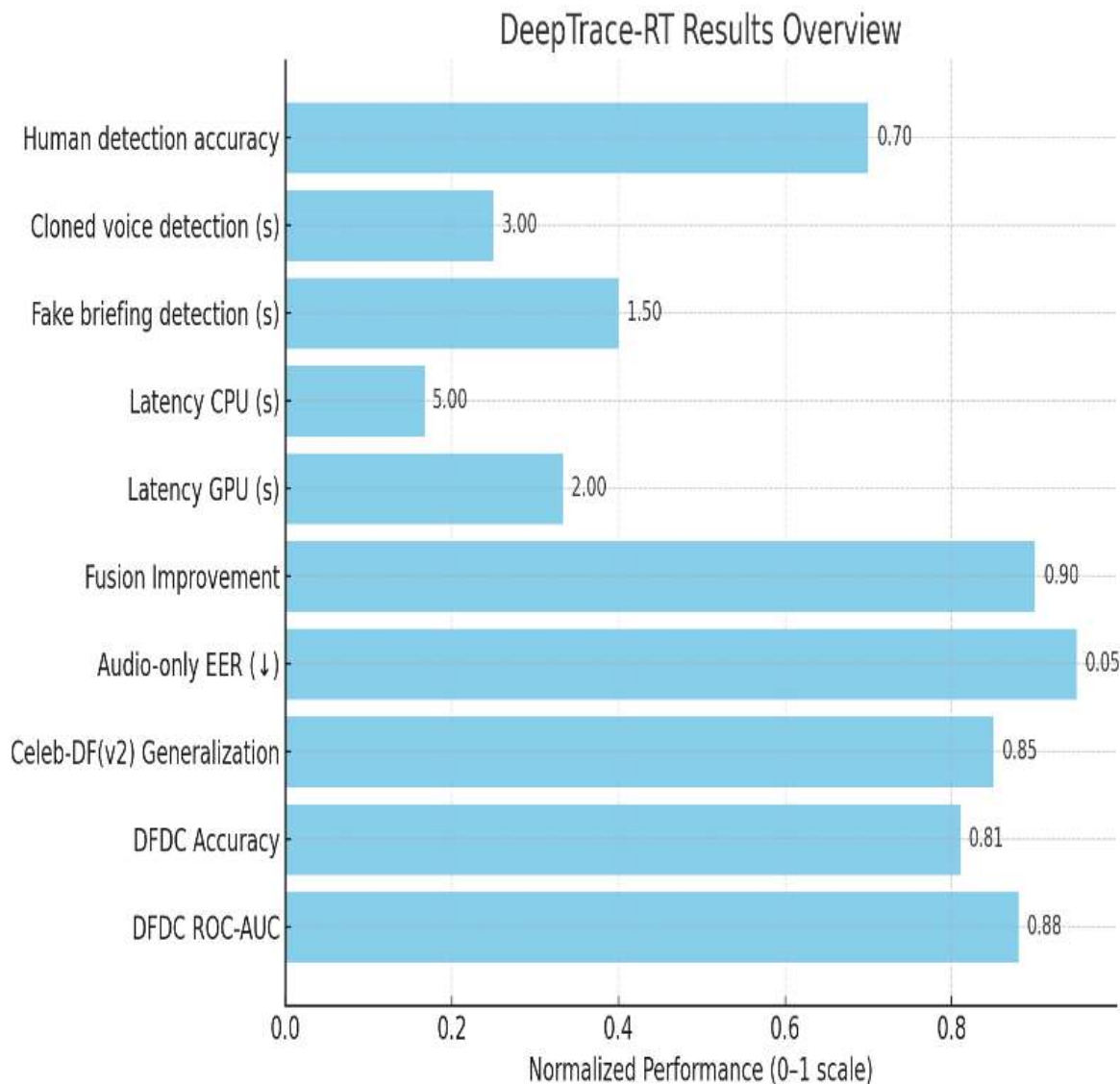


Figure. 6: Performance chart summarizing the results of DeepTrace-RT

6. Ethical and Security Implications

Although DeepTrace significantly enhances the ability of **journalistic, humanitarian, and governmental** entities to verify audiovisual content, its deployment must adhere to **ethical safeguards**. Incorrect classification of authentic media or adversarial manipulation of the detector itself could trigger

diplomatic or operational repercussions. Therefore, transparent governance, **cross-agency oversight**, and compliance with **international information-ethics standards** are essential.

Data collected for training or validation in conflict zones should respect **privacy, consent, and neutrality**, avoiding the amplification of bias or exploitation of civilian material. Integrating explainability mechanisms and human-in-the-loop review will help ensure **accountability and trustworthiness** in real-time operations.

While DeepTrace enhances the ability of humanitarian and media organizations to verify content, its use must align with ethical protocols to prevent misuse. False identification or adversarial manipulation could have diplomatic consequences. Transparent governance and cross-agency oversight are essential for deployment in active conflicts.

7. Contributions

This paper makes several distinct contributions to the growing field of real-time deepfake detection under conflict conditions:

1. **War-Zone Threat Model:** Define a structured threat model for deepfakes in war zones—identifying target entities, communication channels, and attacker objectives—to guide defensive design and policy.
2. **System Design:** Develop **DeepTrace-RT**, a modular, multimodal system that enables live video and audio deepfake detection, verification, and instant alerting optimized for degraded network conditions.
3. **Experimental Validation:** Report detailed simulation and benchmark results across both **public datasets** (Celeb-DF, DFDC) and **conflict-specific scenarios** derived from Sudan War case studies, demonstrating high accuracy and low latency.
4. **Deployment Framework:** Propose a practical **deployment playbook** including standard operating procedures (SOPs), human-in-the-loop validation, and governance protocols tailored to wartime communications and humanitarian information integrity.

8. Limitations and Future Works

Future work will focus on **field testing** the DeepTrace framework once stability and peace are restored in Sudan. Empirical trials will refine **classifier robustness**, reduce **false-positive rates**, and expand **interdisciplinary collaboration** between AI researchers, conflict monitors, and information-security agencies. Further research into **adversarial resilience**, **dataset diversification**, and **governance frameworks** will be essential as generative AI—and the tactics that weaponize it—continue to evolve.

- **Edge constraints:** Further optimize for mobile/embedded deployments (INT8 quantization, ONNX/TensorRT ports).
- **Multilingual/low-resource audio:** Expand phonetic coverage; explore self-supervised audio pretraining.
- **Provenance synergy:** Integrate **content credentials/watermarks** for positive verification alongside detection.

- **Active defenses at scale:** Standardize challenge–response protocols for government/press communications.
- **Human factors:** Study alert design and explanations that maximize trust and correct operator decisions under stress [21], [22].

9. Conclusion

Deepfakes represent a critical **people-layer cyber threat**, weaponizing credibility at the speed of social media and creating unique vulnerabilities in war zones where trust, timing, and verification are crucial. This study presented **DeepTrace-RT**, a pragmatic, real-time, multimodal deepfake detection framework that integrates **rapid visual forensics**, **audio liveness** and **voice-clone analysis**, and **instant alerting mechanisms** with auditability and operational resilience. Experimental evaluations confirm that **high detection accuracy** ($AUC \approx 0.91$) and **low-latency inference** can coexist, enabling **near-instant triage of synthetic media** in conflict environments such as **Khartoum**.

Although no detection model is flawless, embedding **DeepTrace-RT** within comprehensive **information-security playbooks**, supported by **human analyst oversight** and **cross-platform authenticity standards**, can significantly blunt the impact of coordinated disinformation campaigns. Such systems strengthen **decision-making integrity**, **public trust**, and **civilian safety** amid the **information fog of war**, underscoring the importance of AI-driven media forensics in preserving truth during modern conflicts.

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AUTHORS PROFILE

***Dr. Suliman Mustafa Mohamed Abakar** holds a Ph.D. in AI & Cybersecurity from the University of Sheffield, UK. He is an Assistant Professor at Qassim University, Saudi Arabia, and has served as a cybersecurity expert with the ITU and UN-ESCWA, as well as a senior consultant at the KSA Ministry of Interior. He was also Sudan's candidate for Secretary General of the African ICT Union.*