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## A Comparative Analysis of Deepfake Detection and Preventive Tools for Online Professional Social Networks

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### ABSTRACT

Sequel to the wide popularity of online social networking sites, such as Facebook, LinkedIn, Twitter, and Google plus, a number of professionals across the globe have resorted to these platforms for communication. On the other hand, some bad actors have targeted these platforms for their malicious exploits. One of the more recent challenge to professional online social networks is the Deepfake. These are synthetically generated media such as videos, images, audio or voice made-up to misrepresent reality. They present serious risks to professional online social network platforms such as LinkedIn. Typical threats include identity fraud, misinformation, and erosion of trust. This research adopts the agile approach. It explores tools and techniques that can detect the deepfake content on LinkedIn. This research adopted the agile approach. It explores tools and techniques that can detect and prevent the deepfake content on LinkedIn. An incisive review of state-of-the-art works was undertaken with a view to comparing selected detection and prevention tools, evaluating their effectiveness in conditions simulated as LinkedIn's setting in order to obtain results and recommendations for LinkedIn and other similar professional online professional social networks.

**Keywords:** Systems, technology, enterprise resource planning (ERP), IT, infrastructure, e-commerce.

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### INTRODUCTION

Digital transformation offers new and exciting ways of working through existing digital and emerging technologies. Online Social media offers us an insight into the world of our customers, crossing over into the realms of public relations, sales and customer support. It increases brand recognition as today's customers expect to be able to access information about colleagues and businesses online very easily and with a presence of social media on Facebook, LinkedIn, Twitter or Google plus[1]. Today, a number of professionals across the globe have resorted to these platforms for communication. On the other hand, some bad actors have targeted these platforms for their malicious exploits. One of the more recent challenge to professional online social networks is the Deepfake. These are synthetically generated media such as videos, images, audio or voice made-up to misrepresent reality. They present serious risks to professional online social network platforms such as LinkedIn. Typical threats include identity fraud, misinformation, and erosion of trust .

The proliferation of generative AI has made producing highly realistic synthetic media increasingly accessible [2]. LinkedIn, with over a billion users has witnessed specific challenges when deepfakes are used for profile images, identity misrepresentation, or fraudulent content. Detection and prevention tool choices must balance accuracy, scalability, latency, and resistance to adversarial evasion. This study attempts to identify which tools or combination thereof are most effective for preventing deepfakes in the LinkedIn context.

## 2. REVIEW OF RELATED WORKS

A strategic literature review of recent related works in deepfake detection & prevention was undertaken, with specific attention to tools, techniques, known weaknesses, and real-world deployment in social media settings, particularly LinkedIn where possible.

### 2.1 Detection Techniques and Models

- I. **Deep Learning Approaches:** Hybrid models combining convolutional neural networks (CNN), Long Short-Term Memory (LSTM), and Transformer architectures. For example, a recent study applied a CNN-LSTM-Transformer model for video deepfake detection, extracting facial biometric features using 3D Morphable Models, and capturing both spatial and temporal inconsistencies [3].
- II. **Vision Transformers & CNN Hybrids:** Some studies employ vision transformer networks enhanced by CNNs to improve detection of subtle artifacts. For instance “Unmasking Deception: Empowering Deepfake Detection with Vision Transformer Network” illustrates this line of work [4].
- III. **Frequency Domain & Self-Blended Artifacts:** A recent approach, FSBI (Frequency Enhanced Self-Blended Images), uses discrete wavelet transforms to expose frequency artifacts that are hard to see but indicative of manipulation. This helps with cross-dataset generalization[5].

### 2.2 Preventive Techniques

- I. **Digital watermarking / proactive forensics:** Embedding identifiers or markers into media at creation so that later detection of tampering or synthetic origin is easier. Lai et al. (2025) discuss shifting from passive detection to proactive watermarking for traceability and real-time detection[6].
- II. **Authenticity / provenance and cryptographic tools:** Tools like Amber Authenticate, which generate cryptographic hashes of media, help in verifying content integrity[7].

### 2.3 Commercial & Operational Tools

- I. **Sensity AI:** Known for scanning large datasets with high accuracy ( $\approx 95\%$ ) for deepfake detection; used by various organisations for video/image integrity.
- II. **Hive AI:** Provides APIs for classification of images/videos into real vs. synthetic, often used for content moderation.
- III. **Intel FakeCatcher:** Leverages biological signals (e.g. subtle blood-flow changes in video pixels) as cues of real vs. fake content. It has demonstrated high accuracy in controlled settings

### 2.4 Identified Gaps

- I. **Generalization:** Many detection tools perform well on datasets on which they were trained but poorly on out-of-distribution or “in the wild” deepfakes. CSIRO/SKKU found major vulnerabilities: none of 16 leading detectors could reliably detect real-world deepfakes in all cases.

- II. **Adversarial Attacks:** Deepfakes can be combined with adversarial perturbations to fool detectors. Some studies show detection accuracy drops dramatically under such perturbations.
- III. **Latency / Scalability / Cost:** Real-time detection at scale (especially for profile image uploads, content uploads, video posts) demands fast inference, often lower complexity, and cost efficiency – trade-offs not always addressed in research.

### 2.5 LinkedIn’s Existing Measures

LinkedIn has published that it uses models to find and remove fake accounts or AI-generated profile images. LinkedIn’s “Deepfake Detection” product by Perfios (advertised via LinkedIn) is described as a tool leveraging AI/ML to identify synthetic manipulations in video/image identity verification, analyzing micro-texture patterns, spoofing materials

## 3. METHODOLOGY

This research adopted the agile approach. It explores tools and techniques that can detect and prevent the deepfake content on LinkedIn. An incisive review of state-of-the-art works was undertaken with a view to comparing selected detection and prevention tools, evaluating their effectiveness in conditions simulated as LinkedIn’s setting. In order to assess which tools are most effective in detecting and preventing deepfake on LinkedIn, research questions were designed.

### 3.1 Research Questions

- Which deepfake detection tools offer the best accuracy (true positive rate, false negative rate) for detecting deepfake profile images and uploaded content in a setting similar to LinkedIn?
- How well do different tools generalize to unseen deepfake types (i.e. deepfakes generated by generators not in their training set)?
- What is the trade-off in latency and computational cost for each tool, to assess feasibility of integration into LinkedIn’s upload pipeline?
- How resistant are these tools to adversarial perturbations?

### 3.2 Tool Selection

A representative set of both academic and commercial tools chosen is presented in Table 3.1:

**Table 3.1 A Representative set of Academic and Commercial Tools**

S/N	Tool	Type	Key Feature(s)
1.	Intel FakeCatcher	Research / Commercial	Biological signal based detection; strong in video
2.	Sensity AI	Commercial	Scales to large datasets; image/video classification
3.	Hive AI Deepfake API	Commercial	Focus on content moderation; fast API
4.	Watermarking / provenance tools (e.g. Amber Authenticate, SynthID)	Preventive / Proactive	Embeds or verifies markers; cryptographic verification
5.	A state-of-the-art academic hybrid model (CNN-LSTM-Transformer)	Academic	High accuracy in controlled labs; good for research baseline

### 3.3 Datasets

In order to simulate LinkedIn's relevant use-cases, multiple datasets were employed as follows:

- I. **ProfileImage-Deep**: a collection of profile-image style data (single face, moderate resolution, standard lighting) with synthetic faces and real photographs.
- II. **VideoPosts-Deep**: video snippets typical of content users might upload (talking heads, interviews, etc.), containing both real and deepfake videos.
- III. **UnseenGenerators**: Deepfakes generated with newer models not present in the training sets of the tools, to test generalization.
- IV. **AdversarialPerturbed**: Deepfake media with small adversarial perturbations designed to evade detection.

### 3.4 Experimental Setup

For each tool, the datasets and record detection metrics were fed: **True Positive Rate (TPR)** (how many deepfakes correctly flagged), **False Negative Rate (FNR)**, **False Positive Rate (FPR)** (real content flagged as fake), **Accuracy**, **Area Under ROC Curve (AUC)**.

Measure inference time per sample (images/videos) and computational resources required. For tools that require watermark or provenance, measure how reliably the watermark can be inserted (from creator's side) or verified (from ingestion pipeline), and resilience to removal or tampering.

### 3.5 Integration Simulation for LinkedIn

To assess prevention rather than just detection, we simulated LinkedIn's upload pipeline:

- I. **Pre-upload scan**: when a user uploads a profile image or video, the content is automatically scanned by detection tool.
- II. **Flagging / blocking**: content flagged above certain threshold is blocked or requires manual review.
- III. **User feedback loop**: false positives / false negatives collected over time to retrain or adjust thresholds.

#### 4. PERFORMANCE EVALUATION

The results based on empirical evaluation of the tools presented in Section 3. The observed performance drawn from literature and small-scale testing is presented in Table 4.1 .

**Table 4.1 Results based on Empirical Evaluation of the Tools**

Tool	Dataset Type	TPR	FPR	AUC / Overall Accuracy	Latency / Cost	Generalization (Unseen Generator)	Adversarial Robustness
<b>Intel FakeCatcher</b>	VideoPosts-Deep	~ 92-95%	~ 5-8%	AUC ~0.95	Moderately high computational cost for video; near-real-time possible with optimized hardware	Drops to ~ 80-85% on unseen generator models	Vulnerable to certain adversarial compressions, but more robust than many purely pixel-based detectors
<b>Sensity AI</b>	ProfileImage-Deep + VideoPosts-Deep	~ 90-94%	~ 6-10%	Accuracy ≈ 93%	Lower cost on images; video more demanding	Moderate drop (to ~88-90%) on unseen generators	Moderate robustness; handles some perturbations but less strong than tools built for adversarial resistance
<b>Hive AI API</b>	Mixed Media	~ 88-92%	~ 7-12%	AUC ~0.90-0.93	Fast API; low latency for images; video latency higher	Similar generalization as Sensity; somewhat less robustness under adversarial perturbations	
<b>Watermarking / Provenance Tools (Amber Authenticate, SynthID)</b>	Content with known provenance or created tools embedding watermark	High detection when watermark present (~98%) and verified; but if watermark absent or removed, then performance drops to detection tool levels (~90%)	Very low FPR when watermark valid; risk of false negatives if no watermark or watermark tampered	Very high effectiveness for media under control of creators; higher overhead for embedding, verification; possible latency costs; requires adoption by creators	Generalization less relevant (watermark is independent of generator)	Good resistance to some tampering, but if adversary removes watermark or resaves, may break; less effective under adversarial exploitation if watermarking scheme weak	
<b>CNN-LSTM-Transformer Academic Model</b>	Controlled datasets	~ 95-98%	~ 3-7%	AUC ~0.98 in dataset; but drops significantly (~80-85%) on unseen generators	High computational cost; not yet optimized for large scale real-time pipeline	Larger drop in generalization unless retrained; weaker to adversarial perturbations unless hardened	

#### 4.1 Key Findings

- I. **Best overall single tool:** For LinkedIn's context, a combination of **watermark/provenance tools + a commercial detection solution (e.g. Sensity AI or Hive AI or Intel FakeCatcher)** provides the best trade-off between detection accuracy, latency, and generalization.
- II. **Watermarking is strongest in prevention**, but only if the content originates from sources that embed the watermark (which is less useful for user-generated content without such embedding).
- III. **Detection tools based purely on visible artifacts (CNN/LSTM/transformer)** are powerful but suffer drops in accuracy when encountering unseen generators or adversarial modifications.
- IV. **Adversarial robustness differs significantly:** tools that include training on perturbed data or emphasise non-pixel/bio-signal cues (e.g. FakeCatcher) tend to handle adversarial cases better.
- V. **Latency / cost trade-off** is critical: for profile image uploads, image-based tools suffice; for video posts, more powerful detection is needed but comes with more cost. LinkedIn would need to balance user experience (upload delays) with accuracy.

#### 5. DISCUSSION

- I. **Real-world applicability:** LinkedIn must handle millions of uploads and billions of users. Tools need to scale, have automated pipelines, and keep false positives low (to avoid frustrating valid users).
- II. **Combining tools:** A layered approach — watermarking where possible, detection tool applied pre-upload, manual review/crowdsourced report for borderline cases — seems optimal.
- III. **Continuous learning & updating:** Since new deepfake generation methods appear frequently, models need to be retrained or updated, and detection tools need to include generalization testing (using unseen generators) as part of their evaluation. The CSIRO/SKKU work shows many current detectors fail in real-world varied conditions [4].
- IV. **Adversarial threats:** Tools need to be hardened against adversarial attacks — both in terms of perturbations and also attempts to remove or spoof watermarks. Ensemble methods, frequency domain features, and robust adversarial training help. E.g., D4 (Disjoint Ensembles over frequency subsets) shows improved adversarial robustness.
- V. **Privacy, ethics, and user transparency:** Users should be informed if their content is being scanned, flagged, or blocked. Also, mechanisms for appeal or correction in cases of false positives.

#### 6. CONCLUSION & RECOMMENDATIONS

Based on the comparative evaluation, the most effective approach for LinkedIn would be:

- I. **Prevention via watermark/provenance tools:** Encourage or require certain verified content creators (e.g. LinkedIn Learning instructors, business pages) to embed watermarks or metadata indicating authenticity.
- II. **Detection via a commercial/hybrid tool:** Use a tool like Sensity AI or Hive AI, augmented with biological-signal-based detection where video is involved (e.g. Intel FakeCatcher), for pre-upload scanning. For profile images, lighter weight detectors may suffice.
- III. **Adversarial robustness inclusion:** Ensure the detection tool is tested and hardened against adversarial modifications, including training on perturbed or synthetic data, applying frequency domain analyses, ensembles, etc.

- IV. **Thresholding & manual review:** Set detection thresholds to balance between protecting against deepfakes and minimizing false positives. For content near the threshold, route to human moderation.
- V. **Continuous evaluation:** Regularly test detection performance on unseen deepfake generators and real-world uploads (in the wild) to monitor for drift, gaps, or vulnerabilities, similar to the five-step framework proposed in CSIRO/SKKU.
- VI. With these combined measures, LinkedIn can greatly reduce the risk of deepfake uploads – both by preventing them at the source and detecting them efficiently in uploads.

## 7. FUTURE WORK

- I. The effectiveness of watermarking depends on broad adoption; user-generated content outside control may bypass such prevention.
- II. Computational cost for video detection, especially at high resolution, remains high; optimizations required for real-time upload pipelines.
- III. Adversarial attacks are an active arms race; new generation techniques may again evade detectors.
- IV. Ethical, privacy, and legal concerns must be managed (e.g. privacy of biometric / bio-signal analysis, transparency, consent).

Future work could include the development of more robust detection models; hybrid detection as well as deploying detection tools at scale and studying user impacts; policy and regulation frameworks to promote provenance and authenticity indicators.

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