Detecting AI-Generated Content: A Survey on Multimodal Detection of Text, Image, And Video

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Abstract- *Generative AI has advanced very quickly allowing the generation of realistic fake content in text, image, and video domains that is becoming challenging to differentiate from real content. While there has been some progress in developing detectors that work within specific modalities to identify the AI-generated content, all of them suffer from the lack of exploitation of inter-modal contradiction and dependencies. In this survey, the drawbacks of existing systems are described from the points of view of scalability, robustness, the variety of datasets used, and overall efficiency. It then formulates a new scheme for a multimodal detection mechanism that can detect text, image as well as videos all at once. To improve the detection accuracy, scalability and use across broad cultural and language settings this framework utilizes —Efficient multimodal models, cross modal consistency checks, adversarial training, and efficient architecture. The proposed system offsets the gap between standard approaches and the innovative advancement of multimodal generative AI by providing a real-time detection system for adversarial signals. It provides a unifying model that underpins solid, context-sensitive detection schemes to protect society's trust while preventing the abuse of generative AI.*

Keywords- Generative AI, Multimodal Detection, AI-Generated Content, Cross-Modal Consistency, Adversarial Training, Text Detection, Image Detection, Video Detection, Explainable AI, Dataset Diversity, Scalability.

I. INTRODUCTION

Today's AI has become a powerful tool to generate content for a short period of time, developing innovations never seen before and at the same time creating new problems. With such generative models like GPT-4, and Stable Diffusion and rise in deepfakes, text images and videos are no longer generated in the traditional ways. These models can generate very authentic data that may be difficult to differentiate from actual data making the use of fake news even harder to detect.

The significance of such developments is not limited only to the creative economy field. On the one hand, offer stunning uses cases in entertainment, education, and accessibilities as high-impact graphics, realistic virtual assistants, automatic writing content production systems and design augmentation. On the other hand, they present severe threats to society, especially to the users of social networking. These are such as spreading fake news more frequently, generating fake deep fakes, and sanctioning identity thefts and hacking. For example:

- By using deepfake videos, people have impersonated other people, especially political, and social leaders, and created doubt in the information from the media.
- AI-created text has now become weaponized to develop realistic fake news, spam messages, and phishing scheming.
- While synthetic images may sometimes be used to change people's perception or falsify histories.

While these technologies are constantly being developed, their application in text-image and text-video transfer increases the dangers even more. For example, a deep fake video might have the realistic video impression with the audio from a language model and misleading titles. Such multimodal outputs take advantage of existing detection systems by being harder to detect, thus Deceiving AI.

The Need for a Multimodal Detection Framework

The integration of multiple modalities in generative AI represents a significant escalation in the challenge of synthetic content detection. Unlike unimodal outputs, multimodal generative models synthesize coherent and interdependent content across text, images, and videos. This enables them to produce outputs that are far more convincing and difficult to detect. For instance:

A generative AI model might create a **video of a public figure** delivering a speech, accompanied by AI-generated subtitles and synthesized audio. Detecting such a multimodal deepfake requires an analysis of the coherence between the visual, auditory, and textual elements.

A **multimodal detection framework** is essential to address these challenges. By analyzing relationships across modalities, such a system can:

1. Detect **semantic inconsistencies**, such as mismatches between image captions and visual content.
2. Identify **cross-modal artifacts**, such as audio-visual mismatches in deepfake videos.
3. Enhance robustness against adversarial attacks by leveraging contextual information from multiple modalities.

Overview of This Survey

This survey delves into the current state of AI-generated content detection, focusing on its methodologies, limitations, and challenges. It highlights the gaps in unimodal approaches and the escalating risks posed by multimodal generative technologies. The survey introduces a novel **multimodal detection system**, which integrates textual, visual, and video analysis into a unified framework. Key contributions of this system include:

- **Cross-modal consistency checks**: Ensuring semantic coherence across text, images, and videos.
- **Adversarial robustness**: Training models to withstand manipulations such as paraphrasing, image compression, and video editing.
- **Scalability**: Leveraging lightweight architectures and distributed computing for real-time, large-scale deployment.
- **Dataset diversity**: Incorporating multilingual and culturally diverse datasets to improve generalization across global applications.

The key proposition of the creational framework described here can be considered as the advancement to a new level of evolutionary development of methods aimed at detecting malicious activity in generative AI. It provides the general, highly effective, and context-sensitive protection against the potential threat of misuse of synthetic content across the media, security, and education domains.

This paper seeks to give an outline on how researchers and practitioners can work on designing efficient multimodal detection systems for new problems in AI-generated content.

Limitations of Current Detection Systems

Current detection systems are predominantly **unimodal**, focusing on either text, images, or video independently:

- **Text detection** methods analyze linguistic patterns and stylometric features to identify AI-generated text. However, they are limited by their inability to detect semantic inconsistencies when text is paired with images or videos.
- **Image detection** techniques rely on forensic analysis or deep learning models to identify visual artifacts. Yet, these methods cannot evaluate the broader context in which an image appears, such as its relation to accompanying text or audio.
- **Video detection** systems primarily target deepfake manipulation, using frame-by-frame analysis or temporal modeling. Despite their advancements, they often fail to assess whether the video's captions, audio, or context align with its visual content.

The unimodal nature of these systems creates significant blind spots when detecting content that spans multiple modalities. For example:

- A **fake news article** may feature an AI-generated image with a misleading caption that goes undetected by text-only or image-only systems.
- A **synthetic video** with incongruent audio or subtitles can evade detection if analyzed independently by video or text detectors.

In particular, these limitations stress the importance of employing a multimodal detection framework that would allow to work with cross-modal dependencies. Such a framework would also help in evaluation of the content to determine whether it had a good connection between the text, images and videos.

Literature Survey

The increasing availability of generative AI models which enable creation of entirely realistic text, image and video data has stimulated research in methods to detect synthetic content. However, most of the studied methods are unimodal, designed to recognize AI content in a specific domain – text, image or video. In this survey we also explain the existing methods or approaches, their results, the shortcoming and how our proposed framework for multimodal detection fills these void.

Text Detection

Findings from Literature

Text detection has changed over the years as generative language models have improved. Originally,

measures based on the statistical properties of the documents were used to analyse if text was produced by AI or not, for example word frequency, perplexity and the coherence of the sentences. Jawahar et al. [18] did a critique of these methods saying that although they where useful in the modification of simpler models such as the GPT-2, they were very inefficient on GPT-3 and GPT-4, which open human like text that has contextual and syntactic cohesion.

To the best of my knowledge, Fraser et al. [2] went slowly further by using transformer-based models like BERT for the identification of linguistic outliers. These models apply various forms of quantization and aggregations so that distinctive distributional token characteristics in AI-written texts can be found based on embeddings and sentence-level features. This fact has been proved to have a very high accuracy compared to other machine learning algorithms that focuses on a particular context in detecting patterns generated by the machine.

Similarly, Zhang et al. [24] developed a dual approach to enhance the detection's resilience that incorporated stylometric methodologies and deep learning. To overcome some limitations of the purely neural solutions, they proposed to combine neural embeddings with the manually designed linguistic features. Nevertheless, these methods still herb consume considerable time and resources while largely relying upon the quality of the training data.

Others studies by Lu et al. [20] and Majovský et al. [17] studied human-machine performance benchmarks where some of the important findings were evident of limit in ascertaining synthetic text both in humans and AI. These studies underscore the internationalization of these systems for detecting culture and language, as most detect systems do not work for other languages or are domain specific.

Drawbacks of Existing Methods

Despite progress, current text detection methods face critical challenges:

1. **High Computational Costs**

Transformer-based methods, while accurate, require significant computational resources, making them impractical for large-scale real-time detection. Models like BERT or GPT-based classifiers are computationally expensive, especially when applied to large datasets or real-time scenarios.

2. **Sensitivity to Adversarial Paraphrasing**

Advanced language models can easily evade detection by rephrasing sentences while maintaining semantic meaning. Current systems struggle to identify paraphrased or restructured text, reducing their effectiveness in dynamic, adversarial environments.

3. **Linguistic and Cultural Bias**

Most training datasets are biased toward English text and Western contexts. This limits the generalizability of existing models to languages with different syntactic structures, idioms, and cultural nuances. For instance, AI-generated text in Mandarin or Arabic might evade detection due to the lack of representative data in these languages.

4. **Lack of Contextual Awareness**

Current methods analyze text in isolation, without considering its relationship to accompanying modalities like images or videos. This unimodal focus makes it difficult to detect inconsistencies between modalities (e.g., a caption describing an image inaccurately).

5. **Dataset Limitations**

Detection methods rely heavily on annotated datasets of AI-generated text. However, these datasets often lag behind advancements in generative AI, resulting in outdated models that struggle to detect content generated by newer systems.

Proposed Methodology

The proposed multimodal detection framework presents a robust, scalable, and comprehensive detection approach for its AI generated content in multiple modes, text, image, and video. This methodology takes existing limitations into account by integrating techniques such as adversarial training, cross-modal consistency checks and explainable AI, all the while setting a baseline for future advances in detection systems. Below I briefly detail each component of the proposed framework.

1. Cross-Modal Consistency Checks

The framework is built upon cross-modal consistency checks, which provide the ability for the system to check relationships between text, images and videos. The strength of this approach is in ensuring all components of multimodal content linearly align, and thus best detect inconsistencies that are characteristic of AI generated or manipulated content. Compared to unimodal systems, which work on each modality individually, this method provides contextual relation and

anomalies occurring in between modalities, and significantly improves the ability of detection accuracy and reliability. Among other things, text image alignment makes sure that an image is well aligned with its descriptive text. The system checks whether the image matches the caption example – the caption should be like "a red apple on a wooden table." As indicators of manipulation, potential are such discrepancies as a green apple or the absence of a table. Instead, we use pre trained multimodal models such as CLIP and ALIGN for generating text image embeddings in a common semantic space, so the system can compute similarity scores and recognize small mismatches. Audio visual synchronization is another critical aspect where we evaluate the process of whether the audio track of a video matches with its visual content. An example is a video labelled 'stormy weather', to make sure that the audio of rain and thunder does correspond with the visual display of a storm, not for example birds chirping. The temporal coherence of a presentation can also be analyzed in this process, that is, when audio and visuals are synchronized. Finally, text video coherence guarantees both logical consistency between video content and captions or subtitles. Take for instance, a video like "a bustling urban market" needs no captions like "a serene beach." To detect anomalies that might suggest AI generation or tampering, the system takes advantage of semantic relationships observable across all three modalities – text, video and audio. The key limitations of existing systems and how the proposed methodology resolves them are summarized in Table 1 by demonstrating the novelty of using cross modal consistency checks.

Table 1 : How Our Framework Addresses Existing Limitations

Existing Limitation	**Proposed Solution**	**Detailed Explanation**
Unimodal Focus	Integration of text, image, and video detection into a unified framework with cross-modal reasoning.	Combines insights from text, images, and videos to detect inconsistencies across modalities. For example, analyzes whether an image matches its accompanying caption or a video's audio aligns with its visual content. This enables detection of sophisticated, multimodal AI-generated content.
Scalability Issues	Lightweight architectures and distributed computing for real-time, large-scale detection.	Utilizes models like MobileBERT and EfficientNet for reduced computational overhead. Distributed systems process high volumes of data in parallel, enabling real-time monitoring of AI-generated content across platforms like social media or news outlets.
Adversarial Vulnerabilities	Robust adversarial training across all modalities to counter attacks like paraphrasing and post-processing.	Incorporates adversarial examples during training (e.g., paraphrased text, compressed images, altered videos) to make the framework resilient to common evasion techniques. Ensures accurate detection even when inputs are tampered with.
Dataset Bias	Development of diverse datasets covering multiple languages, cultures, and generative models.	Includes AI-generated content in various languages and cultural contexts to address biases found in English-centric datasets. This ensures that the framework generalizes effectively across

		global applications, such as detecting synthetic content in non-English media.
Lack of Multimodal Datasets	Framework inherently learns cross-modal relationships, reducing dependency on annotated multimodal datasets.	Leverages pre-trained multimodal models (e.g., CLIP, FLAVA) to align features across text, image, and video modalities. This reduces reliance on extensive multimodal annotation, which is often costly and time-intensive.
Real-World Applicability	Incorporation of real-world scenarios and continuous model updates.	Trains the framework using real-world examples, such as social media posts, news articles, and advertisements, to improve relevance. Regular updates to the model ensure it stays effective against evolving generative techniques.
Explainability Challenges	Integration of explainable AI (XAI) techniques to enhance trust and transparency.	Provides interpretable outputs such as visual heatmaps (for images/videos) and semantic reasoning (for text) to explain why content was flagged as AI-generated. This is particularly useful in sensitive domains like legal cases or journalism.
Limited Generalization to New Models	Use of zero-shot and transfer learning techniques to adapt to unseen generative architectures.	Incorporates zero-shot learning methods to detect content from emerging generative models without requiring additional labeled data. Transfer learning adapts pre-trained models to new datasets with minimal fine-tuning.
High Computational Costs	Optimized model architectures and cloud-based deployment for cost-efficiency.	Employs resource-efficient models and cloud services to reduce operational costs. This makes the system accessible for organizations with limited computational resources.
Fragmented Detection Systems	Unified platform combining detection, reasoning, and alert systems in a single framework.	Streamlines detection workflows by integrating all modalities and functionalities (e.g., detection, reasoning, notifications) into one cohesive system, reducing complexity for

		end-users.
Insufficient Real-Time Processing	Real-time multimodal inference pipelines with optimized latency.	Combines optimized neural architectures with edge computing to ensure that detection occurs in milliseconds, meeting real-time processing demands for video streams, live captions, and online content.
Limited Feedback Loop for Improvement	Integration of user feedback to continuously refine and update detection models.	Allows users to provide feedback on flagged content, which is used to improve the system's performance over time through continuous learning and retraining.
Contextual Blind Spots	Context-aware detection incorporating temporal, spatial, and semantic relationships.	Examines temporal relationships in videos (e.g., audio-visual synchronization), spatial coherence in images (e.g., object placement), and semantic consistency across text and visuals to improve contextual understanding.

2. Pre-Trained Transformer Models

Without pre-trained transformer models the system cannot analyze textual content and find patterns of artificial intelligence generation. To enable such transformers to identify linguistic anomalies, repetitive structures, unnatural coherence, etc. they are fine tuned on different datasets. However, one of the major benefits of these models are their multilingual capabilities that ensure detection is beyond these English centric datasets. The framework trains on multiple languages, including Mandarin, Spanish and Arabic, and then identifies any patterns in AI generated content that systems with a limited language scope miss. One such example is that the system flags Mandarin text that is overly formal in phrasing, and has repetitive sentence structures, which is common in AI generated Mandarin text. One of the most important features is the capability of the system to do linguistic feature analysis. The process of identifying common irregularities in grammar, syntax and semantic in the machine generated text. For example, an AI generated news article may not have the variety, the nuanced transitions of human writing and instead will end up sounding too smooth and repetitive sounding paragraphs. The framework leverages the capabilities of transformer models to greatly increase the precision with which textual anomalies are detected.

3. Adversarial Training

Learning with adversarial training increases the system's robustness to the manipulated and adversarial content presented during the learning phase. This approach renders the system ready to discriminate and neutralise actual world efforts to bypass detection, so as to be effective in a wide variety of difficult situations. Adversarial examples are paraphrased sentences, altered punctuation, and syntactically restructured content for the use of text detection. A simple example would be the phrase "A quick brown fox jumps over the lazy dog" altered to "A swift fox leaps above a sluggish hound." The proposed framework effectively flags these subtle modifications which are usually used to bypass simpler detection models. Adversarial training is applied to image detection where the system is given manipulated images, creating images that have been resized, compressed, or have had noise added to them. Though often imperceptible to the eye, these alterations can disrupt less robust detection algorithms. This includes for example subtle pixel value changes that change shadows or lighting in an image, indicating potential tampering. The system is trained on adversarial manipulated videos, including videos with mismatched audio tracks, altered frame rates and injected visual artifacts. Let's suppose a deepfake video contains consistent visuals as well as a few buggy lip syncing — a situation, which the proposed system is capable of detecting.

- **4. Scalable Architectures for Real-Time Detection**

The proposed framework relies on scalability, which is a hallmark of the framework as it can handle the huge amount of content generated in a day from social media and video streaming sites. The system is designed for Rate and for performance without compromising accuracy. An important component involves coupling lightweight models like EfficientNet and MobileBERTthat are designed to be computational efficient. Furthermore, these models are suitable for deployment into resource constrained environments such as mobile devices and edge computing platforms. Although those anatomic modalities are quite lightweight, they still have high accuracy in detecting anomalies across modalities. Distributed processing is used by the system also to handle large scale data streams. Application of GPU acceleration and the cloud, enables detection to be performed simultaneously on thousands of content streams, despite high traffic, with high timeliness guarantees. With such a large volume of upload (in the order of millions of uploads daily), a video streaming platform, for example, relies on this system to flag suspicious uploads in real time, for proactive intervention. Figure 1 shows the system architecture, in which we combine text, image, and video detection modules into a unified cross-modal reasoning framework.

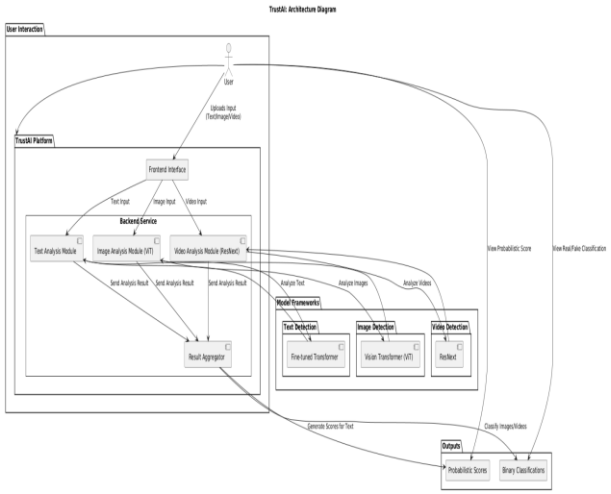

Fig 1 System Architecture

5. Dataset Diversity

Performance of the proposed framework is greatly enhanced with the diversity and quality of its training dataset. The proposed methodology which leverages a curated dataset aims to solve linguistic, cultural, and adversarial gaps that are not covered in existing datasets. The existence of multi language text to ensure the system can analyse AI generated content across a great many different languages. For example, the dataset has both AI written and human written text in underused languages like Swahili and Tamil. The diversity of this system allows it to generalize well and detect synthetic content in global contexts. In addition, the dataset contains culturally diverse imagery of traditional clothing, regional artifacts, and architecture from various sides of the world. For instance, the system is good at finding anomalies in cultural specifically content like images of traditional Indian weddings or African tribal ceremonies. The dataset also includes adversarial scenarios to emulate real world challenges. Paraphrased text, compressed images and tampered videos are some of the examples of the dataset, to improve the system's robustness against evolving threats .

Table 2 : How the Proposed Framework Addresses Existing Challenges

Challenge	Proposed Solution
Scalability	Lightweight models and distributed computing enable real-time processing of high volumes of multimodal content.
Robustness	Adversarial training enhances resilience against paraphrasing, image post-processing, and video manipulations.
Generalization	Multilingual and culturally diverse datasets ensure broader applicability across global contexts.
Dataset Limitations	A curated, comprehensive dataset incorporates adversarial and multimodal examples to improve model robustness.
Adversarial Evolution	Continuous model updates and adversarial training keep the framework adaptive to emerging generative techniques.

6. Context-Aware Detection

In doing so, we increase the system's precision by bringing in context due to detection; it evaluates content holistically, considering interrelations across modalities and their components. Temporal coherence is measured to make sure audio and visual of video are consistent with each other over time. Say a video of a sunny day and the sound of rainfall will be flagged for temporal incoherence. Just like for images, spatial consists are measured by object placement and relationship analysis. An example would be shadows misalligned with their light sources or an object perceived out of scale which indicates manipulation. Semantic alignment across modalities is also evaluated using the framework. In

our example, we could not have captions on the visuals of a deserted street alongside 'a bustling marketplace'. The analysis of these relationships enables the system to detect anomalies that traverse beyond unimodal analysis.

7. Explainable Detection

The framework embeds explainable AI (XAI) techniques to make underlying decisions made by the framework interpretable and transparent. This is particularly important for applications for journalism, legal investigation, and public policy. The system then highlights, through visual heatmaps, where different areas of an image or video have been involved in the decision to detect the target. For example, a deepfake video may display a manipulated facial region that is marked so that it is visually obvious that something has been faked. Likewise, applying semantic highlighting will identify dubious phrases in text (e.g. repetitions or 'spookier' unusual phrases) to provide knowledge about why specific content was flagged.

The proposed framework determines a robust, scalable, and adaptable solution for AI generated content detection by integrating these methodologies. Not only does it overcome the present shortcomings of unimodal systems, but also sets the groundwork for future advances in content authenticity verification.

Conclusion and Future Scope

AI-generated content detection has become increasingly critical in an era where synthetic text, images, and videos are seamlessly integrated into various aspects of society. These advancements, while fostering creativity and innovation, pose significant risks to societal trust, digital integrity, and security. The misuse of generative AI for misinformation, deepfakes, and fraud has underscored the urgent need for robust and scalable detection frameworks.

Existing detection systems, though effective in unimodal scenarios, fall short when faced with the complexity and sophistication of multimodal AI-generated content. Current methods are limited by their scalability, robustness against adversarial attacks, and inability to generalize across diverse cultural and linguistic contexts. The proposed **multimodal detection framework** addresses these gaps by integrating text, image, and video analysis into a unified system. Through cross-modal consistency checks, adversarial training, and scalable architectures, the framework represents a transformative leap forward in the detection of synthetic content.

By leveraging state-of-the-art technologies, such as pre-trained multimodal models and shared embedding spaces, this framework ensures that inconsistencies across modalities can be identified effectively. The use of diverse datasets and lightweight architectures further enhances its robustness and scalability, making it suitable for real-time applications across platforms. This unified approach not only strengthens current detection capabilities but also sets the foundation for addressing the dynamic challenges posed by evolving generative models.

Future Scope

While the proposed framework addresses many limitations of current systems, there remain several areas for improvement and innovation. Future research directions include:

Enhancing Dataset Diversity and Standardizing Benchmarks

- Developing comprehensive datasets that encompass a wider range of languages, cultures, and generative architectures is essential for improving generalization and robustness.
- Establishing standardized benchmarks and evaluation metrics for multimodal detection systems will enable consistent and fair comparisons across methodologies.
- Including real-world scenarios and adversarial examples in datasets will ensure that models are better equipped to handle practical applications.

Developing Explainable Detection Methods

- Explainability is critical for building trust in detection systems, especially in sensitive domains like legal investigations, journalism, and cybersecurity.
- Future systems should integrate **Explainable AI (XAI)** techniques that provide interpretable outputs, such as visual heatmaps for images/videos or semantic reasoning for text.
- Transparency in decision-making will not only enhance user trust but also facilitate compliance with regulatory frameworks.

Exploring Lightweight and Privacy-Preserving Models

- Real-time detection at scale requires efficient and lightweight architectures that can operate on edge devices or low-resource environments.

- Privacy-preserving techniques, such as federated learning and differential privacy, should be incorporated to protect sensitive user data during model training and inference.
- These advancements will make detection systems more accessible and scalable across a wider range of applications, from mobile devices to large-scale social media platforms.

Adapting to Generative Model Evolution

- The arms race between generative models and detection systems necessitates continuous innovation.
- Future systems should incorporate **transfer learning** and **zero-shot detection** capabilities to adapt quickly to emerging generative architectures without requiring extensive retraining.
- Collaboration with developers of generative AI technologies could help identify potential vulnerabilities and develop proactive detection measures.

Multimodal Fusion and Contextual Awareness

- Further research is needed to refine cross-modal reasoning and improve contextual understanding in multimodal detection systems.
- Incorporating temporal and spatial analysis in videos, along with semantic alignment across modalities, will enhance the ability to detect complex inconsistencies.
- Advanced multimodal fusion techniques, such as graph-based reasoning or attention mechanisms, could improve coherence evaluation across modalities.

Interdisciplinary Collaboration

- Effective AI-generated content detection requires collaboration between fields such as computer vision, natural language processing, cybersecurity, and ethics.
- Engaging with policymakers, media organizations, and the public will ensure that detection systems are aligned with societal values and legal requirements.
- Establishing interdisciplinary partnerships will also foster the development of comprehensive solutions to address the broader implications of generative AI.

II. CONCLUSION

The proposed multimodal detection framework represents a transformative advancement in addressing the challenges of detecting AI-generated content. By integrating innovative components such as cross-modal consistency checks, adversarial training, scalable architectures, and explainable AI techniques, the system overcomes the limitations of existing unimodal approaches. This robust and unified solution enhances detection accuracy, scalability, and generalization, ensuring its applicability across diverse platforms and contexts.

Furthermore, the inclusion of diverse and comprehensive datasets addresses linguistic and cultural gaps, making the system adaptable to global applications. The real-time detection capabilities, powered by lightweight architectures and distributed computing, enable the system to handle the vast volume of multimodal content generated daily on digital platforms, including social media and video streaming sites.

This framework not only provides an effective solution for detecting AI-generated content but also establishes a foundation for future advancements in this field. Moving forward, research efforts will focus on optimizing computational efficiency, enhancing explainability for greater user trust, and expanding the framework's capabilities to anticipate and counteract evolving generative techniques.

By laying the groundwork for scalable, reliable, and adaptable detection systems, this research contributes to safeguarding digital platforms against the proliferation of synthetic content, ensuring the integrity and trustworthiness of digital information.

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