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Fake News Detection: A Comprehensive Taxonomy of Text, Image, Video, and Multi-Modal Techniques

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Abstract

The widespread dissemination of fake news across digital platforms has posed significant challenges to information integrity, social stability, and public trust. Traditional fake news detection approaches, primarily based on text analysis, are no longer sufficient. Misinformation now integrates multi-modal content, including images, videos, and manipulated metadata. This paper presents a comprehensive taxonomy of fake news detection techniques, categorizing existing methods into text-based, image-based, video-based, and multi-modal approaches. We review the evolution of detection methodologies from traditional machine learning models to advanced deep learning architectures, including transformers, convolutional neural networks (CNN), and hybrid AI models. Additionally, we analyze the growing challenge of adversarial attacks, where malicious actors manipulate text, images, and videos to bypass detection systems. Finally, we highlight emerging research directions, such as adversarial-resilient AI models, cross-modal fact verification, and human-AI hybrid fact-checking systems. These directions are crucial for developing trustworthy, explainable, and robust fake news detection frameworks. This study is a foundation for researchers and practitioners to advance multi-modal misinformation detection and strengthen AI-driven fact-checking mechanisms.

1. Introduction

The rapid proliferation of fake news across digital platforms has become a global challenge, influencing political discourse, public health policies, financial markets, and social stability [1]. The increasing ease of generating and disseminating misinformation, mainly through social media and AI-driven content creation tools, has made traditional manual fact-checking and rule-based detection methods ineffective [2]. In recent years, attempts to spot news have mainly concentrated on uncovering false information within written content. With the rise of AI-generated images (GAN), deep-fake videos, and diverse disinformation tactics, pinpointing deceptive content across media has become notably more complex [3]. Misinformation no longer pertains to information; it now encompasses visuals, artificially crafted videos, and coordinated misinformation campaigns spanning multiple platforms to deceive viewers [4]. During the Russia-Ukraine conflict, there was a video on the social media platforms TikTok and Twitter that falsely depicted a girl confronting a Russian soldier; however, the girl in question was Palestinian, named Ahed Al Tamimi, who bravely faced a Zionist soldier back in 2012 following her brother's arrest. The post on Twitter was flagged as "out of context ". It still received millions of views and comments, showing how challenging it is to combat misinformation once it spreads online. Figure 1 illustrates this case as reported by BBC News, highlighting the viral impact and persistence of misleading content. Such examples underscore the urgent need for AI-powered detection systems capable of analyzing and flagging deceptive content across text, image, and video modalities.

Instances such as this emphasize the pressing requirement for AI-powered detection systems to recognize and address deceptive content that incorporates text, images, and videos.

Figure 1: An article from BBC News discussing misinformation and false information circulating online. (BBC News, 2022).

Current methods for spotting information depend heavily on the use of Machine Learning (ML), Deep Learning (DL), and innovative technologies like Natural Language Processing (NLP). And computer vision techniques to identify misinformation patterns [5]. Traditional detection methods analyse syntactic, lexical, and statistical features to detect the news post as real or fake [6]. However, these models often face challenges such as cynicism, implicit bias, evolving misinformation tactics, and adversarial manipulations [7]. The development of transformer-based NLP models, including BERT, RoBERTa, and GPT, has significantly enhanced semantic understanding and contextual fact verification. Yet, these models remain sensitive to adversarial text perturbations, which can manipulate content to bypass detection systems [8]. In parallel, image-based fake news detection leverages convolutional neural networks (CNN) and forensic analysis techniques to identify manipulated images, deep-fake content, and AI-generated misinformation [9]. Similarly, video-based detection methods incorporate frame-level analysis, audio-visual consistency checks, and deep-fake identification models to detect synthetic or altered video content [10]. With the rise of multimodal misinformation, where text, images, and videos are strategically combined to enhance credibility, there is a growing need for integrated multimodal fake news detection models that cross-verify information across different formats [11]. Despite advancements in AI-driven detection, significant challenges persist. Adversarial attacks allow misinformation to evade detection through subtle textual modifications, pixel-level image alterations, and deep-fake frame manipulations [12]. Dataset biases and generalization issues further limit model effectiveness across different languages, cultural contexts, and misinformation formats. Additionally, real-time scalability remains a concern, as high computational costs and slow inference times hinder the ability to filter misinformation at scale [13]. Ethical considerations, including privacy risks, algorithmic bias, and potential over-censorship of legitimate journalism, add another layer of complexity to deploying automated fake news detection systems [14]. This paper provides a comprehensive taxonomy of fake news detection techniques, categorizing them into text-based, image-based, video-based, and multi-modal approaches. It examines machine learning, deep learning, and hybrid AI models, highlighting their strengths and limitations. Additionally, it discusses adversarial threats and future challenges in developing robust, real-time, and ethical misinformation detection systems.

The key contributions of this study include the following:

- A structured taxonomy of fake news detection techniques, categorizing methods based on text, image, video, and multi-modal approaches.
- An in-depth discussion on challenges, including text perturbations, deep-fake evasion strategies, and cross-platform misinformation.
- Future research directions, exploring multi-modal adversarial defenses, real-time scalable AI models, and AI-human hybrid verification systems to strengthen misinformation detection.

The paper is structured as follows: Section 2 introduces the taxonomy of fake news detection techniques. Section 3 discusses key challenges, while Section 4 explores future directions, including advanced AI and real-time fact verification. Finally, Section 5 summarizes key findings and implications.

2- Taxonomy of Fake News Detection Techniques

The rapid evolution of fake news dissemination methods calls for a structured framework to analyze and categorize detection techniques. Misinformation spans multiple modalities, including text, images, videos, and multimodal content, making detection increasingly complex. Addressing this challenge requires sophisticated methodologies to identify deceptive patterns across different formats. Figure 2 provides a visual taxonomy of fake news detection techniques, organizing them into four primary classifications: text-based, image-based, video-based, and multi-modal approaches.

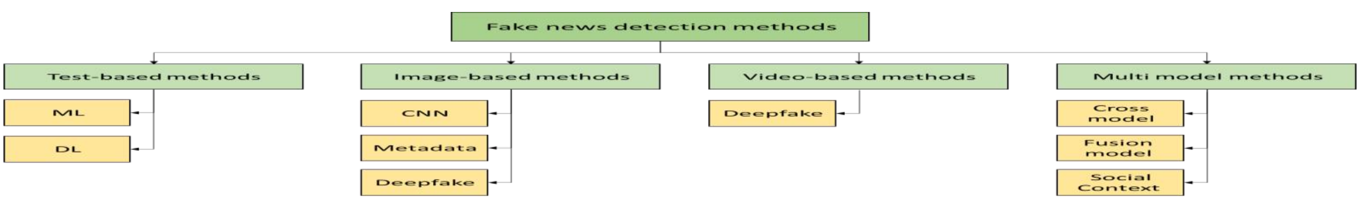

Figure 1. Fake news detection approaches taxonomy

2-1 Text-Based Fake News Detection

Text-based fake news detection relies on NLP techniques to analyze linguistic patterns, factual consistency, and contextual coherence in news articles. Over time, detection approaches have evolved from traditional machine learning models to more sophisticated deep learning techniques and, more recently, hybrid models that integrate many detection techniques for improved accuracy. This section categorizes text-based detection techniques into three groups: traditional machine learning approaches, deep learning methods, and hybrid models.

2.1.1 Traditional Machine Learning Approaches

Early fake news detection methods primarily relied on statistical and rule-based machine learning models, which classified news articles based on handcrafted linguistic features. These approaches involved feature extraction and supervised learning techniques to distinguish between real and fake news.

- Lexical and Syntactic Feature Analysis: Traditional models used word frequency, n-grams, Part-of-Speech (POS) tagging, and sentiment analysis to identify misinformation patterns [16].
- Supervised Classifiers: Techniques such as Naïve Bayes, Support Vector Machines (SVM), Random Forest (RF), and Decision Trees (DT) were widely employed to classify news articles based on pre-defined linguistic features [18-20].

While computationally efficient, these methods often failed to capture semantic meaning and contextual relationships, limiting their effectiveness against evolving misinformation strategies [21].

2.1.2 Deep Learning-Based Fake News Detection

Deep learning has revolutionized fake news detection by automating feature extraction, capturing semantic context, and enhancing text classification accuracy. Unlike traditional machine learning models, deep learning methods eliminate the need for manual feature engineering, making them more adaptable to evolving misinformation tactics [22]. These methods leverage neural network architectures to analyse text meaning, contextual relationships, and factual consistency. Deep learning-based detection techniques can be broadly classified into sequence-based, transformer-based, and hybrid deep learning models.

2.1.2.1 Sequence-Based Models

Sequence-based deep learning models process text as sequential data, capturing contextual dependencies and detecting linguistic patterns in fake news articles. These models are particularly effective in identifying grammatical inconsistencies, sentiment shifts, and manipulation tactics.

- **Recurrent Neural Networks (RNN):** extract sequential patterns, which helps them identify misleading narratives in fake news [23]. However, RNNs are limited in their effectiveness in processing longer text sequences.
- **Long-Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) Networks:** LSTM addresses the limitations of RNN by retaining long-range dependencies, making it more effective in detecting subtle misinformation cues within the extended text [24]. BiLSTM processes text forward and backward, enhancing the model's understanding of contextual relationships and identifying inconsistencies in fake news articles [25].

While sequence-based models improve text representation, they struggle with long, complex sentences and are computationally expensive compared to newer transformer-based models [26].

2.1.2.2 Transformer-Based Models

Transformer-based models have revolutionized NLP-based fake news detection by leveraging self-attention mechanisms to capture contextual relationships across long text sequences. These models excel at understanding deep semantic structures and fact-checking information.

- **Bidirectional Encoder Representations from Transformers (BERT):** BERT improves fake news detection by analyzing both left and right contexts simultaneously, making it highly effective in semantic understanding and contextual coherence [27]. Fine-tuned versions, such as RoBERTa and ALBERT, enhance efficiency and performance [28].
- **Generative Pre-trained Transformers (GPT):** GPT models focus on text generation and understanding, making them practical for identifying linguistic inconsistencies and misinformation patterns [29]. However, they require extensive labeled data for fine-tuning fake news detection.

- **XLNet and T5 Models:** Advanced transformer models like XLNet and T5 offer improved performance by leveraging autoregressive and encoder-decoder architectures, making them highly adaptable for multi-modal fake news detection [30-31].

Transformer-based models significantly outperform traditional deep learning models due to their superior ability to capture contextual semantics. However, they demand high computational resources and require careful tuning to maintain robustness in dynamic online environments.

2.1.2.3 Hybrid Deep Learning Models

Hybrid deep learning models combine multiple deep learning architectures to enhance fake news detection.

- **CNN- LSTM Hybrid Models:** These models utilize CNN for local feature extraction and LSTM or BiLSTM for sequence processing, effectively identifying context-based misinformation patterns in text [32-33].

- **Attention-Based Hybrid Models:** Some detection systems integrate attention mechanisms within LSTM or CNN to enhance focus on misleading phrases and deceptive narratives [34].

While hybrid models enhance detection accuracy, they introduce higher computational complexity and require multi-source data aggregation, making real-world deployment more challenging.

2.2 Image-Based Fake News Detection

With the increasing prevalence of AI-generated images, manipulated photographs, and deep-fake visuals, fake news detection now requires advanced image analysis techniques. Unlike textual misinformation, visual deception is more challenging to detect, as deep-fake technology and AI-enhanced image generation create highly realistic fake content that can mislead even sophisticated AI models. Researchers have developed image-based detection methods using deep learning and forensic analysis to counter this. These approaches can be categorized into CNN-based feature extraction, deep-fake detection models, and metadata-based forensic analysis.

2.2.1 CNN-Based Feature Extraction

Convolutional Neural Networks (CNN) detect manipulated images by identifying distortions, inconsistencies, and hidden artifacts [35]. These models analyze visual patterns that may not be noticeable to the human eye.

- **Texture and Artifact Analysis**: CNN detects unnatural textures, noise patterns, and blurry regions, often indicating image tampering [36].

- **Lighting and Shadow Inconsistencies**: Fake images may have mismatched lighting effects, shadows, and reflections, which CNN-based models can detect by analyzing brightness and shading [37].

- **Face Manipulation Detection**: Many fake news images involve edited human faces. CNN trained on facial datasets to identify face-swapping, unnatural skin tones, and asymmetric features [38].

While CNN-based methods work well for low-quality fake images, they struggle against high-resolution AI-generated visuals, particularly those created using GAN [39].

2.2.2 Deepfake Detection Models

Deep-fake technology, powered by GAN, has enabled realistic synthetic image and video generation, making detection more complex [40]. To combat this, deep-fake detection models focus on finding subtle flaws in AI-generated images.

- **Pixel-Level Analysis**: AI-generated images often contain minor inconsistencies in pixel distribution and unnatural skin textures. Detection models scan these distortions to flag synthetic photos [41].

- **Facial Artifact Detection**: Deep-fake images may have irregular facial expressions, strange eye movements, or inaccurate lip shapes, which specialized AI models can recognize [42].

- **GAN Fingerprinting**: Each GAN model leaves behind unique "digital fingerprints" in synthetic images, which detection models use to trace the origin of AI-generated media [43].

Although deep-fake detection models are compelling, GANs continue to evolve, producing better-quality synthetic images that make detection increasingly challenging [44].

2.2.3 Metadata and Forensic Analysis

In addition to deep learning, image forensics and metadata analysis play an essential role in verifying the authenticity of images [45]. Many fake images leave behind digital traces, which can be detected using forensic tools.

- **EXIF Metadata Analysis**: Images contain hidden metadata (EXIF data) that stores details such as camera settings, timestamps, and editing history. Modified or AI-generated images often lack original metadata or show inconsistencies [46].

- **Error Level Analysis (ELA):** This technique examines image compression artifacts to find tampered areas, as altered regions often have different noise levels than unedited parts [47].

However, metadata-based methods are not foolproof, as attackers can remove or modify metadata to bypass detection systems [48].

2.3 Video-Based Fake News Detection

With the rise of AI-generated deep-fake videos, manipulated clips, and synthetic media, detecting video-based misinformation has become a critical challenge. Unlike static image manipulation, video-based misinformation is more complex due to the integration of motion, facial expressions, lip-syncing, and audio elements [49]. Deep- fake technologies, powered by GAN and Autoencoder-based models, have created highly realistic but entirely fake videos [50]. Researchers have developed deep learning and forensic-based video detection methods to address this growing concern. These approaches can be grouped into three categories: deep-fake detection, audio-visual consistency analysis, and forensic video analysis.

2.3.1 Deepfake Video Detection

Deep-fake videos manipulate facial expressions, speech, and body movements to create realistic but entirely synthetic content [51]. To detect these manipulations, deep-fake detection models focus on subtle artifacts and inconsistencies introduced during video synthesis.

- **Facial Inconsistencies Analysis:** Deep-fake videos often exhibit unnatural blinking patterns, asymmetrical facial features, and inconsistencies in facial textures, which detection models can identify [52].

- **Lip-Sync Mismatch Detection:** AI-generated deep-fake videos often fail to synchronize lip movements with speech, allowing detection models to analyze frame-by-frame discrepancies [53].

- **Frame-Level Artifacts Detection:** Deep-fake synthesis may introduce blurry patches, unnatural skin textures, and motion distortions, which neural networks can identify [54].

While deep-fake detection models have significantly improved, they remain vulnerable to rapidly evolving GAN-based deep-fake generators that produce increasingly convincing synthetic videos.

2.4 Multi-Modal Fake News Detection
Fake news is no longer confined to text-based misinformation; modern disinformation campaigns often combine text, images, videos, and manipulated metadata to create more persuasive and harder-to-detect misinformation [55]. Multi-modal fake news detection leverages cross-modal relationships to improve detection accuracy, integrating NLP, computer vision, and audio analysis to verify content authenticity [56]. Since multi-modal fake news spreads across social media platforms, news articles, and manipulated multimedia, detection systems must analyze consistency across different data types. Multi-modal detection approaches can be classified into three main categories: cross-modal consistency analysis, fusion-based AI models, and social context analysis.

2.4.1 Cross-Modal Consistency Analysis
Cross-modal consistency analysis verifies whether different content modalities (text, images, and videos) align [57]. Many fake news pieces use authentic images with misleading text, creating a false narrative without modifying the image [58].

- **Text-image mismatch Detection:** AI models compare headlines, captions, and textual content with accompanying images to detect inconsistencies [59]. For example, a misleading headline about a protest may use an unconnected image from a different event.

- **Visual-Text Semantic Verification:** NLP models analyze image descriptions and compare them with textual claims, checking whether the semantic meaning aligns [60].

- **Video-Text Alignment Analysis:** AI models analyze video transcripts and verify whether speech content aligns with visual evidence, detecting fabricated or edited content [61].

The cross-modal analysis is adequate but limited when attackers subtly modify narratives without creating apparent contradictions.

2.4.2 Fusion-Based AI Models
Fusion-based models integrate multiple deep learning techniques, such as NLP, computer vision, and speech recognition, to jointly analyze different content types [62]. These models improve accuracy by capturing patterns across modalities rather than treating each separately [63].

- **Multi-Stream Neural Networks:** Some architectures use parallel CNN and LSTM to simultaneously analyze images and textual descriptions, detecting inconsistencies across features [64].

- Attention-Based Fusion Models: Transformer-based models like Vision-Language BERT (VL-BERT) integrate image and text embedding to improve fake news detection accuracy [65].

While fusion models improve detection, they require extensive training datasets and are computationally expensive, making large-scale deployment challenging [66].

2.4.3 Social Context and Metadata Analysis

Beyond analyzing content, multi-modal detection methods can examine social media metadata, user interactions, and propagation patterns to assess credibility [67]. Social context helps identify coordinated misinformation campaigns and bot-generated fake news [68].

- **User Behavior and Bot Detection:** AI models analyze posting frequency, engagement patterns, and network relationships to detect automated misinformation campaigns [69].

- **Fact-checking with External Knowledge Bases:** Hybrid AI-human systems cross-reference claims against fact-checking databases like Snopes, Politi Fact, and Wiki data to assess truthfulness [70-71].

Social context analysis enhances detection accuracy but faces challenges like privacy restrictions, data access limitations, and evolving misinformation strategies [72]. Table 1 summarizes the fake news detection models.

Table 1: Taxonomy of Fake News Detection Techniques

Category	Subcategory	Description
Text-Based Detection	**Traditional ML**	Uses lexical, syntactic, and supervised classifiers such as Naïve Bayes, SVM, and Decision Trees.
	Deep Learning	Leverages deep neural networks like RNN, LSTM, and Transformer-based models.
	Hybrid Models	Combines multiple architectures, e.g., CNN-LSTM hybrids, for improved text analysis accuracy.
Image-Based Detection	**CNN-Based Feature Extraction**	It uses CNN to detect manipulated textures, lighting, and artifacts.
	Deepfake Detection Models	Detects deep-fake images using AI-generated pattern analysis, facial artifacts, and GAN fingerprints.
	Metadata & Forensic Analysis	Analyzed metadata (EXIF) and forensic techniques like error level analysis to verify image authenticity.
Video-Based Detection	**Deepfake Video Detection**	Identifies deep-fake videos through facial inconsistency detection, lip-sync mismatch, and frame artifacts.
Multi-Modal Detection	**Cross-Modal Consistency Analysis**	Cross-verifies consistency between different modalities (text, images, videos) to detect misinformation.
	Fusion-Based AI Models	Integrates NLP, computer vision, and speech processing in multi-modal AI models for better detection.
	Social Context & Metadata Analysis	Examines social media metadata, user behavior, and network interactions to identify misinformation spread.

While this taxonomy outlines primary fake news detection methods, their real-world effectiveness varies. Traditional ML models are fast but lack semantic depth. Deep learning models like BERT and RoBERTa offer high accuracy but are resource-intensive and vulnerable to adversarial text. CNN-based image detectors struggle with realistic GAN-generated content, while video models face scalability issues. Multi-modal systems improve accuracy but require large, diverse datasets and are complex to deploy at scale. Dataset biases and computational demands remain key limitations. Figure 2. Comparison of accuracy ranges for fake news detection techniques across three modalities, text, image, and video, plotted against their relative model difficulty. The figure illustrates how detection accuracy generally improves with increased model complexity, with deep learning and hybrid approaches showing higher accuracy but at greater computational cost. This highlights the trade-off between detection effectiveness and model scalability in practical applications.

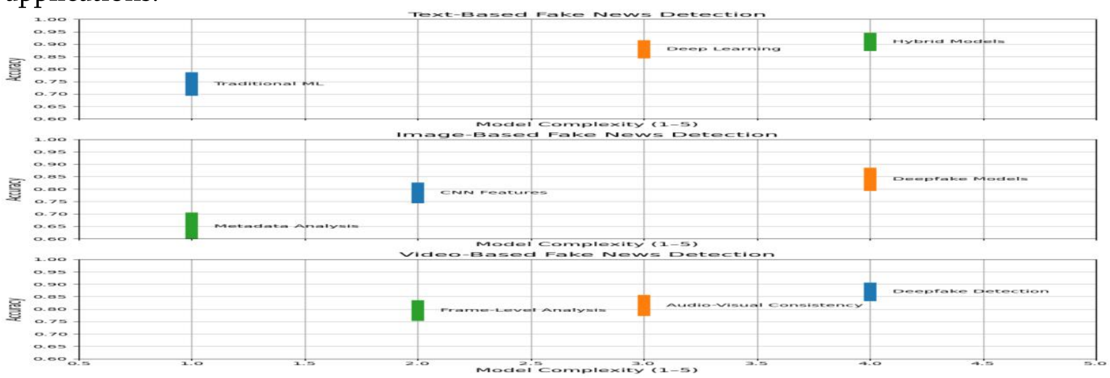

Figure 2. Accuracy ranges of fake news detection methods across text, image, and video modalities relative to model complexity, highlighting the trade-off between detection performance and computational cost.

3. Challenges in Fake News Detection

Rapid AI and profound learning advancements have significantly improved fake news detection capabilities. However, several critical challenges persist, hindering effectiveness, scalability, and ethical implementation. Addressing these challenges is crucial to enhancing misinformation detection systems and ensuring their reliability across diverse contexts.

3.1 Dataset Limitations and Generalization Challenges

Fake news detection models heavily rely on labeled datasets to train machine learning classifiers. Yet, existing datasets have several limitations, including sampling biases, political or ideological imbalances, and domain-specific constraints. Many publicly available datasets focus primarily on English-language misinformation, limiting their ability to detect fake news in low-resource languages or culturally diverse contexts [73]. Another important issue is dataset generalization. Models trained on one dataset or platform (e.g., Twitter-based misinformation) often fail when applied to different sources, such as news websites, video-based content, or messaging apps. Additionally, many datasets lack multi-modal integration, primarily focusing on text-based detection while overlooking the interplay between text, images, and videos in misinformation campaigns [74]. This hinders the ability of AI models to cross-verify and fact-check misinformation spread through diverse media formats. Future research should focus on expanding multi-modal datasets, applying domain adaptation techniques, and developing synthetic data augmentation methods to develop model generalization and robustness across different sources of misinformation [75].

3.2 Real-Time Detection and Computational Constraints

Fake news spreads rapidly across social media, news platforms, and messaging services, often outpacing fact-checking efforts. However, most AI-based detection models and intense learning approaches, such as BERT, RoBERTa, and GPT, are computationally intensive, making real-time detection challenging [76]. The inference time required for complex NLP models and multi-modal AI systems prevents large-scale, instant misinformation filtering. Another challenge is the speed of misinformation propagation. Studies show that fake news spreads faster than real news, often containing emotionally charged, sensationalized content designed to maximize engagement [77]. Fact-checking organizations struggle to verify news quickly, as the process involves cross-referencing multiple sources, consulting domain experts, and ensuring accuracy before issuing corrections. Developing efficient, lightweight AI architectures, such as pruned transformer models, knowledge distillation techniques, and hardware-optimized inference, will be critical to scaling real-time misinformation detection while maintaining computational efficiency [78].

3.3 Ethical and Privacy Concerns

AI-based misinformation detection involves analyzing large-scale user-generated content, which raises concerns about privacy rights, data protection, and algorithmic bias [79]. Many detection systems rely on metadata analysis, user behavior tracking, and engagement pattern modeling, raising legal and ethical concerns regarding mass surveillance and the potential misuse of AI in online monitoring. Additionally, automated content moderation runs the risk of over-censorship, where legitimate journalism, satire, or opinion-based discussions are mistakenly flagged as fake news [80]. This issue is particularly sensitive in politically polarized environments, where biased AI models could favor one ideological stance over another. Ensuring fair, unbiased, and explainable AI (XAI) in fake news detection is essential to maintaining public trust. Future research should focus on developing interpretable AI models, ensuring fairness in detection algorithms, and complying with legal frameworks such as GDPR and AI governance policies.

3.4 The Growing Complexity of Multi-Modal Misinformation

Misformation tactics have evolved from simple text-based hoaxes to multi-modal disinformation campaigns incorporating manipulated images, deep-fake videos, and cross-platform misinformation narratives [81]. Text-only AI models struggle to detect misinformation from misleading visuals or out-of-context images. Similarly, image-based deep-fake detection models often fail when paired with credible-sounding text that reinforces deception. Multi-modal misinformation detection remains an open research challenge, as AI models must process and cross-verify information across diverse data formats. To address this, future research should focus on improving multi-modal fusion techniques, integrating cross-modal consistency analysis, and developing fact-checking mechanisms that simultaneously verify content across text, images, and videos.

3.5 Adversarial Attacks Across Modalities

Adversarial attacks pose a significant threat to fake news detection systems across all modalities. In text-based systems, subtle manipulations such as synonym replacement, sentence reordering, or character-level perturbations can fool even advanced transformer models like BERT and RoBERTa. Image-based detectors, especially those using CNNs, are susceptible to pixel-level noise, AI-generated content from GANs, or realistic visual distortions that evade detection. In the video domain, adversarial techniques include frame injection, inconsistent lip-syncing, and synthetic facial manipulations, which compromise deep-fake detection models. These attacks exploit model vulnerabilities by introducing minimal, often imperceptible changes that lead to incorrect classification. As shown in Table 2, although many models achieve high accuracy, they remain vulnerable to adversarial perturbations, which limits their reliability in real-world, adversary-rich environments. Defending against such manipulation requires cross-modal adversarial training, robust feature extraction, and scalable, real-time detection strategies.

Table 2. Summary of Key Challenges in Fake News Detection

Challenge	Description
Dataset Bias & Generalization	Fake news datasets often contain sampling biases, are domain-specific, and lack multi-modal integration, reducing model effectiveness across diverse misinformation sources.
Real-Time & Computational Constraints	Many AI-based detection models require high computational power, making large-scale misinformation filtering challenging. Fact-checking organizations struggle to keep pace with rapid misinformation propagation.

Ethical & Privacy Concerns	AI-driven detection raises concerns about user privacy, mass surveillance, algorithmic bias, and the unintended censorship of legitimate journalism and free speech.
Multi-Modal Misinformation Complexity	Fake news is increasingly multi-modal, involving text, images, and videos. Current detection models struggle to verify cross-modal misinformation.

4. Discussion

The study presents a comprehensive taxonomy of fake news detection techniques, categorizing methods into text-based, image-based, video-based, and multi-modal approaches. The findings highlight the strengths and limitations of various machine learning (ML) and deep learning (DL) models, demonstrating the evolution of misinformation detection techniques. This section critically discusses the implications of the taxonomy, the gaps in existing methods, and potential strategies for improvement in future research.

4.1 Effectiveness of Detection Techniques

Text-based fake news detection has historically been the most researched domain, leveraging traditional ML models (e.g., Naïve Bayes, SVM, Random Forest) and more recent deep learning architectures (e.g., LSTM, BERT, RoBERTa). While transformer-based NLP models have significantly improved semantic understanding and contextual analysis, they remain vulnerable to adversarial text manipulations, including synonym replacements, character perturbations, and misleading sentence structures. Additionally, linguistic biases in training datasets may lead to false positives or the misclassification of satirical or opinion-based content. Image-based detection, mainly using CNN-based anomaly detection and GAN-based deep-fake detection models, has shown promise in detecting manipulated media and AI-generated images. However, GAN-generated misinformation continues to evolve, producing high-resolution, realistic deep-fakes that evade detection. The lack of large-scale, high-quality labeled datasets for image-based fake news limits generalization across different misinformation sources. Video-based detection methods, incorporating frame-by-frame analysis, audio-visual consistency checks, and deep-fake recognition techniques, have made progress in identifying synthesized media. However, attackers employ sophisticated techniques such as frame injection, lip-sync alterations, and motion-based deep-fake generation to bypass detection systems. Moreover, real-time detection remains computationally expensive, making large-scale deployment challenging. Multi-modal detection, integrating text, image, and video analysis, represents a promising direction for comprehensive misinformation detection. However, fusion-based AI models require high computational resources and large, well-annotated multi-modal datasets. Furthermore, inconsistencies in text-image or video-text relationships pose additional challenges, as some misinformation deliberately pairs misleading text with authentic images to evade detection.

4.2 Challenges and Limitations

Despite significant advancements, fake news detection faces persistent challenges, including adversarial robustness, dataset biases, real-time scalability, and ethical considerations. Adversarial attacks remain an essential concern as creators of misinformation continuously refine their techniques to exploit vulnerabilities in AI models. Additionally, dataset limitations hinder generalization across different languages, cultural contexts, and misinformation formats, often resulting in biased detection models. Real-time detection also presents challenges due to the high computational demands of deep learning models, particularly transformer-based NLP systems and deep-fake detection networks. Ethical concerns further complicate the deployment of automated fake news detection systems, raising critical questions about privacy, fairness, and censorship. AI models must balance effectively filtering misinformation and preserving freedom of speech. False positives can lead to over-censorship, while false negatives allow misinformation to proliferate unchecked. Developing explainable AI (XAI) approaches is essential to address these challenges. Providing transparent and interpretable decision-making in fake news detection can enhance trust, improve accountability, and support the responsible deployment of AI-driven misinformation detection systems. Recent advances in hybrid and ensemble methods with explainable AI, such as the MIX-Hybrid CNN framework [82][83], show promise for improving both performance and transparency.

4.4 Research Gaps and Future Directions

Despite progress in fake news detection, several critical research gaps remain. Most existing frameworks lack robustness against cross-lingual and cultural biases, especially in multi-modal misinformation scenarios where text and imagery may carry culturally specific meanings or be manipulated out of context. Current models often underperform when deployed in non-English environments due to training on monolingual datasets, limiting global applicability. Additionally, fusion techniques used in multi-modal detection systems, such as simple concatenation or early/late fusion, often fail to capture nuanced semantic alignments between modalities. More sophisticated attention-based and dynamic fusion methods are needed to model the complex interactions among text, image, and video representations in misinformation narratives. There is also a notable absence of a standardized evaluation framework that can be used to consistently benchmark fake news detection models across different modalities, languages, and adversarial conditions. The development of such a framework, including multi-modal datasets, unified performance metrics (e.g., precision, recall, F1-score, robustness score), and adversarial testing protocols, is essential for fair comparison and reproducibility of research findings. Future work should advocate for community-driven initiatives to establish these benchmarks and promote collaborative development.

5. Conclusion

This paper presented a comprehensive taxonomy of fake news detection techniques, categorizing existing approaches into four key branches: text-based, image-based, video-based, and multi-modal methods. While AI-driven models have significantly advanced the field, numerous challenges remain, particularly in the areas of adversarial manipulation, dataset bias, scalability, and cultural adaptability. Text-based models, despite their maturity, remain vulnerable to linguistic perturbations and require context-aware enhancements. Similarly, image- and video-based systems are challenged by the growing realism of GAN-generated content and deep-fakes. Multi-modal frameworks have demonstrated the potential to improve detection accuracy by integrating information across modalities, yet they remain computationally expensive and challenging to deploy in real-time environments. Despite these advancements, there are still notable research gaps. Current detection frameworks often lack robustness in cross-lingual and culturally diverse contexts, limiting their effectiveness outside high-resource language settings. Most multi-modal detection systems also rely on fundamental or static fusion strategies, which fail to adequately model the complex interdependencies between modalities like text, image, and video. Future work should explore dynamic, context-sensitive fusion architectures that better capture semantic alignment across sources of information.

Moreover, the field lacks a standardized evaluation framework that can facilitate fair and reproducible comparisons across studies. We advocate for the development of a unified benchmarking protocol that incorporates multi-modal datasets, cross-lingual test sets, standardized performance metrics, and adversarial robustness evaluations. Such a framework would provide a foundation for systematically evaluating detection models and accelerating innovation in the field. To address these challenges holistically, interdisciplinary collaboration is essential. Researchers, fact-checkers, and policymakers must work together to develop detection systems that are not only technically effective but also ethically grounded and context-aware. By advancing research on adversarial resilient architectures, scalable AI deployment, and transparent evaluation standards, the community can build more trustworthy and adaptable fake news detection frameworks. These efforts are critical to preserving information integrity and public trust in the digital age

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