International Journal of Technology Research and Management
ISSN (Online): 2348-9006
Vol 13 Issue 05 May 2026

A Survey on Fake News Detection Using Machine Learning and Deep Learning Techniques

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Abstract: *The rapid proliferation of digital platforms and social media has significantly transformed the way information is generated and consumed. However, this transformation has also facilitated the widespread dissemination of fake news, which poses serious threats to societal stability, political systems, and public trust. Fake news refers to deliberately fabricated or misleading information presented as legitimate news, often created to achieve political, financial, or social gains. In recent years, automated fake news detection has emerged as a critical research area leveraging machine learning (ML), deep learning (DL), and multimodal analysis techniques. This paper presents a comprehensive survey of state-of-the-art approaches for fake news detection, including supervised, unsupervised, and semi-supervised learning methods. Furthermore, recent advancements such as transformer-based models, multimodal fusion techniques, and graph-based learning frameworks are discussed. The survey also highlights commonly used datasets, evaluation metrics, and open challenges in the domain. Finally, future research directions are outlined to guide the development of more robust and scalable fake news detection systems.*

Keywords: *Fake News Detection, Machine Learning, Deep Learning, Transformer Models, Multimodal Learning, Social Media Analytics, Misinformation, NLP.*

1. INTRODUCTION

In the digital era, online news platforms and social media have become primary sources of information for millions of users worldwide. Platforms such as Twitter, Facebook, and online news portals enable rapid dissemination of information; however, they also provide fertile ground for the spread of misinformation and fake news. Fake news is intentionally crafted to mislead readers and often exploits emotional triggers to increase its reach and impact.

The exponential growth of social media usage has amplified the problem, making it easier for false information to spread faster than verified news. Studies have shown that fake news propagates more rapidly and widely than true information due to its sensational nature and emotional appeal [1]. This widespread dissemination can influence public opinion, disrupt democratic processes, and even incite social unrest.

Traditional manual fact-checking methods are insufficient to handle the scale and speed of online information flow. Consequently, automated fake news detection systems using machine learning and artificial intelligence have gained significant attention. Early approaches relied on handcrafted linguistic features, whereas recent advancements focus on deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures like BERT and GPT.

Furthermore, modern fake news often includes multimodal content (text, images, videos), making detection more complex. Therefore, integrating textual, visual, and contextual information has become essential for improving detection accuracy.

The primary contributions of this survey are as follows:

- To provide a structured overview of fake news detection techniques across different learning paradigms.
- To analyse recent advancements including transformer-based and multimodal approaches.
- To discuss evaluation metrics and benchmark datasets.
- To identify key challenges and future research directions in fake news detection.

2. BACKGROUND

2.1 Understanding Fake News and Misinformation

Fake news is broadly defined as intentionally fabricated information that mimics legitimate news content but lacks factual accuracy. It is a subset of the larger misinformation ecosystem, which also includes misinformation (false information shared without harmful intent) and disinformation (false information deliberately created to deceive) [1]. Another related concept is mal-information, which involves sharing truthful information with malicious intent.

The lifecycle of fake news typically involves three stages: creation, propagation, and consumption. During propagation, social media platforms play a crucial role by enabling rapid sharing through user interactions such as reposts, likes, and comments. Research has shown that false information spreads significantly faster than true information due to novelty and emotional engagement factors [2].

2.2 Evolution of Fake News Detection Techniques

Early fake news detection approaches relied on manual verification and journalistic fact-checking. However, with the exponential growth of online content, automated techniques became necessary.

1) Traditional Machine Learning Approaches

Initial computational methods focused on extracting handcrafted features, such as:

- Linguistic features (e.g., syntax, semantics, sentiment)
- Stylometric features (e.g., writing style, punctuation)
- Metadata (e.g., user profile, publishing source)

Classifiers such as Support Vector Machines (SVM), Naïve Bayes, and Decision Trees were widely used [3]. Although effective for structured datasets, these approaches struggled with scalability and contextual understanding.

2) Deep Learning-Based Approaches

The emergence of deep learning significantly improved fake news detection by enabling automatic feature extraction. Key architectures include:

- **Convolutional Neural Networks (CNNs):** Effective for capturing local textual patterns
- **Recurrent Neural Networks (RNNs) / LSTM:** Useful for sequential text modelling
- **Attention Mechanisms:** Help focus on important parts of the text

Rashkin et al. [4] demonstrated that neural models leveraging linguistic cues outperform traditional models. Similarly, emotional signals extracted from text have been shown to improve detection performance [5].

3) Transformer-Based Models (Recent Advances)

Recent research has shifted toward **Transformer-based architectures**, such as:

- **BERT (Bidirectional Encoder Representations from Transformers)**
- **RoBERTa**
- **DeBERTa**
- **GPT-based models**

Transformer architectures such as BERT [4], RoBERTa [20], and DeBERTa [21] have significantly improved contextual understanding in NLP tasks. These models capture deep contextual relationships within text and significantly outperform earlier methods. For example, transformer-based models can identify subtle semantic inconsistencies and contextual mismatches in news articles [6].

Recent advancements in natural language processing have been driven by transformer architectures, which rely on self-attention mechanisms for contextual understanding. The transformer model introduced by Vaswani *et al.* [15] forms the foundation of modern language models. Subsequent improvements such as RoBERTa [20] and DeBERTa [21] further enhance contextual representation and model performance in fake news detection tasks.

Moreover, fine-tuned transformer models have achieved state-of-the-art performance on benchmark datasets such as LIAR, FakeNewsNet, and CoAID.

2.3 Multimodal Fake News Detection

Modern fake news often includes images, videos, and textual content, making multimodal analysis essential. Multimodal fake news detection integrates:

- **Textual features** (content, semantics)
- **Visual features** (image manipulation, inconsistencies)
- **Cross-modal relationships** (text-image alignment)

Models such as EANN (Event Adversarial Neural Network) and MVAE (Multimodal Variational Autoencoder) combine textual and visual representations to improve detection accuracy [7], [8]. Recent transformer-based multimodal models further enhance performance by learning cross-modal interactions.

2.4 Problem Formulation

Fake news detection is generally formulated as a **binary classification problem**:

- **Class 1:** Fake News
- **Class 2:** Real News

Given a news article N, the objective is to learn a function:
$f(N) \rightarrow \{Fake, Real\}$

In more advanced settings, the problem may be extended to:

- **Multi-class classification** (e.g., satire, propaganda, biased news)
- **Early detection** (identifying fake news during initial propagation)
- **Explainable detection** (providing justification for predictions)

2.5 Challenges in Fake News Detection

Despite significant progress, several challenges remain:

- **Data scarcity and imbalance:** Limited availability of labelled datasets
- **Dynamic nature of fake news:** Continuous evolution of misinformation strategies
- **Multimodal complexity:** Difficulty in aligning text and visual features
- **Explainability:** Lack of interpretability in deep learning models
- **Cross-domain generalization:** Models trained on one dataset may not perform well on others

2.6 Benchmark Datasets

Several publicly available datasets are widely used in fake news detection research:

- **LIAR Dataset** [3] – Short political statements labelled for truthfulness
- **FakeNewsNet** – Combines news content with social context
- **CoAID** – COVID-19 misinformation dataset
- **Fakeddit** – Multimodal dataset with text and images
- **FakeNewsNet [13]** – provide both content and social context information

These datasets enable standardized evaluation and comparison of detection models.

3. LITERATURE REVIEW

Fake news detection has been widely studied in recent years, with several comprehensive surveys summarizing existing techniques and challenges. Zhou and Zafarani [12] provided a detailed overview of fake news detection methods, including content-based, social context-based, and hybrid approaches.

3.1 Text-Based Fake News Detection

Early research on fake news detection primarily relied on textual analysis using linguistic and statistical features. Castillo *et al.* [1] analysed credibility on Twitter using features such as message content, user behavior, and propagation patterns. Similarly, Wang [2] introduced the LIAR dataset, which became a benchmark for evaluating fake news detection models.

Rashkin *et al.* [3] explored linguistic differences between fake and real news using neural networks, showing that deceptive content often exhibits distinct stylistic patterns. With the advancement of deep learning, models such as CNNs and LSTMs became widely used for automatic feature extraction.

More recently, transformer-based architectures such as BERT have significantly improved performance by capturing contextual semantics [4]. Studies demonstrate that fine-tuned transformer models (e.g., RoBERTa, DeBERTa) outperform traditional and earlier deep learning approaches in fake news classification tasks. Recent studies have explored transformer-based models such as FakeBERT for improved classification performance [24]. Recent transformer-based models such as FakeBERT have demonstrated improved performance by combining contextual embeddings with classification layers [24].

3.2 Social Context-Based Approaches

Fake news propagation is heavily influenced by user interactions and network dynamics. Vosoughi *et al.* [5] showed that false news spreads faster and reaches more people than true news due to its novelty and emotional appeal.

Shu *et al.* [6] incorporated user profile features and social context into fake news detection models, demonstrating improved performance when combining textual and user-based features. Recent studies have further extended this idea using Graph Neural Networks (GNNs) to model information diffusion patterns across social networks.

GNN-based approaches capture structural relationships between users, posts, and communities, enabling early detection of fake news during its propagation phase.

3.3 Multimodal Fake News Detection

Modern fake news often includes multimedia content such as images and videos, necessitating multimodal analysis.

Wang *et al.* [7] proposed Event Adversarial Neural Networks (EANN), which combine textual and visual features to improve detection performance.

Khattar *et al.* [8] introduced a Multimodal Variational Autoencoder (MVAE) that learns joint representations of text and images. Similarly, Singhal *et al.* [9] proposed the SpotFake model, which integrates BERT for textual encoding and VGG-19 for image feature extraction. Jin *et al.* [23] proposed multimodal fusion techniques that integrate textual and visual features using deep neural networks, significantly improving detection accuracy.

Recent advancements leverage multimodal transformers and vision-language models such as CLIP, enabling better alignment between textual and visual content. These approaches significantly improve detection accuracy in real-world scenarios where fake news often includes manipulated images.

3.4 Emotion and Sentiment-Based Approaches

Fake news often exploits emotional triggers to enhance engagement. Giachanou *et al.* [10] demonstrated that emotional signals extracted from text improve credibility detection. Similarly, Ghanem *et al.* [11] showed that fake news tends to evoke emotions such as fear, anger, and surprise.

Recent works integrate sentiment analysis with deep learning and transformer models, enabling more accurate detection of emotionally manipulative content.

3.5 Large Language Model (LLM)-Based Approaches

Recent advancements in large language models (LLMs) have opened new directions in fake news detection. Models such as GPT, PaLM, and LLaMA enable zero-shot and few-shot learning for misinformation detection tasks [12].

Studies focus on:

- Automated fact-checking using LLM reasoning
- Explainable fake news detection
- Retrieval-augmented generation (RAG) for verification

Although LLMs improve reasoning capabilities, challenges such as hallucination, bias, and computational cost remain critical concerns.

3.6 Comparative Analysis

Approach	Strengths	Limitations
Traditional ML	Simple, interpretable	Limited context understanding
Deep Learning	Automatic feature extraction	Data-intensive
Transformers	High accuracy, contextual	High computational cost
Multimodal Models	Real-world applicability	Complex training
GNN-Based Models	Captures propagation	Scalability issues
LLM-Based Models	Reasoning + explainability	Hallucination risk

4. METHODOLOGIES

Fake news detection methods can be broadly categorized into supervised, unsupervised, and semi-supervised learning approaches, along with recent deep learning and transformer-based pipelines. This section presents a structured overview of these methodologies.

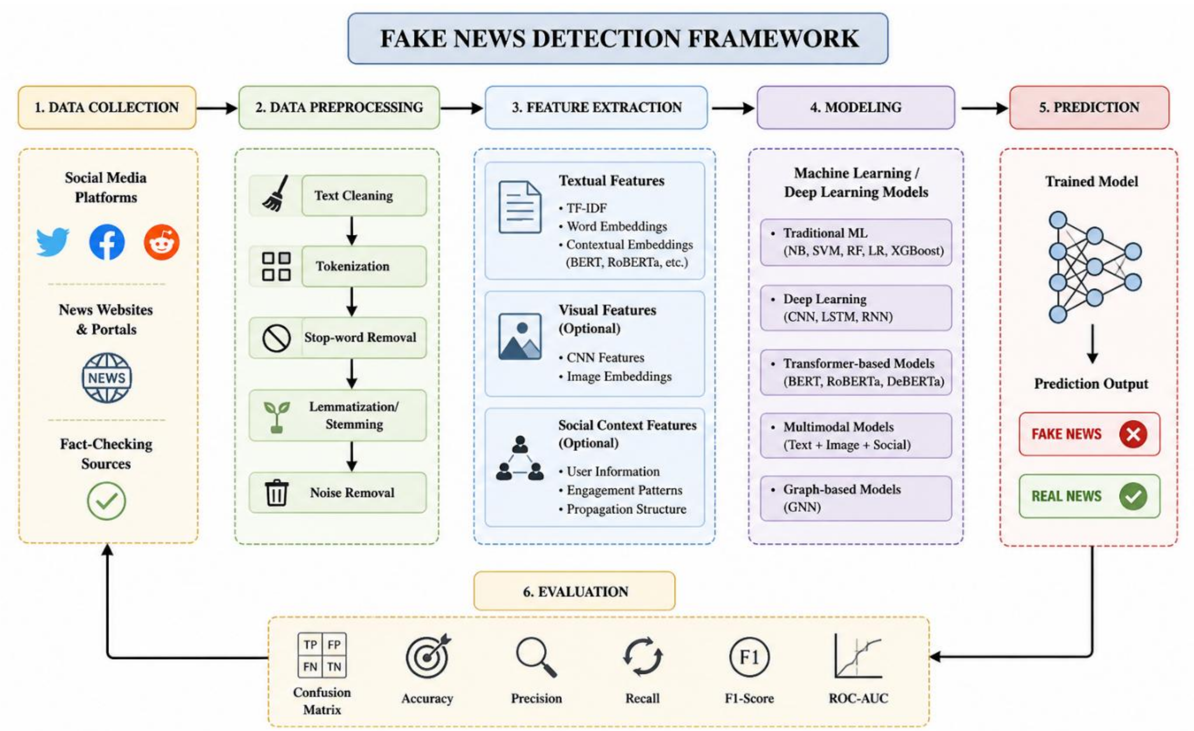

Fig. 1. Overall architecture of a fake news detection system.

The overall architecture of a fake news detection system is illustrated in Fig. 1. The process begins with data collection from multiple sources such as social media platforms, news websites, and fact-checking repositories. The collected data is then subjected to pre-processing steps including text cleaning, tokenization, stop-word removal, and lemmatization to ensure data quality.

Subsequently, feature extraction techniques are applied to obtain meaningful representations from the data. These include textual features such as TF-IDF and contextual embeddings, visual features extracted using convolutional neural networks, and social context features derived from user interactions and propagation patterns.

The extracted features are then utilized by various machine learning and deep learning models, including traditional classifiers, neural networks, transformer-based architectures, and multimodal models, to perform classification. Finally, the system outputs predictions indicating whether the news is fake or real. The performance of the model is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

4.1 Supervised Learning Approaches

Supervised learning techniques rely on labelled datasets where news articles are annotated as *fake* or *real*. These methods typically involve **feature extraction** followed by classification.

1) Feature Engineering

Traditional approaches **extract** features such as:

- **Linguistic features:** syntax, semantics, Part-of-Speech (POS)
- **Statistical features:** word frequency, n-grams
- **Sentiment features:** polarity and subjectivity
- **Metadata features:** source credibility, user profile

Castillo *et al.* [1] demonstrated that combining content and social features improves credibility assessment.

2) Classification Algorithms

Common supervised algorithms include:

- Naïve Bayes (NB)
- Support Vector Machines (SVM)
- Decision Trees and Random Forests
- Logistic Regression

These models have been widely used due to their simplicity and interpretability. However, they depend heavily on feature quality and struggle with complex semantic relationships.

3) Deep Learning-Based Supervised Models

Deep learning models overcome feature engineering limitations by automatically learning representations:

- **CNNs:** capture local textual patterns
- **LSTMs/RNNs:** model sequential dependencies
- **Attention-based models:** focus on important content

Rashkin *et al.* [3] showed that neural networks outperform traditional classifiers in detecting deceptive language patterns.

4) Transformer-Based Supervised Models

Transformer models such as BERT significantly enhance fake news detection by capturing contextual relationships [4]. Recent works employ:

- Fine-tuned BERT/RoBERTa/DeBERTa
- Hybrid transformer + CNN models
- Attention-enhanced architectures

In addition to traditional classifiers, ensemble methods such as gradient boosting (e.g., XGBoost) have been widely adopted for classification tasks due to their scalability and performance [14].

4.2 Unsupervised Learning Approaches

Unsupervised methods do not require labelled data and instead identify hidden patterns within datasets.

1) Clustering Techniques

Clustering algorithms such as:

- K-means
- Hierarchical clustering

Group similar news articles based on content similarity. These methods help identify anomalous or suspicious patterns.

2) Anomaly Detection

Fake news can be treated as an anomaly in a dataset of genuine news. Techniques include:

- Density-based methods
- Autoencoders
- Outlier detection algorithms

These approaches are useful when labelled datasets are scarce.

3) Limitations

- Lower accuracy compared to supervised methods
- Difficulty in interpreting clusters
- Sensitive to feature representation

4.3 Semi-Supervised Learning Approaches

Semi-supervised learning combines labelled and unlabelled data to improve performance.

1) Positive-Unlabelled (PU) Learning

PU learning assumes:

- Positive samples → fake news
- Unlabelled samples → mixture of fake and real

The model iteratively refines classification boundaries. This approach is useful when negative samples are unavailable.

2) Self-Training and Co-Training

- **Self-training:** model labels unlabelled data iteratively
- **Co-training:** multiple classifiers collaborate

These methods improve learning efficiency with limited labelled data.

4.4 Multimodal Detection Techniques

Fake news often contains both text and images. Multimodal approaches integrate:

- Textual features (NLP models)
- Visual features (CNN-based image models)
- Cross-modal consistency

Wang *et al.* [7] proposed EANN, which combines textual and visual representations. Similarly, Khattar et al. [8] used variational autoencoders for joint feature learning. Recent approaches utilize vision-language models such as CLIP to learn joint representations of textual and visual data, improving multimodal fake news detection [19].

Recent multimodal transformers use cross-attention mechanisms to align text and images, significantly improving detection accuracy.

4.5 Graph-Based and Social Network Approaches

Graph-based methods model relationships between users, posts, and news articles.

- Nodes → users/news/posts
- Edges → interactions (shares, likes, comments)

Graph Neural Networks (GNNs) capture propagation patterns and help detect fake news early in its spread.

Shu *et al.* [6] highlighted the importance of user behavior in fake news dissemination. Graph-based approaches using Graph Neural Networks (GNNs) have been explored for modelling rumour propagation. Ma *et al.* [25] demonstrated that GNN-based models effectively capture structural relationships in social networks.

4.6 End-to-End Detection Pipeline

A typical fake news detection system follows these steps:

- 1) Data Collection
- Social media platforms (Twitter, Facebook)

- News websites and fact-checking sources
- 2) Data Preprocessing
- Tokenization
- Stop-word removal
- Stemming/Lemmatization
- Noise removal
- 3) Feature Extraction
- Text embeddings (TF-IDF, Word2Vec, BERT)
- Visual features (CNN embeddings)
- Social context features
- 4) Model Training
- Supervised / semi-supervised / deep learning models
- 5) Evaluation
- Accuracy, Precision, Recall, F1-score

4.7 Comparative Insights

Technique	**Advantages**	**Limitations**
Supervised Learning	High accuracy	Requires labeled data
Unsupervised Learning	No labelling required	Lower performance
Semi-Supervised	Uses limited labels	Complex training
Deep Learning	Automatic feature extraction	Data-intensive
Multimodal Models	Real-world applicability	High complexity
Graph-Based Models	Captures propagation	Computational cost

5. CHALLENGES, OPEN ISSUES, AND FUTURE RESEARCH DIRECTIONS

Despite significant advancements in fake news detection using machine learning and deep learning techniques, several challenges and open research issues persist. This section discusses the major limitations in current approaches and highlights promising future research directions.

5.1 Key Challenges in Fake News Detection

1) Data Scarcity and Imbalance

One of the primary challenges is the limited availability of high-quality labeled datasets. Most datasets are:

- Domain-specific (e.g., political news)
- Imbalanced (more real news than fake news or vice versa)
- Lacking multimodal annotations

Wang [2] introduced the LIAR dataset, but its size and scope are limited. Similarly, datasets like FakeNewsNet often suffer from incomplete social context [6].

2) Dynamic and Evolving Nature of Fake News

Fake news strategies continuously evolve, making static models ineffective over time. Adversaries frequently adapt by:

- Modifying writing styles
- Using paraphrasing tools
- Generating AI-based fake content

This dynamic nature makes it difficult for models trained on historical data to generalize effectively.

3) Multimodal Complexity

Modern fake news often combines text, images, and videos, increasing detection complexity. Although models like EANN [7] and MVAE [8] address multimodal fusion, challenges remain:

- Aligning cross-modal features
- Detecting subtle inconsistencies
- Handling manipulated multimedia content

4) Lack of Explainability

Deep learning and transformer-based models often act as black-box systems, making it difficult to interpret predictions. This lack of transparency limits their adoption in critical domains such as journalism and law enforcement.

Explainable AI (XAI) techniques are still under development for fake news detection.

5) Early Detection and Real-Time Processing

Detecting fake news at an early stage is crucial to prevent its spread. However:

- Most models rely on fully developed propagation patterns
- Real-time detection systems are computationally expensive
- Early signals may be insufficient for accurate classification

6) Cross-Domain Generalization

Models trained on one dataset often fail when applied to another due to:

- Domain-specific language variations
- Cultural and regional differences
- Topic-specific biases

This limits the scalability of fake news detection systems.

7) Adversarial Attacks

Fake news detection systems are vulnerable to adversarial techniques such as:

- Text perturbation
- Image manipulation
- Deepfake content generation

These attacks can significantly degrade model performance.

5.2 Open Research Issues

Based on the above challenges, several open research problems remain:

- Development of large-scale, high-quality multimodal datasets
- Designing robust and adaptive models for evolving misinformation
- Improving interpretability and explainability of AI models
- Creating real-time detection frameworks
- Enhancing cross-lingual and cross-domain learning

5.3 Future Research Directions

1) Integration of Large Language Models (LLMs)

Recent advancements in LLMs (e.g., GPT [17] and LLaMA [18]) provide new opportunities:

- Zero-shot and few-shot fake news detection
- Automated fact-checking and reasoning
- Explainable decision-making

Future systems can integrate LLMs with retrieval-based mechanisms for improved verification.

2) Multimodal Transformer Models

Future research should focus on:

- Vision-language transformers (e.g., CLIP-based models)
- Cross-modal attention mechanisms
- Unified frameworks for text, image, and video analysis

These models can better capture complex misinformation patterns.

3) Graph Neural Networks with Temporal Modelling

Combining Graph Neural Networks (GNNs) with temporal learning can improve early detection by modelling how fake news spreads over time.

4) Explainable AI (XAI) for Fake News Detection

Developing interpretable models is essential for trust and adoption. Future work should focus on:

- Attention visualization
- Rule-based explanations
- Human-interpretable decision systems

5) Real-Time and Scalable Systems

Future systems should be:

- Efficient and scalable
- Capable of handling streaming data
- Deployable in real-world platforms

6) Cross-Lingual and Multilingual Detection

Most current models focus on English datasets. Future research should address:

- Multilingual fake news detection
- Low-resource languages
- Cross-cultural misinformation patterns

7) Robustness against Adversarial Attacks

Developing robust models that can resist adversarial manipulation is critical. Techniques include:

- Adversarial training
- Data augmentation
- Robust optimization methods

6. CONCLUSION

The rapid growth of social media and digital communication platforms has significantly amplified the spread of fake news, posing serious challenges to information credibility, public trust, and societal stability. This survey presented a comprehensive review of fake news detection techniques, covering traditional machine learning approaches, deep learning models, transformer-based architectures, multimodal frameworks, and recent advancements involving large language models.

From the literature, it is evident that early approaches based on handcrafted features and classical classifiers such as Naïve Bayes and Support Vector Machines provided foundational insights but lacked the ability to capture complex semantic relationships [1], [2]. The emergence of deep learning techniques, including CNNs and LSTMs, improved detection performance by enabling automatic feature extraction [3]. More recently, transformer-based models such as BERT and its variants have demonstrated superior performance by effectively modelling contextual dependencies within textual data [4].

Furthermore, the integration of multimodal information, including textual and visual features, has significantly enhanced the robustness of fake news detection systems. Models such as EANN and MVAE demonstrated the importance of combining multiple modalities to capture complex misinformation patterns [7], [8]. In addition, graph-based approaches leveraging social network structures have provided valuable insights into the propagation dynamics of fake news [6].

Despite these advancements, several challenges remain unresolved, including data scarcity, lack of explainability, cross-domain generalization issues, and vulnerability to adversarial attacks. The dynamic and evolving nature of fake news further complicates the development of reliable detection systems. Recent trends indicate a shift toward hybrid models that combine transformers, graph neural networks, and multimodal learning to achieve higher accuracy and robustness.

In conclusion, fake news detection remains an active and challenging research area requiring interdisciplinary approaches that integrate natural language processing, computer vision, and social network analysis. Future research should focus on developing scalable, explainable, and real-time detection systems, as well as leveraging emerging technologies such as large language models and multimodal transformers to address the limitations of existing methods.

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