



Fake News Detection: Methods, Datasets, and Challenges

Nimra Mirza^{*1}  and Vishal Kohli¹ 

¹Neelkanth Institute of Technology, Meerut, Uttar Pradesh, India

*nimramirza1111@gmail.com

Abstract. The exponential growth of online platforms, has accelerated the dissemination of both authentic and misleading information. Researchers adopt the machine learning (ML) and deep learning (DL) based approaches for fake news detection in the recent years, in which the performance of DL models has been found to be quite promising compared to conventional ML techniques. The main focus of this review is to systematically explore the existing research. This review analyses 68 research articles published between 2011 and 2025 focusing on machine and deep learning approaches for fake news detection. It presents a comparative analysis of models, feature engineering techniques, widely used datasets, and language-specific efforts. The aim is to gain clarity as to which approach is more effective in which context, and where limitations exist. The paper highlights the challenges and open issues, like dataset bias, interpretability problems and evaluation inconsistencies. It further identifies critical research gaps and outlines future directions including robust dataset development, integration of explainable AI techniques, and standardized evaluation frameworks. Overall, this survey provides a structured taxonomy and comparative insight that can guide future research and real-world deployment of fake news detection systems.

Keywords: Fake news detection · machine learning · deep learning · artificial intelligence · transformer models · RNN · CNN · Hybrid models · benchmark · datasets · low-resource language · code-mixed datasets · Feature Engineering.

1 Introduction

In today's digital era, social media become a very powerful information dissemination tool [1]. Social media platform provides news in the real-time, along with that there is a big challenge of rapid spread of fake news and misinformation [2], [3]. These platforms are also used for political campaigns, social movements, and global news trends. This fake information distort the perception of the people, affects decisions, and sometime become the threat to public safety [4], [5]. Fake news detection has become a critical and emerging field in research and technology because it is essential that people get real-time accurate information[6], [7].

The motivation behind this study, To analyze how language and multilingual challenge, technological gap, AI/ML opportunity can directly impact the fakes news detection process [8], [9], [10], [11], [12].

Majority of studies were focused on English-language, whereas fake news was spread in multilingual environments and code-mixed content. A lot of datasets were outdated and doesn't reflect latest social media trends. Datasets have limited domain coverage, mostly focuses on political, healthcare. Representation of real-world noisy data (spelling errors, slang, memes) is insufficient[13]. Different studies use the different feature extraction methods, but their systematic comparative analysis is rare. Other research gaps are Model Generalization problem, Lack of Multi Modal Fake News Detection, Explainability and Trust Issue.

The primary aim of this review is to present the structured overview of the domain of fake news detection. Some specific objectives are: Systematic classification and evaluation of existing Machine Learning (ML), Deep Learning (DL) and Hybrid models. Detailed Comparison of fake news detection datasets on language. Analysis of text representation techniques like TF-IDF, word embeddings. Pointing out the current research trends, challenges, and yet to be explored areas.

2 Methodology for Literature Selection

The most important step for a systematic review is to design a clear and structured methodology, so that the literature selection is transparent and reproducible. In this study, literature process will be divided into multiple stages, where everything from defining the research questions to final data synthesis was done using a systematic approach.

2.1 Research Questions (RQs) Formulation

First, some Research Questions (RQs) were formulated which provided the foundation of the entire review. These RQs were designed to cover multiple aspects of fake news detection, such as which machine learning and deep learning models are effective, which datasets are commonly used, and how evaluation is done. Having RQs, clearly defined the scope of literature selection and made it easy to exclude irrelevant studies.

2.2 Search Strategy

A systematic search strategy was designed so that relevant research papers can be collected. Multiple reputed databases were searched such as, IEEE Xplore, SpringerLink, ACM Digital Library, Elsevier ScienceDirect, Google Scholar. Search queries are carefully designed using keywords and Boolean operators.

- For fake news detection: ("Fake news" OR "disinformation" OR "misinformation") AND ("detection" OR "classification") AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "automated approaches")

- For model/ algorithm focused: (“Fake news” OR “disinformation” OR “misinformation”) AND (“deep learning models” OR “transformer models” OR “RNN” OR “CNN” OR “Hybrid models”)
- For Datasets: (“Fake news” OR “disinformation” OR “misinformation”) AND (“benchmark” OR “datasets”) AND (“multimodal datasets” OR “low-resource language” OR “code-mixed datasets”)
- For Feature Engineering: (“Fake news” OR “disinformation” OR “misinformation”) AND (“benchmark” OR “datasets”) AND (“Feature Engineering” OR “Text-based feature” OR “Content-based feature” OR “embedding techniques” OR “user profile features”)

These combinations ensures that maximum relevant and high-quality papers are retrieved.

2.3 Inclusion and Exclusion Criteria

To filter out the collected studies inclusion and exclusion criteria has been applied.

Paper was published between 2011-2025 and in peer-reviewed journals and conferences, ML / DL approaches used in the studies, Work done on datasets of multilingual and English languages , are been treated as the inclusion criteria.

For Exclusion the criteria is Duplicate records, Papers without proper experimental validation, articles which are opinion-based or non-scientific.

Using the defined inclusion and exclusion criteria, irrelevant and low-quality studies were systematically filtered out.

2.4 Screening Process

First title and abstract were screened in which irrelevant papers were removed. After that full-text eligibility check was done where only those papers which satisfied the criteria were retained. In this process initially there was a large pool of articles but after multiple filtering high-quality papers came in the final selection.

2.5 Quality Assessment

Each selected paper was assessed on the basis of a quality checklist. The checklist included factors such as methodology clarity, dataset details, reproducibility of results, and evaluation metrics. Only those papers were retained that met the minimum quality threshold.

2.6 Data Extraction and Synthesis

Data extraction is done from the final selected studies which takes information on model type, dataset, feature engineering, evaluation metrics, and performance. The extracted data is categorized and analyzed so that comparative study and meaningful synthesis is possible.

2.7 Summary

480 records were first obtained from the chosen databases by the structured search procedure. 410 distinct studies were left for screening after 70 duplicate entries were eliminated. 245 articles were eliminated during the title and abstract screening process because they were deemed irrelevant or did not fit the inclusion requirements. The remaining 165 studies were assessed through full-text evaluation. After applying eligibility and quality assessment criteria, 65 studies were finally included in the review.

3 Classification & Analysis

The main focus of this section is to systematically classify and analyse the literature of fake news detection, so that there is a clear understanding of patterns, trends and research gap. For every dimension of classification, there is a separate table and subsection.

3.1 Classification by ML vs DL

Machine Learning (ML) and Deep Learning (DL) both are widely adopted methodologies in the domain of fake news detection. Machine Learning approaches are effective for smaller datasets and provide high explainability. Deep Learning approaches directly learn from featured text/embeddings, because of that their performance on large datasets are superior.

As summarized in Table 1, traditional machine learning models predominated before to 2016. Models such as CNN/LSTM show growth beyond 2018. Transformer-based architectures gain dominance after 2019, while hybrid and multi-modal architectures start to gain traction in 2021. The implication of this trend is that ML is still competitive in low-resource contexts, transformer models suffer from large computational costs, DL enhances performance but decreases interpretability, and cross-lingual fake news detection is still not well studied. The creation of lightweight DL models can also be in a significant area of study. Additionally, optimized machine learning models remain applicable in low-resource environments.

3.2 Classification by dataset

The choice of dataset is a critical factor in the performance of fake news detection. There is a direct impact on model's accuracy and generalization based on the dataset's size, diversity, domain relevance, and real-world noise representation.

while analysing Table 2, this comes to light that LIAR, FakeNewsNet, PolitiFact datasets have commonly used and trained models achieve high accuracy on large, balanced datasets. But there is an underuse of multilingual and code-mixed datasets, which creates the performance gaps.

Table 1. Classification by ML vs DL

Reference	Year	Approach Type	Specific Model(s)	Model Complexity	Performance Metric Type	Value (s)
[14]	2014	ML	SVM (SMO) & Naive Bayes	Low	F1-score	SMO 84%, NB 74%
[15] , [16]	2017	ML	SVM	Low	Accuracy	92%
[17]	2019	ML	Word2Vec embeddings	Low	Accuracy	95%
[18]	2016	ML	Logistic Regression, Linear Regression	Low	Accuracy	91%
[19]	2020	DL	CNN	Medium	Accuracy	98.36%
[20]	2021	Hybrid	LSTM + ML models	Medium	Accuracy	99.4%
[21]	2021	DL	CNN + RNN	Medium	Accuracy	50% generalization accuracy
[22]	2021	DL	CNN + Bi-LSTM + Attention	Medium–High	Accuracy	35.1%
[23]	2019	DL	BERT	High	F1-score	improved by 0.14
[24]	2020	ML	Gaussian Naïve Bayes	Low	Accuracy	87% Accuracy
[25]	2018	ML	Decision Tree	Low	F1-score	88% F1-score
[26]	2019	DL	BERT		Accuracy	
[27]	2022	Hybrid	Random Forest, CNN	Random Forest = Low–Medium, CNN = Medium	Accuracy	RF: 93%, CNN: 98% Accuracy
[28]	2022	DL	DBN, RBM	Medium–High	Accuracy	97.82% Accuracy
[29]	2021	ML	Random Forest, SVM	Random Forest = Low–Medium, SVM = Low	Accuracy	79% Accuracy
[30]	2021	DL	BERT		Accuracy	
[31]	2021	DL	CNN		Accuracy	
[32]	2021	DL	BERT, CNN		Cross Entropy Loss	
[33]	2022	DL	Transformer- Based Approach		Precision, Recall	
[34]	2023	DL	Swin Transformer, dense network layers		Accuracy, Precision, Recall. F1-Score	

Table 2. Classification by dataset

Reference	Year	Model Type	Specific Model(s)	Dataset Name	Language	Accuracy
[35]	2017	Hybrid	CNN	LIAR dataset	English	Outperformed traditional ML
[21]	2021	Hybrid	CNN + RNN	FA-KES, ISOT	English	50% generalization accuracy
[15]	2017	Machine Learning (ML)	LSVM	25,200 news articles	English	92% Accuracy
[24]	2020	Machine Learning (ML)	Gaussian Naïve Bayes	538 Bangla news instances	Bangla	87% Accuracy
[25]	2018	Machine Learning (ML)	Decision Tree	613,033 tweets	English	88% F1-score
[36]	2019	Hybrid	HAN and SVM	PHEME Twitter dataset	English	86% Accuracy
[37]	2017	Machine Learning (ML)	SVM	BuzzFeed, Burfoot & Baldwin	English	71% Accuracy
[38]	2021	Hybrid	Random Forest, LSTM, Bi-LSTM, VGG16, ResNet-50	IFND dataset	English	RF: 94%, Bi-LSTM: 92.7%, ResNet-50: 70.8%, LSTM+VGG16: 74%
[32]	2021	Deep Learning (DL)	BERT, CNN	LIAR dataset	English	
[39]	2020	Deep Learning (DL)	CNN, image2sentence	PolitiFact, GossipCop	English	89.5% F1-score
[28]	2022	Deep Learning (DL)	DBN, RBM	CASIA-WebFace, FFHQ, DFFD, 100K-Faces	English	97.82% Accuracy
[33]	2022	Deep Learning (DL)	Transformer-Based approach	PolitiFact	English	

3.3 Classification by Language

A major challenge in the fake news detection is the language coverage. There is a different pattern of misinformation in every language. The overuse of English-dominated datasets is causing low accuracy in detection in multilingual and low-resource languages.

Table 3. Classification by language

Reference	Year	Language(s)	Dataset Name
[40]	2021	English	WELFake dataset (Kaggle, McIntire, Reuters, BuzzFeed merged)
[41]	2021	English	ISOT and KDnugget
[42]	2020	English	Fake News Challenge (FNC) dataset
[18]	2016	Italian	Italian Facebook dataset
[43]	2020	English	Newpolitifact
[21]	2021	English	FA-KES, ISOT
[22]	2021	English	LIAR dataset
[44]	2019	English	Hyperpartisan dataset
[22]	2021	English	ISO, FA-KES
[28]	2022	English	CASIA-WebFace, FFHQ, DFFD, 100K-Faces
[29]	2021	English	ASVspoof 2019
[45]	2023	English	Facebook AI's Deepfake Detection Challenge (DFDC) Dataset
[46]	2022	English	DFDC, FF++, Celeb-DF
[47]	2021	Urdu	Bend The Truth
[48]	2020	English	FakeNewsNet
[49]	2020	Hindi	Scraped from AltNews, Boomlive, IFCN sources
[50]	2021	English	Politifact, Gossipcop
[30]	2021	Chinese	Weibo
[26]	2019	English	FakeNewsNet

As observed in Table 3, there is an overwhelming dominance of English, and limited presence of Chinese, Spanish and Urdu. Representation of Indian regional languages and code-mixed Hinglish data is extremely low. The implications of this analysis are that there is an urgent requirement of development of multilingual and code-mixed large-scale datasets. Along with, performance can be improved by the adoption of cross-lingual transfer learning and multilingual embeddings.

3.4 Classification by Feature Engineering

Feature engineering is the core of the fake news detection because the quality of the input feature directly affects the accuracy of the model. There is primary three categories used in this domain are Manual features, Embeddings-based Features, Multimodal Features.

As summarized in Table 4, 5 and 6, there is decline in use of manual features and dominance of embedding-based approaches, especially contextual

Table 4. Classification by Feature Engineering Approach- Traditional Feature Engineering

Reference	Year	Feature Engineering Type	Example
[51]	2011	Text-based (Sentiment features)	Sentiment words
[26]	2012	Text-based (Word embeddings)	Deep syntax features
[52]	2013	Text-based (Stylometric + Syntactic)	234 stylometric features (linguistic + syntactic), Lexical and Syntactic Features
[14]	2014	Text-based (Lexical	Syntactic)& Lexical + syntactic features
[53]	2014	Text-based (Word embeddings)	N-grams, sentiment polarity, topic features
[54]	2016	Text-based (Stylometric + Psycholinguistic)	Absurdity, grammar, punctuation features
[15]	2017	Text-based (Lexical, Syntactic, Hybrid, sentiment)	N-gram features, TF-IDF
[37]	2017	Text-based (Statistical vectorization)	Complexity, psychology, style features
[55]	2018	Text-based (Topic modeling)	LDA topic modelling
[56]	2018	Text-based (Linguistic + Statistical vectorization)	Network structure (node proximity, social dimension)
[57]	2020		Sentiment analysis, Segmentation method
[40]	2021	Text-based (Word embeddings)	20 linguistic features + count vectorizer + TF-IDF embeddings

Table 5. Classification by Feature Engineering Approach- Neural Embedding

Reference	Year	Feature Engineering Type	Example
[35]	2017	Text-based (Syntactic features)	Word embeddings (GloVe)
[17]	2019	Text-based (N-grams)	Word2Vec embeddings
[22]	2021	Network-based features	GloVe embeddings
[58]	2020	Hybrid / Multimodal	Semantic + contextual embeddings
[50]	2022	Text-based (Contextual Embeddings) + Neural Capsule Network Features	BERT, CapsNet
[59]	2021	Image-based (CNN + Tensor Factorization Features)	CNN, Coupled matrix-tensor factorization

Table 6. Classification by Feature Engineering Approach-Multimodal

Reference	Year	Feature Engineering Type	Example
[39]	2020	Text-based (Stylometric + Syntactic)	Cosine similarity on text & image features
[28]	2022	Hybrid / Multimodal	Fisherface LBP histogram
[60]	2018	Image-based (Facial texture features)	Multimodal feature extractor
[61]	2020	Hybrid / Multimodal	Multimodal embeddings
[26]	2019	Hybrid / Multimodal	Multimodal fusion
[46]	2022	Text-based (Contextual embeddings — e.g., BERT)	Optical flow features
[62]	2022	Image/Video-based (Face + Time features)	Augmented forgery synthesis
[63]	2022	Video/Image-based (Forgery pattern features)	Local motion features
[64]	2023	Video-based (Motion features)	Frame-level feature extraction
[65]	2022	Hybrid (Text Contextual Embeddings + CNN Image Features)	BERT and VGG-16
[30]	2021	Multimodal (Text + Image) with Contextual Embeddings & Similarity Features	BERT
[26]	2019	Hybrid (Text Contextual Embeddings + Image Visual Features)	BERT, Pre-train model on ImageNet

embedding like BERT. The adoption of multi modal approaches is growing in recent years but on a limited scale. The implication of this observation is that hybrid feature engineering method can be the next big step in which textual and multi modal data will be integrated. The development of the specialized embedding for the noisy and code-mixed text can be a crucial research area.

4 Comparative Discussion & Trends

The important part of this review is the comparative discussion. The cross-table analysis reveals that performance is better in deep learning (DL) models like CNNs, RNNs and transformers than traditional ML models, especially when there is a use of embeddings like contextual word representation (BERT, fast-Text, Word2Vec). The size and quality of the dataset have a direct impact on the accuracy of model. Large and balanced datasets performed stable, whereas in low-resource performance is degraded. In the aspect of the language, results are best on English datasets, but accuracy is comparatively low on multilingual and code-mixed datasets. In feature engineering there is an outperformance TF-IDF and BoW, especially when deep learning is integrated.

There are some clear emerging trends in the literature. First, the rapidly adoption of DL models as it effectively handle the unstructured and noisy social media data. Second, there is growing interest in datasets standardization so

that a fair comparison can be enabled. Interest is rising in multilingual and low-resource languages, because fake news can be spread in any language and region. Fourth, there is a clear dominance of embedding like contextual representation, which better captures the semantic context as compared to the traditional statistical methods.

The important gaps identified in this review are Rare availability of high-quality datasets in low-resource languages. Lack of unified benchmarks, each study uses different datasets and metrics, making a fair comparison of performance difficult. Need of a consistent and practical evaluation framework to validate the generalization of models in real-world scenarios.

5 Challenges & Open Issues

In the field of fake news detection there are numerous technical, datasets and evaluation related challenges, which limits the both research and deployment. Fake news datasets are either very small or they are biased in nature, based on specific events, regions and languages. Along with that there is an issue of representation that datasets could't capture the real-world fake news diversity. because of that trained models will fail in actual scenario. From modeling perspective, DL models have significantly high computational cost and training time, which makes it difficult to deploy in resource-constrained environment. Interpretability is another issue, mostly complex models (especially deep architecture) have the black-box nature, which creates the barrier in trust and adoption. Additionally, Metric's inconsistency is very much prevalent in evaluation. Some studies report in accuracy, some F1 and some reports precision-recall trade off. As a result of direct comparison is unreliable. Second problem is the shortage of real-world validation, quite models were tested on controlled datasets, but they don't perform well on live social media streams and on evolving fake news patterns.

6 Future Directions

A major direction of future research will be large-scale, balanced and multilingual dataset's creation. These datasets reflect the real-world scenarios and applicable on different domains like politics, health, finance, entertainment. Along with, there is a need of temporal datasets which captures the evolving pattern of fake news. An important role in the future will be played by the Explainable AI (XAI), which interpret the decision of the models and builds the trust on the system. Other than this, there is a need to adopt the multimodal learning (text + image + videos), because fake news is not only in the textual format, but it can be spread through the multimodal content. Furthermore, evaluation inconsistency is another challenge. Every study uses the different datasets and performance metrics, by which fair compensation is not possible. There is the need of a standardized benchmark framework, in which common datasets and common metrics (F1-score, AUC, accuracy, precision) are mandatory. Along

with inculcation of cross-platform and real-time validation in required, so that practical deployment can be feasible.

7 Conclusion

Fake news detection is still an active and rapidly evolving research area, with machine learning and deep learning both showing promising results. This review makes it clear that despite progress, challenges such as dataset limitation, model interpretability, and evaluation inconsistencies still exist. Focus area for the future can be, Development of high-quality, multilingual and temporal datasets, Designing of innovative and interpretable model architecture, Establishment of standardized evaluation framework. If these gaps were effectively addressed, then fake news detection systems will go from research phase to real-world deployment phase.

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