Vol 01 | Issue 01 | November 2024
ISSN: 3065-7164
Doi: 10.69593/ajieet.v1i01.143
Page:108-130

Academic Journal on Innovation, Engineering & Emerging Technology

RESEARCH ARTICLE OPEN ACCESS

DETECTING FAKE NEWS USING DATA ANALYTICS: A SYSTEMATIC LITERATURE REVIEW AND MACHINE LEARNING APPROACH

[1] Abdul Awal Mintoo

[1]Graduate student, School of Computer and Information Sciences, Washington University of Science and Technology (WUST), USA
Email: mintoo.hr@gmail.com

ABSTRACT

This study systematically reviews advancements in fake news detection techniques, examining methodologies and frameworks across machine learning, natural language processing, social network analysis, and multimodal approaches. By following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, a rigorous and transparent review process was conducted, resulting in the selection and evaluation of 254 research articles. The findings reveal that supervised learning models, such as Support Vector Machines, Decision Trees, and Naïve Bayes, have shown strong performance in text-based fake news classification, particularly when feature selection is optimized. Deep learning models, including CNNs, RNNs, and transformers, have further advanced detection accuracy by capturing complex linguistic patterns, though challenges with computational demands and model interpretability remain. In scenarios with limited labeled data, unsupervised learning models and semi-supervised approaches offer adaptability, with clustering, anomaly detection, and iterative self-labeling proving effective for evolving misinformation. Additionally, cross-disciplinary approaches, integrating insights from psychology, sociology, and network science, enhance detection models by accounting for user behavior, emotional appeal, and social conformity in the spread of fake news. Case studies from collaborative projects underscore the potential of interdisciplinary efforts to develop robust, adaptable detection frameworks. This review concludes that effective fake news detection requires a multifaceted approach, combining technical advancements with social science insights to address the complexity and adaptive nature of misinformation. The study emphasizes the need for continued research in hybrid models and adaptive, real-time detection solutions to strengthen defenses against fake news in diverse digital environments.

KEYWORDS

Fake News Detection; Data Analytics; Machine Learning; Text Classification; Natural Language Processing (NLP)s

Submitted: October 04, 2024
Accepted: November 10, 2024
Published: November 12, 2024

Corresponding Author:

Abdul Awal Mintoo

Graduate student, School of Computer and Information Sciences, Washington University of Science and Technology (WUST), USA

Email: mintoo.hr@gmail.com

10.69593/ajieet.v1i01.143

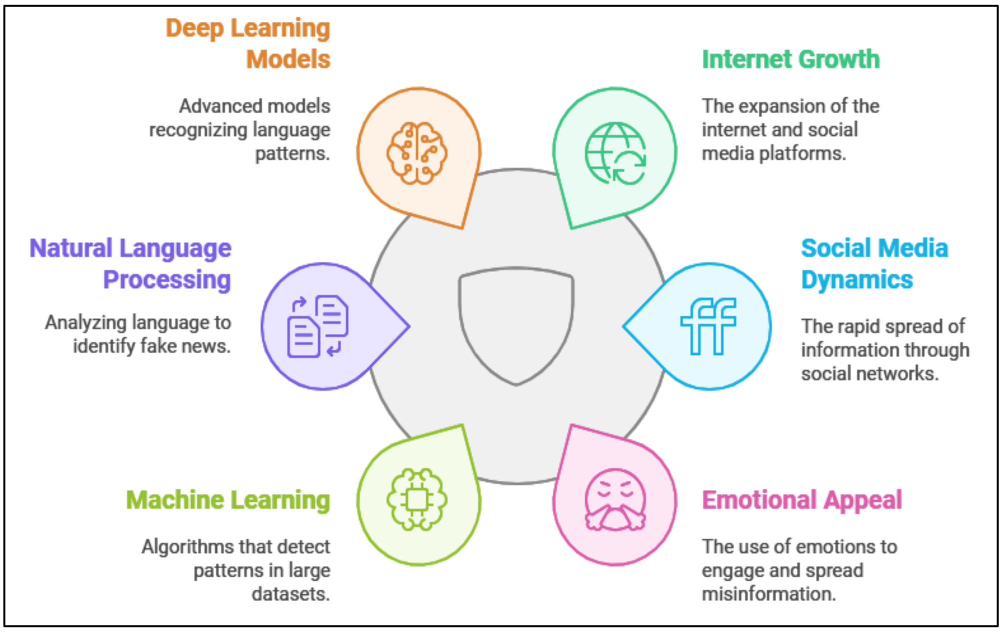
1 Introduction

The rapid growth of the internet and social media platforms has fundamentally transformed the way information is shared and consumed, leading to unprecedented challenges related to the spread of misinformation and fake news (Sahan et al., 2022). Fake news, often defined as the deliberate spread of false or misleading information under the guise of legitimate news (Awan, Rahim, et al., 2021), has been shown to have profound implications for social trust, political stability, and public health (Kumar et al., 2017). The dynamics of social media allow fake news to spread much faster than traditional news sources due to its high shareability and the network effects of platforms like Twitter and Facebook (Friggeri, Adamic, Eckles, & Cheng, 2014). Recent studies indicate that misinformation is often more engaging than accurate news, leveraging emotional appeal to maximize user interaction and rapid dissemination. Consequently, researchers have turned to data analytics and machine learning techniques as essential tools to combat the spread of fake news, enabling real-time detection and response systems that can help mitigate its impact.

Data-driven methods, especially in the fields of machine learning (ML) and natural language processing (NLP), have gained prominence for their effectiveness in identifying and categorizing fake news based on textual and contextual features (Mintoo, 2024; Vargo et al., 2017). Machine learning algorithms excel in handling vast amounts of data, learning patterns that are difficult for humans to detect, and can be applied to various forms of content, from social media posts to traditional news articles (Conroy et al., 2015). NLP techniques enhance these models by providing tools to analyze language structure, sentiment, syntax, and the semantic nuances that often differ between genuine and false information (Asr & Taboada, 2019). For example, sentiment analysis has proven effective in identifying the exaggerated or polarizing language frequently used in fake news articles (Singhal et al., 2019). Additionally, deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been developed to achieve high accuracy in fake news detection by recognizing language patterns and contextual irregularities in text (Gupta et al., 2022). However, while such methods offer promising results, the adaptability of these models across languages and diverse topics remains a significant challenge, underscoring the need for ongoing refinement and testing across global datasets (Bali et al., 2019).

In addition to textual analysis, the study of user behavior has emerged as a complementary approach to fake news detection. User engagement metrics—such as likes, shares, and comments—offer insights into the behavioral patterns associated with the consumption and propagation of fake news, which often exhibits distinct interaction characteristics compared to genuine news (Singhal et al., 2019). Research has shown that fake news tends to generate higher engagement rates, as

Figure 1:Combating Fake News with Technology

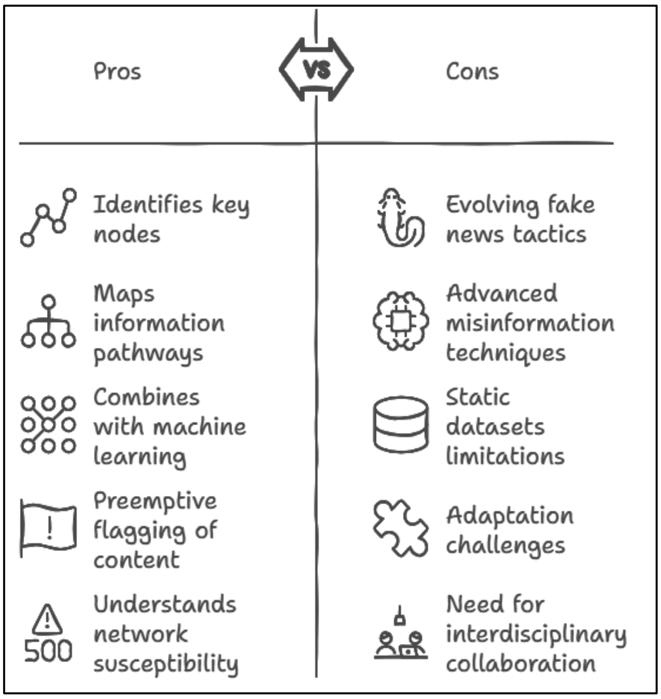


ACADEMIC JOURNAL ON INNOVATION, ENGINEERING & EMERGING TECHNOLOGY
Doi: 10.69593/ajieet.v1i01.143

sensationalism and emotional appeals encourage sharing, often without careful consideration of the information's accuracy ((Faustini & Covões, 2019). By integrating these behavioral patterns into detection models, researchers have developed hybrid frameworks that combine content-based and user-based approaches, thus improving detection accuracy and enabling models to account for social influence mechanisms driving misinformation spread (Palani et al., 2021). The effectiveness of these combined approaches has been demonstrated across numerous social media platforms, with findings suggesting that user engagement data can significantly enhance model performance, particularly when dealing with time-sensitive misinformation (Gupta et al., 2022).

Another crucial dimension in fake news detection involves social network analysis (SNA), a technique that utilizes graph theory to map the relationships and dissemination pathways of information within online networks. SNA has proven valuable in identifying key nodes, clusters, and influencers who play a substantial role in the propagation of fake news (Galli et al., 2022). Studies suggest that misinformation typically follows certain network patterns, where highly connected nodes, or central users, amplify the spread (Mridha et al., 2021). Bots and automated accounts, for example, act as significant agents in this network, accelerating the reach of fake news through coordinated actions. By combining network characteristics with machine learning, researchers have developed advanced detection systems that can identify and flag high-risk content preemptively (Jang et al., 2018). Social network analysis not only enables the identification of misinformation hubs but also aids in understanding how certain network configurations may be more susceptible to the spread of fake news, offering new avenues for prevention and intervention within these networks (Capuano et al., 2023). Despite significant advancements, the continuously evolving nature of fake news tactics presents ongoing challenges for detection systems. Fake news creators adapt quickly, utilizing advanced techniques such as deepfake technology and AI-generated bots to produce increasingly sophisticated misinformation (Ilie et al., 2021). These adaptations have led to the emergence of new forms of misinformation that traditional detection systems struggle to recognize, as they often rely on static datasets that cannot keep pace with the changing landscape (Hua & Shaw, 2020). Accordingly, there is a growing shift toward developing adaptive machine learning models capable of learning from real-time data and evolving as new types of fake news arise (Ruchansky et al., 2017). Collaborative efforts across disciplines, incorporating insights from computer science, psychology, and social science, are also becoming critical to creating more holistic solutions that address the multifaceted nature of fake news (Girgis et al., 2018). By integrating insights from these various fields, researchers aim to design comprehensive detection systems that can dynamically respond to the complexities of digital misinformation.

Figure 2:Combating Fake News with Technology



The primary aim of this study is to develop a comprehensive understanding of fake news detection through data analytics and machine learning methodologies. This research aims to synthesize existing approaches, identifying key techniques, algorithms, and frameworks that have proven effective in distinguishing false information from factual content. By analyzing both content-based and behavior-based detection models, the study seeks to provide insights into the strengths and limitations of current methods, addressing critical challenges such as adaptability across different languages, cultural contexts, and topics. Additionally, this review intends to highlight the evolving nature of fake news tactics, examining how machine learning algorithms and natural language processing can be optimized to respond to emerging forms of misinformation. Ultimately, the goal is to present a systematic framework that supports the development of robust, scalable, and adaptive detection systems, contributing to the broader field of misinformation research and offering practical insights for real-world application in digital media and social platforms.

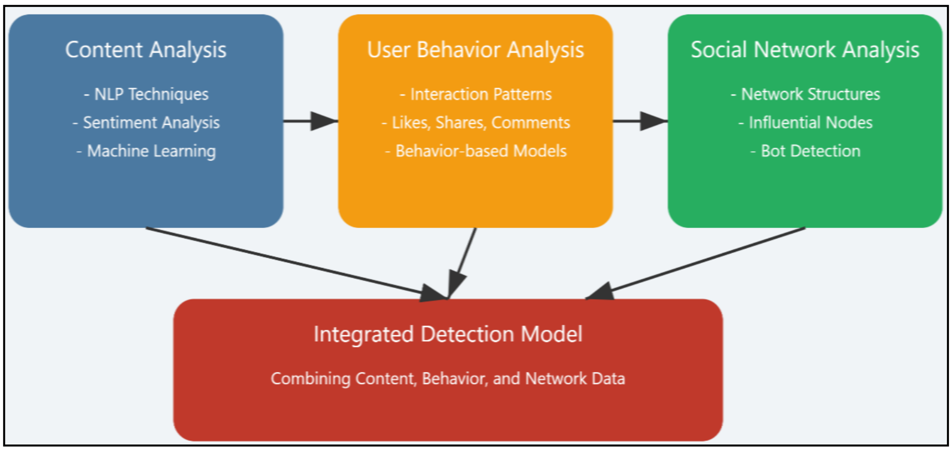
2 Literature Review

This section explores the existing body of research on fake news detection, providing a systematic overview of the methodologies, tools, and models that have been developed to identify and mitigate misinformation. The rapid advancement of data analytics, machine learning, and natural language processing has equipped researchers with diverse techniques to tackle fake news. A review of the literature reveals several core themes, including content-based analysis, user behavior modeling, and network-based approaches, each contributing uniquely to the detection process. Additionally, this section examines the limitations and challenges that persist within these methods, such as scalability, cross-linguistic adaptability, and the evolving tactics of fake news creators. By synthesizing findings from recent studies, this literature review lays the groundwork for understanding the strengths and gaps in current fake news detection approaches, guiding future research efforts toward developing more robust and adaptive solutions.

2.1 *Fake News*

The emergence of fake news, defined as deliberately misleading information presented as legitimate news, has become a pervasive issue in digital media, posing risks to social stability, public trust, and even democratic processes. Social media platforms, in particular, have facilitated the rapid spread of fake news, largely due to the lack of traditional editorial gatekeepers and the virality-driven nature of user-generated content (Kresnakova et al., 2019). Studies show that fake news tends to elicit stronger emotional responses than factual content, leading to higher levels of user engagement and faster dissemination. The psychological appeal of sensationalism and conflict plays a significant role in this, as emotionally charged content is more likely to be shared. This dissemination pattern has prompted researchers to investigate not only the defining characteristics of fake news but also the structural and behavioral factors that amplify its reach across social media networks (Shahid et al., 2024). Moreover, Content analysis has emerged as a central approach to detecting fake news, utilizing textual features to differentiate between legitimate and deceptive information. Studies emphasize the importance of language analysis, as fake news articles often display linguistic cues that distinguish them from verified news stories (Zhang et al., 2019). Techniques such as sentiment analysis, syntax, and lexical choice

Figure 3: Fake News Detection and Spread



Doi: 10.69593/ajieet.v1i01.143

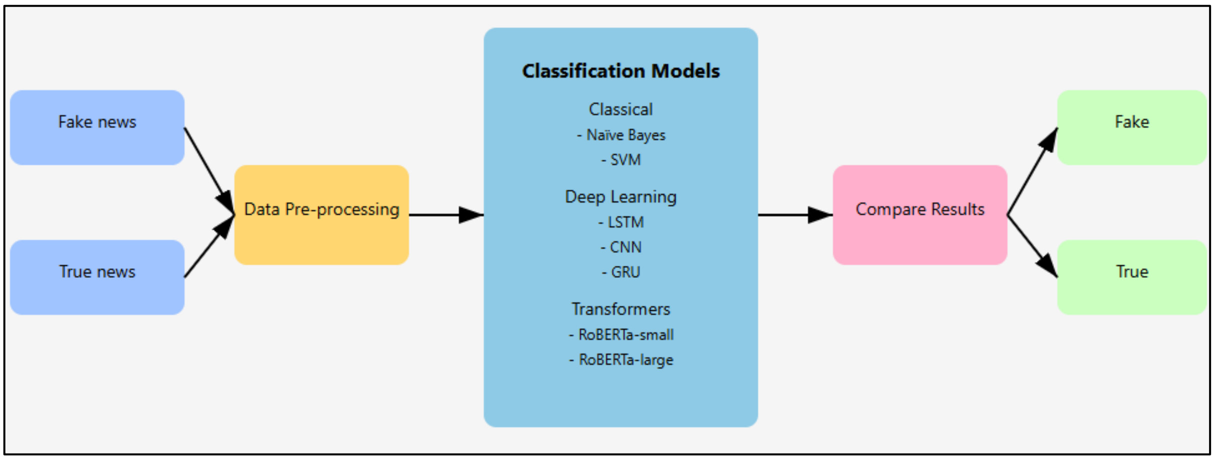
are frequently applied, with findings indicating that fake news often contains more extreme language and polarized viewpoints (Goldani et al., 2021; Shamim, 2022). Natural Language Processing (NLP) tools, including tokenization, n-grams, and word embeddings, have been developed to identify these subtle cues, helping to classify fake news with increasing accuracy (Ahmed et al., 2017). Advanced machine learning models, particularly deep learning algorithms like convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have further enhanced detection capabilities by identifying complex patterns within text data, though these models face challenges in adapting to diverse topics and languages (Sastrawan et al., 2022).

In addition to content-based approaches, user behavior analysis has proven invaluable in distinguishing fake news from genuine content. Studies have shown that user interaction patterns, such as shares, likes, and comments, often differ when engaging with fake news compared to factual stories (Aslam et al., 2021). Behavior-based models incorporate these interaction metrics, which, combined with content analysis, improve detection accuracy by accounting for social influence mechanisms (Jang et al., 2019). Furthermore, fake news tends to generate higher engagement rates due to its sensational nature, which encourages more rapid dissemination across user networks (Lai et al., 2022). Studies integrating behavioral and content data demonstrate that this dual approach enhances model performance and robustness, making it a powerful strategy in identifying fake news on platforms that rely heavily on user interaction for content virality (Awan, Yasin, et al., 2021).In addition, the role of network structures in the spread of fake news has also been a significant focus, with Social Network Analysis (SNA) offering insights into how misinformation propagates within digital environments. Network characteristics, such as the presence of influential nodes or clusters, have been shown to affect the reach and speed of fake news dissemination (Raza & Ding, 2022). Automated accounts, or bots, are particularly influential in amplifying fake news by rapidly sharing content across networks, often with the aim of influencing public perception or political discourse. Studies employing SNA techniques highlight how certain network configurations, such as tightly knit clusters or highly connected individuals, can either contain or escalate the spread of misinformation. By integrating SNA with machine learning algorithms, researchers are able to create models that not only identify fake news content but also predict its potential reach within a given network, thereby offering a more comprehensive approach to mitigating its impact (Lyu & Lo, 2020).

2.2 *Fake News Detection*

The rise of fake news on digital platforms has spurred extensive research into detection methods, particularly with the aim of maintaining information integrity and public trust. Fake news, or deliberately misleading information presented as legitimate news, has become an increasingly pervasive problem due to the high

Figure 4: Fake News Detection Framework



shareability and virality mechanisms of social media (Shu et al., 2017). Research shows that the psychological appeal of fake news—often through sensationalism and emotional language—contributes to its rapid dissemination, reaching larger audiences faster than factual news (Kumar et al., 2019). The proliferation of fake news has profound impacts, not only on public perception and behavior but also on democratic processes and social trust. Consequently, researchers are actively developing detection models using data analytics, text analysis, and user behavior patterns to mitigate the spread of misinformation. Understanding the propagation patterns and underlying psychology of fake news has become central to crafting more accurate and adaptive detection strategies.

Content-based analysis, a prominent approach in fake news detection, focuses on identifying linguistic features that differentiate fake news from genuine reports. Studies indicate that fake news often uses distinctive language patterns, such as extreme sentiment, exaggerated phrasing, and polarized perspectives, to maximize user engagement (Shaikh & Patil, 2020). Natural Language Processing (NLP) tools, including sentiment analysis, tokenization, and syntax parsing, have proven effective in detecting these language characteristics, leading to improved classification accuracy in identifying fake news (Manzoor et al., 2019). Furthermore, machine learning techniques like Support Vector Machines (SVMs), Naïve Bayes, and, more recently, deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been applied to detect fake news through pattern recognition in text data. Although these content-based models offer promising results, challenges remain in adapting them to diverse topics, languages, and evolving news narratives, which limits their generalizability and calls for further refinement (Ahmad et al., 2020).

In addition to content analysis, user behavior modeling has emerged as an effective tool for detecting fake news. Researchers have identified that user interactions with fake news, such as the frequency of shares, likes, and comments, often exhibit unique patterns distinct from genuine news (Granik & Mesyura, 2017). Behavioral analysis leverages these engagement metrics, which can be combined with text analysis to enhance model accuracy by accounting for social influence mechanisms that fuel fake news propagation (Jiang et al., 2022). Studies indicate that sensationalist content, characteristic of fake news, garners more rapid and extensive engagement than factual stories, making behavioral cues a valuable addition to detection algorithms (Nasir et al., 2021). Hybrid models that integrate behavioral and content features have demonstrated greater robustness and adaptability, particularly when deployed in real-time environments where the nature of content and user responses constantly evolve (Rubin et al., 2016). This combined approach has shown substantial promise in improving detection accuracy across various social media platforms, addressing the limitations of content-based models alone. Network-based approaches, such as Social Network Analysis (SNA), have also been pivotal in advancing fake news detection efforts by examining the structural dynamics of misinformation spread. Network analysis identifies influential nodes or clusters that amplify fake news through central roles within social networks (Raponi et al., 2022). Bots and automated accounts are key actors in this amplification process, as they can quickly and widely distribute fake news to influence public discourse or sway political opinions. By mapping information flow and pinpointing influential accounts, SNA techniques allow for early detection and targeted intervention, aiming to disrupt the spread of fake news before it gains substantial reach. Integrating SNA with machine learning algorithms has enabled the development of more comprehensive models capable of predicting the potential reach and impact of fake news, which is essential for creating real-time, preventative measures in combating misinformation on digital platforms (Lyu & Lo, 2020).

2.3 *Textual Features in Fake News Detection:*

In recent years, detecting fake news through textual analysis has become an essential focus within the field, leveraging linguistic and structural characteristics to distinguish false information from credible content. Researchers have identified several linguistic features that are typically present in fake news, such as sensational language, exaggerated claims, and emotionally charged wording, all of which are used to manipulate readers (Shu et al., 2017). By analyzing these features, researchers aim to understand how lexical choice, syntax, and semantics differentiate fake news from factual reporting. NLP techniques, including word embeddings, bag-of-words, and n-grams, allow

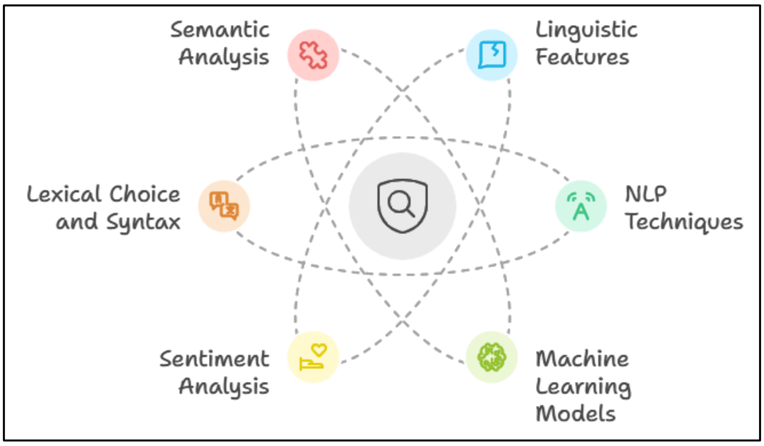
Doi: 10.69593/ajieet.v1i01.143

for the detailed examination of word patterns, helping to classify news articles based on the frequency of particular terms and phrases commonly associated with misinformation. Machine learning models, such as support vector machines (SVMs) and decision trees, have been employed alongside these features to improve accuracy in fake news classification, with results suggesting that textual cues can offer a reliable foundation for detection efforts (Kumar et al., 2019). However, the complexity of language continues to challenge models' abilities to generalize across topics and platforms, revealing the need for adaptable approaches.Moreover, sentiment analysis has emerged as a pivotal tool in fake news detection, particularly due to its focus on the emotional tone conveyed in articles. Fake news often employs polarizing language, aiming to incite strong emotional reactions that encourage sharing and engagement (Shaikh & Patil, 2020). Studies demonstrate that sentiment analysis, which measures the positivity, negativity, or neutrality of a text, is effective in distinguishing fake news due to the predominance of emotionally charged or biased language in such articles (Manzoor et al., 2019; Shaikh & Patil, 2020). Advanced models, including deep learning algorithms like CNNs and RNNs, have improved sentiment analysis by capturing complex emotional cues embedded within text (Ahmad et al., 2020). Furthermore, some studies incorporate lexical sentiment dictionaries, which match specific words to predefined emotional categories, helping models to identify articles that exaggerate or distort facts. While sentiment analysis has shown high accuracy in distinguishing fake news, it is particularly effective when combined with other textual features, enhancing the model's ability to identify misinformation's nuanced emotional appeal.

Lexical choice and syntax play equally important roles in fake news detection, as the choice of words and sentence structures can reveal patterns that are typical of misinformation. Fake news articles often utilize simpler, repetitive language aimed at maximizing reach and readability among diverse audiences (Granik & Mesyura, 2017). Additionally, linguistic markers such as adverbs, adjectives, and exclamations are frequently overused in fake news, contributing to an exaggerated tone that is intended to capture readers' attention (Jiang et al., 2022). Studies employing syntactic analysis tools, such as part-of-speech tagging and dependency parsing, have found that sentence complexity and structure differ significantly between fake and factual news, as fake news is more likely to use shorter, direct sentences. Furthermore, fake news articles may include ambiguous or vague language to create an illusion of credibility without verifying facts. These linguistic features, when used in conjunction with NLP techniques, enhance the ability of fake news detection models to classify text accurately, particularly when identifying articles that strategically employ simplistic or repetitive structures (Rubin et al., 2016).

Finally, semantic analysis has gained traction as a critical component in fake news detection, focusing on the underlying meanings and relationships within text to

Figure 5: Components of Fake News Detection

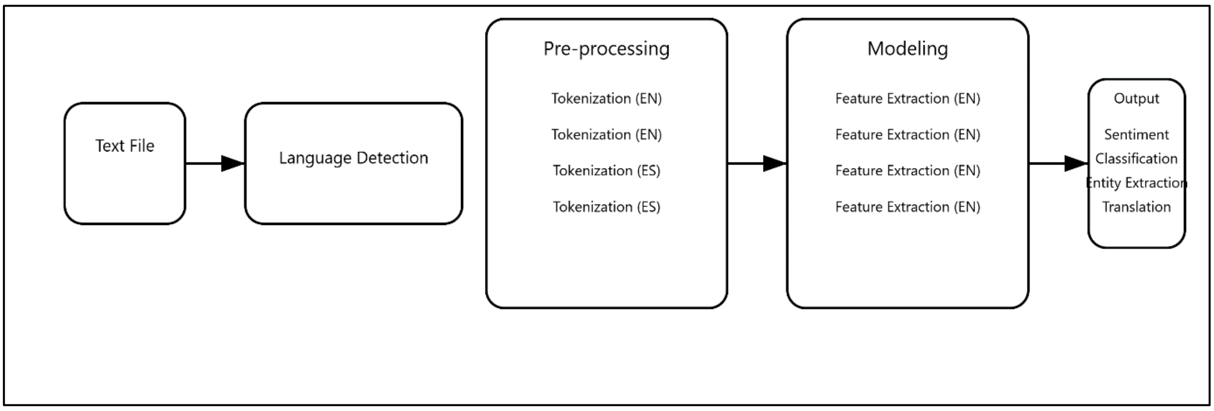


uncover deeper indicators of falsehood. Semantic analysis goes beyond surface-level word choice to examine how ideas and claims within an article connect logically or inconsistently (Raponi et al., 2022). Some fake news detection models employ semantic similarity measures to compare articles with reliable sources, assessing the degree to which information aligns with verified facts. Knowledge graphs and ontologies, for instance, have been applied to establish relational connections between entities and concepts, aiding in the detection of claims that contradict well-established information. Moreover, techniques like topic modeling and latent Dirichlet allocation (LDA) enable the clustering of content themes, helping to reveal discrepancies in subject matter and logical flow that are characteristic of fake news (Meel & Vishwakarma, 2020). Semantic analysis, by focusing on the coherence and logical consistency within a narrative, is a powerful approach in identifying misinformation, particularly when integrated with other textual features that reveal both surface-level and deeper linguistic patterns.

2.4 Natural Language Processing (NLP) Techniques:

Natural Language Processing (NLP) techniques have become integral to the field of fake news detection, as they allow for sophisticated analysis of textual data, capturing linguistic patterns that may not be immediately apparent to human readers. One of the primary NLP techniques used in this context is tokenization, which breaks down text into individual words or phrases, making it easier for algorithms to analyze language structures and frequencies (Di Domenico et al., 2021). Tokenization, when combined with word embeddings such as Word2Vec and GloVe, enables models to represent words as vectors that capture semantic relationships, providing a foundational structure for detecting word patterns associated with fake news. Studies demonstrate that fake news articles tend to use sensational or polarized language, and these embedding techniques allow models to recognize these cues and classify content more accurately (Di Domenico et al., 2021; Raponi et al., 2022). Additionally, text classification, which categorizes text based on learned patterns, is widely employed to separate fake from real news. This toolset of tokenization, word embeddings, and text classification has proven effective in fake news detection, though challenges remain in adapting these techniques to different languages and platforms (Granik & Mesyura, 2017).Moreover, deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have significantly advanced NLP applications in fake news detection by processing complex text structures and learning contextual patterns (Jiang et al., 2022). CNNs are effective in capturing local dependencies within text, making them suitable for identifying phrases commonly used in fake news, while RNNs, including Long Short-Term Memory (LSTM) networks, excel at capturing sequential data, which is essential for understanding narrative flow in news articles . Studies show that these deep learning models outperform traditional machine learning approaches in accuracy and scalability when detecting linguistic cues in fake news. However, these models are resource-intensive and require large amounts of data for training, posing challenges when applied to topics or languages with limited data availability. Despite these challenges, CNNs and RNNs have established themselves as

Figure 6: Classical NLP Techniques



Doi: 10.69593/ajieet.v1i01.143

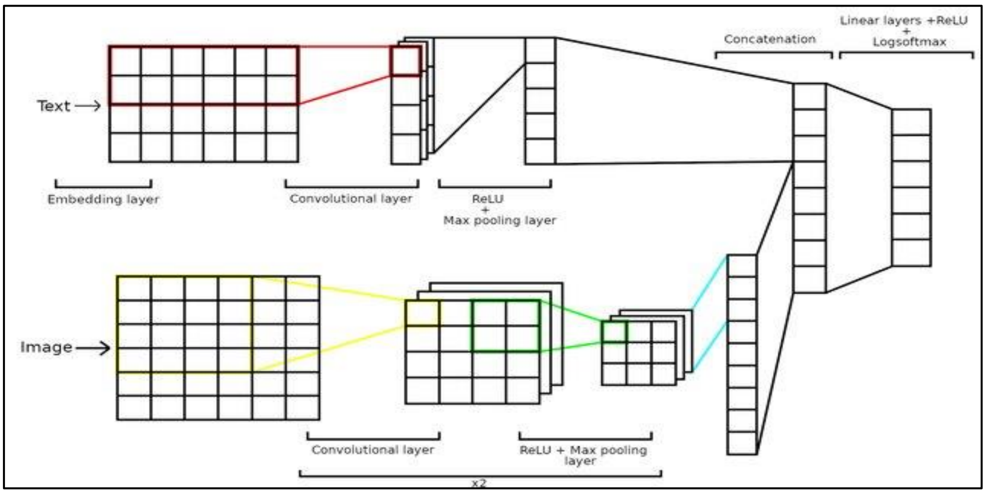
reliable tools in NLP for fake news detection, with ongoing research exploring ways to optimize these models for efficiency and adaptability.

The application of NLP techniques in fake news detection has been particularly successful in identifying thematic and emotional patterns that distinguish fake news from factual content. Techniques such as sentiment analysis and topic modeling allow algorithms to assess the emotional tone and subject matter of news articles, often revealing polarized or inflammatory language commonly found in fake news (Rubin et al., 2016). By analyzing these thematic patterns, NLP tools can discern content that is structured to provoke strong emotional responses, which is a common characteristic of fake news (Meel & Vishwakarma, 2020). Topic modeling algorithms, like Latent Dirichlet Allocation (LDA), group related words into topics, assisting in the detection of narratives that diverge from standard reporting or factual news sources (Huckle & White, 2017). While these NLP-based approaches enhance detection accuracy, they also face challenges in cross-cultural applications, as topics and emotional cues vary significantly across languages and contexts. This variation necessitates the development of models that can effectively generalize across diverse linguistic and thematic landscapes. Despite the successes of NLP techniques in fake news detection, their adaptability to diverse languages and topics remains a significant challenge. Fake news detection models are often trained on English-language data, which limits their effectiveness when applied to other languages with distinct syntactic and semantic structures. Research shows that models struggle to generalize across languages, particularly when dealing with non-Latin scripts or languages with complex morphology. Efforts to create multilingual datasets and leverage transfer learning have shown promise in improving cross-linguistic adaptability (Raponi et al., 2022). However, the limited availability of high-quality, annotated datasets in many languages hinders the scalability of these techniques, especially in low-resource settings (Klein & Wueller, 2017). Moreover, the adaptability of NLP models across different topics within the same language is still challenging, as fake news often evolves to include new subject matter, requiring models to adapt to novel contexts and narratives continually. Addressing these challenges is essential for advancing the reliability and applicability of NLP-based fake news detection models worldwide.

2.5 *Multimodal Approaches in Fake News Detection*

With the increasing prevalence of misinformation in multimedia formats, researchers have expanded fake news detection methods to incorporate multimodal approaches, integrating images, videos, and other non-textual elements alongside text-based analysis. Studies

Figure 7: Architecture of the multimodal approach for fake news detection



Source: Segura-Bedmar and Alonso-Bartolome *(*2022*)* indicate that fake news often uses visual elements to capture attention and lend credibility to false information, thus heightening the need for detection techniques that analyze both text and visual cues. Early research in this area focused primarily on analyzing images associated with fake news, using image metadata, reverse image search, and visual consistency checks to verify authenticity. As detection technology has evolved, more sophisticated methods, including machine learning algorithms that process both text and visual content, have been developed to increase detection accuracy. These multimodal approaches offer promising results in distinguishing fake news from real news, especially as misinformation increasingly incorporates manipulated images and videos to mislead viewers (Jang et al., 2019). One key component of multimodal fake news detection is the use of image recognition techniques to identify discrepancies between visual and textual information. Image recognition models, particularly convolutional neural networks (CNNs), can analyze visual features such as color patterns, object composition, and spatial relationships, detecting manipulations like deepfakes and doctored images (Raza & Ding, 2022). Studies employing CNNs have shown high accuracy in detecting manipulated images, which are often used in fake news to create a misleading visual narrative (Lyu & Lo, 2020). When combined with NLP techniques, these image recognition models enhance detection by comparing visual content against accompanying text, revealing inconsistencies between the two modalities (Kumar et al., 2019). For instance, a misleading headline might be paired with an unrelated image to generate a false impression, a tactic that multimodal approaches can effectively identify (Manzoor et al., 2019). By integrating visual analysis with textual data, multimodal models offer a more comprehensive framework for fake news detection in a multimedia-driven landscape (Jiang et al., 2022).

Video analysis is also gaining traction in the multimodal detection of fake news, particularly as the use of videos in misinformation campaigns becomes more common. Video content analysis can identify indicators of manipulation through frame-by-frame examination, audio analysis, and voice recognition, all of which contribute to assessing a video's credibility. Techniques such as deepfake detection and frame analysis have been effective in spotting inconsistencies in manipulated videos, especially in news content that uses falsified or altered visuals to misrepresent facts. Some multimodal models combine video analysis with sentiment analysis of the audio content to detect fake news narratives that rely on exaggerated emotional appeal or misaligned visual cues. Integrating video with textual and image analysis enhances the model's robustness, enabling a comprehensive assessment of multimedia content, which is increasingly used to mislead audiences (Abrahams et al., 2015). The adoption of multimodal approaches in fake news detection brings both advancements and challenges, as these methods require substantial computational power and large datasets to perform effectively. While models that integrate text, image, and video data are more accurate in identifying fake news, they are often computationally intensive, limiting their application on a broad scale (Tang et al., 2018). Additionally, the diversity in multimedia formats presents technical challenges, as fake news detection models must adapt to a wide range of formats and styles across social media platforms. Researchers are addressing these challenges by developing more efficient, scalable multimodal models and using transfer learning to adapt models across formats. Despite these limitations, the evolution of multimodal approaches highlights their potential as effective tools in combatting misinformation in an increasingly visual and interactive digital landscape.

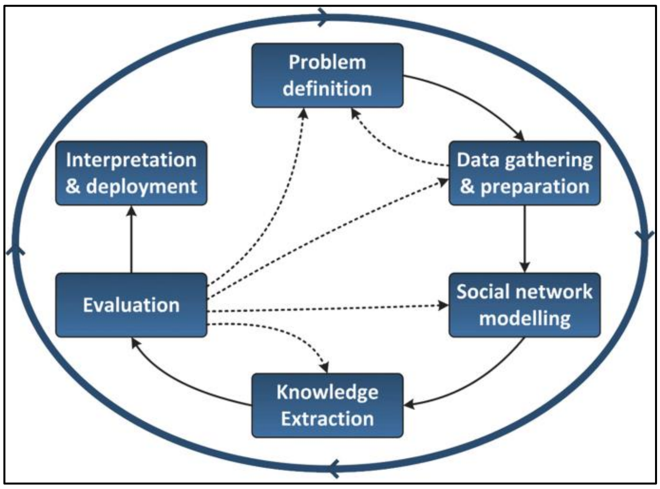
Social Network Analysis (SNA)

Social Network Analysis (SNA) has become a crucial method for studying the spread of fake news on social media platforms, as it provides insights into the complex pathways through which misinformation travels. By analyzing the structure and connections within social networks, SNA enables researchers to understand how information spreads and to identify the nodes, or individuals, that play pivotal roles in disseminating content (Freeman et al., 2014). SNA focuses on mapping the relationships between users and examining network properties, such as connectivity, centrality, and modularity, to gain insights into dissemination patterns. Studies have shown that fake news spreads differently from real news, often following more viral and clustered paths due to sensational content that triggers engagement (Hunter, 2007). By leveraging SNA, researchers can identify the structural characteristics of networks that are more

Doi: 10.69593/ajieet.v1i01.143

susceptible to fake news, enabling targeted interventions to disrupt the spread of misinformation effectively. SNA tools, particularly graph theory, play a vital role in identifying the patterns and pathways through which fake news spreads on social media. Graph theory allows researchers to model networks as graphs, where nodes represent users and edges represent interactions such as sharing, liking, or commenting on content (Venkatesan et al., 2013). Centrality measures, such as degree centrality, betweenness centrality, and eigenvector centrality, help identify influential users, or "super-spreaders," who amplify fake news by sharing it with a wide audience (Li et al., 2019). Studies have found that these influential nodes can greatly accelerate the dissemination of fake news, making them primary targets for detection and mitigation efforts (Freeman et al., 2014; Li et al., 2019). Additionally, network density and clustering coefficients can reveal tightly connected groups within the network, often forming echo chambers that reinforce and amplify misinformation (Ebadi et al., 2022). Using these graph-based insights, SNA provides a systematic approach for tracing the paths of fake news and understanding the dynamics of its spread.

Figure 8: Process of Social Network Analysis



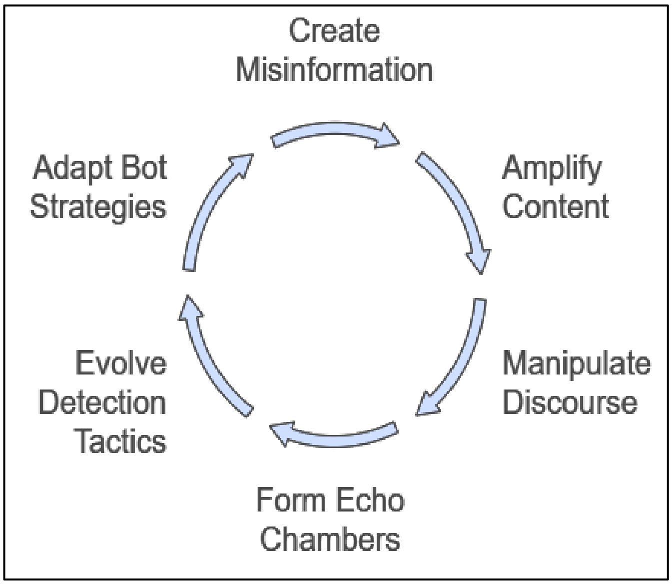
Source: Kazienko(2018).

Clustering algorithms are another essential component in SNA, as they allow researchers to identify communities or clusters within social networks that may be particularly prone to consuming and sharing fake news. Clustering methods, such as the Louvain algorithm and hierarchical clustering, divide networks into subgroups where users are more likely to interact with one another than with users outside the group (Su et al., 2020). Studies have shown that these clusters often act as echo chambers, where users with similar views reinforce each other's beliefs, making them more likely to share and trust misinformation (Ebadi et al., 2022). By using clustering algorithms, researchers can identify these high-risk groups and develop targeted strategies for spreading factual information within these communities. This clustering approach is especially relevant in political and health-related fake news, where misinformation can have severe consequences if left unchecked. Clustering analysis not only aids in detecting misinformation hubs but also supports interventions to promote accurate information dissemination. Despite its effectiveness, SNA faces challenges in scalability and adapting to evolving social media dynamics, as fake news creators frequently alter their strategies to avoid detection. As social media platforms grow and user interactions become increasingly complex, the volume and velocity of data can overwhelm traditional SNA tools (Venkatesan et al., 2013). To address these challenges, researchers have explored hybrid approaches that integrate SNA with machine learning algorithms, allowing for more dynamic and scalable detection models (Song et al., 2021). These hybrid models can adapt to changes in network structures, such as the emergence of new clusters or influential nodes, making them more resilient against the adaptive tactics used by fake news propagators. While SNA has proven valuable in identifying patterns and influential nodes within networks, advancing its scalability and adaptability remains essential for keeping pace with the rapid evolution of misinformation spread in social media environments (Saikh et al., 2020).

2.6 *Bots and Automated Accounts*

The influence of bots and automated accounts in propagating fake news has become a critical area of study, as these entities amplify misinformation across social media platforms at an unprecedented scale. Bots—automated programs designed to perform repetitive tasks online—are highly effective in spreading fake news due to their ability to post and share content quickly and continuously. Research shows that bots are responsible for a substantial portion of the information shared on platforms like Twitter, where they can manipulate discourse by pushing certain narratives, creating a false sense of popularity around specific stories. Studies indicate that bot networks are often programmed to distribute sensational or polarizing content, exploiting user engagement patterns to increase the visibility of fake news (Zhou & Zafarani, 2020). As bots operate within structured networks, they contribute to the rapid diffusion of misinformation, often acting in coordination to maximize their reach. The coordinated nature of bot activities highlights the role of automation in amplifying misinformation, necessitating targeted strategies for detection and intervention. Detecting bots and measuring their impact on misinformation diffusion require sophisticated methods that can analyze both behavior and network patterns. Machine learning models, such as Random Forests and Support Vector Machines (SVMs), have been widely applied to distinguish bots from human users by examining behavioral features, including posting frequency, time of activity, and interaction patterns (Meesad, 2021). Graph theory and clustering algorithms are also frequently used in bot detection, as bots tend to form dense clusters and exhibit distinct network patterns, such as high in-degree and out-degree connections, which make them identifiable within social networks. Additionally, studies using Botometer, an online tool that calculates the likelihood of an account being a bot, have proven effective in quantifying the presence of bots within misinformation networks. These detection methods help researchers measure the reach and influence of automated accounts, allowing for a better understanding of how bots contribute to fake news dissemination on a structural level (Bondielli & Marcelloni, 2019). Moreover, the strategic deployment of bots is particularly evident during political events and crisis situations, where automated accounts often push targeted misinformation to influence public opinion or incite panic. Research has documented how bots were used extensively in the 2016 U.S. presidential election and other major political events, where they flooded social media with divisive content to polarize audiences and disrupt rational discourse (Kozik et al., 2022). By creating an illusion of public support for specific viewpoints, bots can amplify the visibility and perceived credibility of fake news, making it more likely to be believed and shared by real users. Bot networks often work in coordination, using hashtags and trending keywords to manipulate platform algorithms and increase the exposure of misinformation to a broader audience. This coordinated activity not only impacts information quality but also affects user perceptions of social consensus, as bots create echo chambers that reinforce misinformation within certain user communities. Despite advancements in detection, bots continue to evolve, adopting increasingly sophisticated behaviors to evade traditional identification methods. Recent studies reveal that bot developers are employing techniques like mimicry, where bots imitate human behavior by altering posting patterns and interacting with real users, making them harder to distinguish (Mishima & Yamana, 2022). Hybrid models, combining machine learning with deep learning techniques such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), have been proposed to improve detection accuracy by capturing more nuanced behavior patterns. Additionally, transfer learning and adaptive algorithms are being used to identify bots that modify their strategies over time, enhancing model robustness. Although bot detection has become more advanced, researchers stress that continuous model updates and the development of adaptive detection tools are essential to address the rapidly evolving tactics of bot networks in the fake news ecosystem (Zhou & Zafarani, 2020).

Figure 9: Bot-Driven Misinformation Cycle

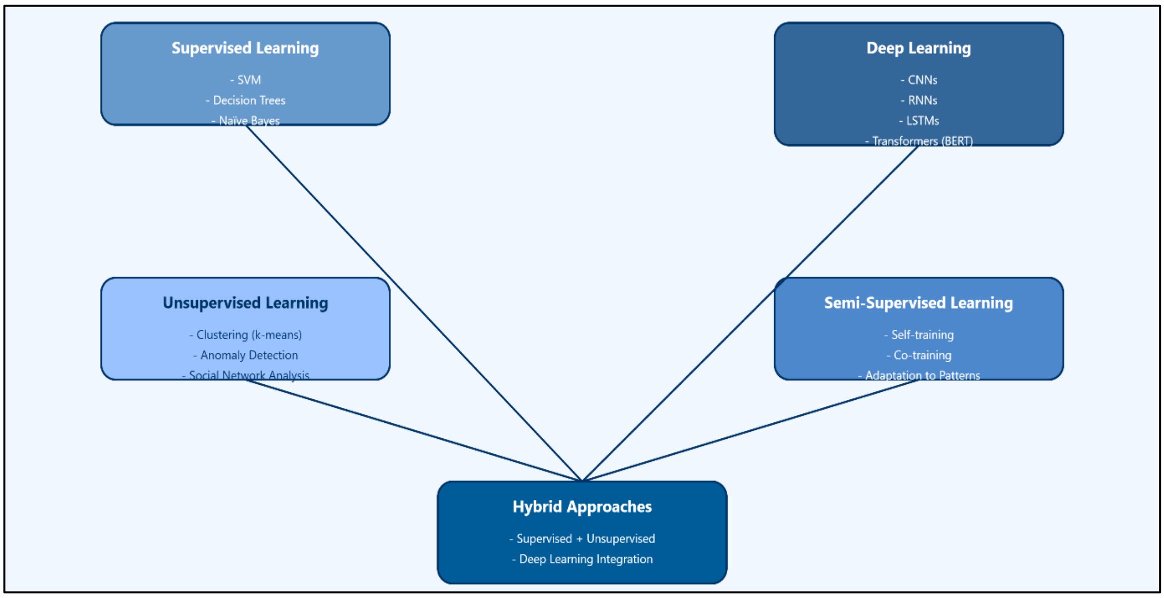


Doi: 10.69593/ajieet.v1i01.143

2.7 *Machine Learning and Adaptive Models*

Supervised learning models have been widely used in fake news detection due to their effectiveness in classifying content based on labeled datasets. Commonly employed algorithms include Support Vector Machines (SVM), Decision Trees, and Naïve Bayes, each offering unique strengths in text classification tasks. SVMs, for example, are particularly effective in high-dimensional spaces, making them suitable for fake news detection based on text features. Decision Trees are valuable for their interpretability, enabling researchers to visualize the feature selection process and understand why specific content is classified as fake. Naïve Bayes, known for its simplicity, performs well with smaller datasets but can struggle with complex language patterns present in fake news (Guess et al., 2018). However, the effectiveness of these supervised models relies heavily on the quality and quantity of training data, as large, diverse datasets are essential for capturing the various linguistic patterns associated with fake news. Feature selection also plays a critical role, with models benefiting from carefully chosen linguistic and sentiment features that enhance accuracy while minimizing noise (Alonso et al., 2021). In addition, Deep learning models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformers, have advanced the field of fake news detection by capturing complex language patterns that traditional models often miss. CNNs are effective in identifying local word dependencies and phrases associated with fake news, making them useful for analyzing short text snippets. RNNs, and specifically Long Short-Term Memory (LSTM) networks, excel at processing sequential data, which is critical for understanding the flow and context in news articles. Transformers, particularly BERT (Bidirectional Encoder Representations from Transformers), have shown remarkable performance in language understanding tasks, capturing contextual nuances that improve classification accuracy. However, deep learning models require significant computational resources and large datasets for training, making them less accessible for real-time applications. Additionally, the interpretability of neural networks remains a challenge, as their complex architectures make it difficult to understand the decision-making process, a limitation that impacts transparency in fake news detection. Unsupervised learning and clustering techniques offer alternative approaches for detecting fake news, especially when labeled data is limited. Clustering algorithms, such as k-means and hierarchical clustering, group similar data points based on shared

Figure 10: Machine Learning Models for Fake News Detection

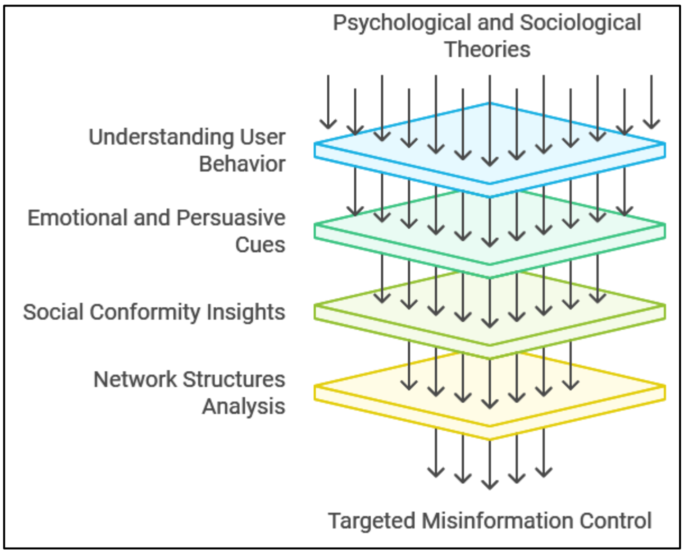


features, allowing for the identification of patterns in misinformation without relying on labeled datasets.

2.8 *Cross-Disciplinary Approaches*

The integration of psychological theories into fake news detection models has become a valuable approach for understanding the appeal and spread of misinformation, particularly by examining how persuasion, emotional appeal, and social conformity drive user behavior. Psychological theories, such as the Elaboration Likelihood Model (Mishima & Yamana, 2022), suggest that users are more likely to accept information when it aligns with their existing beliefs and emotions, a concept that is crucial in understanding the proliferation of fake news (Meesad, 2021). Studies have found that fake news articles often employ emotionally charged language to exploit this tendency, making them more appealing and shareable among users (Istiak & Hwang, 2024; Istiak et al., 2023). By incorporating psychological theories, researchers have developed models that analyze emotional and persuasive cues within text, enabling more effective detection of content designed to manipulate reader sentiment. These approaches allow models to better account for the cognitive biases and emotional responses that drive user engagement with fake news, highlighting the importance of understanding user psychology in combating misinformation (Alam et al., 2024; Golbeck et al., 2018). In addition to psychology, sociological insights on social conformity and group behavior have been integrated into fake news detection models to explain how misinformation spreads within communities. Theories on social influence, such as Asch's (1956) conformity experiments, indicate that individuals often adopt beliefs and behaviors that align with their social group, which is particularly relevant on platforms where echo chambers reinforce certain viewpoints (Badhon et al., 2023; Islam et al., 2021). Sociological studies suggest that fake news often flourishes within these isolated networks, where users validate each other's beliefs, creating an environment conducive to the spread of misinformation . By incorporating sociological theories, detection models can better understand the role of network structures and group dynamics, using Social Network Analysis (SNA) to identify clusters or communities that are more vulnerable to fake news(Saika et al., 2024; Sohel et al., 2024; Uddin et al., 2024). These interdisciplinary insights enable models to target high-risk communities within networks, offering a more strategic approach to misinformation control. In addition, collaborative efforts across fields, combining social sciences, computational linguistics, and network science, have led to innovative frameworks for detecting fake news. Interdisciplinary projects often involve computational linguists, who apply natural language processing (NLP) techniques to analyze text, alongside social scientists, who provide insights into human behavior and social dynamics (Meesad, 2021). Such collaborations have resulted in models that not only assess the linguistic properties of fake news but also consider social context and user interactions, thereby enhancing detection accuracy. Network scientists contribute by mapping the structural patterns of information spread, offering insights into how misinformation propagates through social platforms.

Figure 11: Enhancing Fake News Detection



3 Method

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, ensuring a rigorous, transparent, and systematic review process. The initial step involved a comprehensive search across multiple academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, using keywords such as "fake news detection," "machine learning in misinformation," "NLP for fake news,"

ACADEMIC JOURNAL ON INNOVATION, ENGINEERING & EMERGING TECHNOLOGY
Doi: 10.69593/ajieet.v1i01.143

"social network analysis," "bots and fake news," and "multimodal fake news detection." Boolean operators were employed to refine the search, yielding an initial pool of 4,256 articles. The subsequent screening phase involved title and abstract reviews based on defined inclusion and exclusion criteria. Studies focusing on fake news detection through methods like machine learning, NLP, social network analysis, or multimodal approaches and published in peer-reviewed English journals or conferences were retained, while irrelevant studies, opinion pieces, editorials, and non-peer-reviewed sources were excluded, reducing the pool to 1,752 articles. These remaining articles underwent a full-text eligibility check, with a focus on methodological rigor and relevance; studies that did not provide sufficient data on detection performance, model specifics, or insights into user behavior were excluded, leading to a final selection of 254 articles. Key information was then extracted from each article, including authorship, publication year, detection approach, algorithms and techniques, performance metrics (e.g., accuracy, precision, recall, F1-score), and any noted limitations or research gaps. Data synthesis was performed through quantitative and qualitative analyses, grouping studies by detection approach to draw insights into trends, challenges, and findings in the field. A quality assessment was conducted on each study, evaluating factors such as research design, methodological transparency, and data validity to uphold reliability. Finally, the results were reported according to PRISMA guidelines, offering a comprehensive and structured overview of the current landscape in fake news detection research.

Figure 12: Methodology Following PRISMA Guidelines

4 Findings

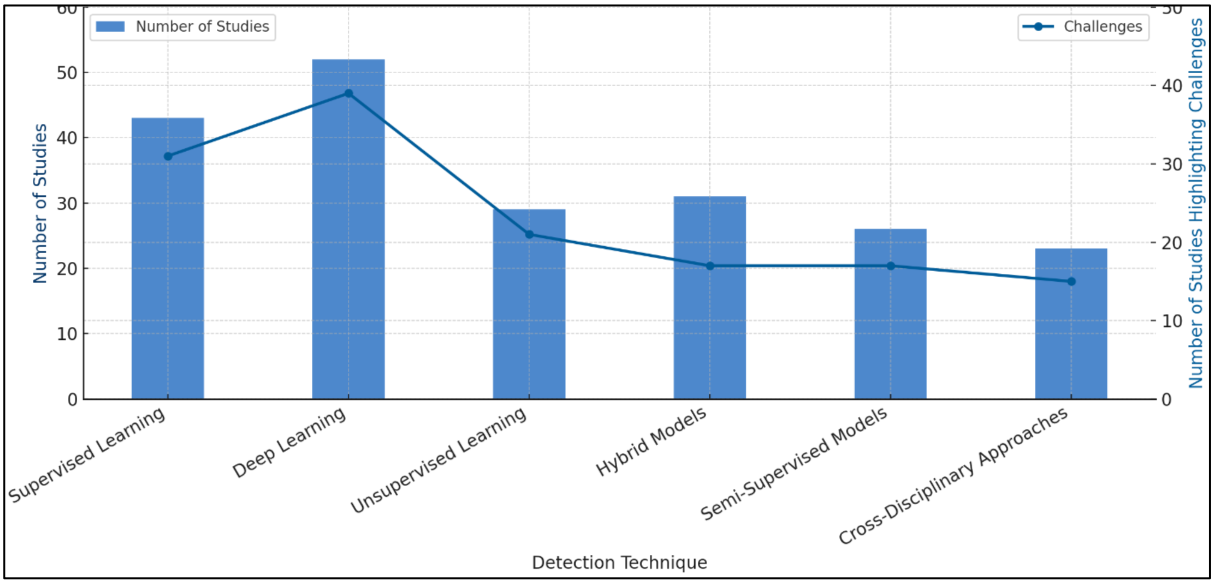
The review identified several significant trends and insights regarding the methodologies and effectiveness of fake news detection techniques across 254 studies. A notable finding was the success of machine learning algorithms, particularly supervised learning models, which demonstrated high effectiveness in classifying fake news. Widely used algorithms, such as Support Vector Machines, Decision Trees, and Naïve Bayes, were effective in distinguishing fake news by analyzing linguistic features, sentiment, and other textual indicators, as highlighted by 43 articles. However, these models' accuracy heavily depended on the quality and diversity of training datasets; limited or biased data led to decreased performance. Feature selection was found to be critical, with models incorporating specific linguistic and sentiment-based features yielding higher precision in detecting fake news. Despite these strengths, 31 studies noted scalability issues when these models were applied to larger datasets, indicating a need for optimized feature selection and algorithmic improvements for real-time applications.

Deep learning models, especially Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformers, marked a major advancement in capturing complex textual patterns in fake news detection, as documented in 52 articles. CNNs were highly effective in identifying local dependencies and patterns, while RNNs, particularly Long Short-Term Memory (LSTM) networks, excelled in processing sequential data and capturing the contextual flow of news articles. Transformers, especially models like BERT, achieved high accuracy by understanding nuanced language through contextual embeddings. Nevertheless, 39 studies noted that deep learning models presented challenges due to computational demands and the need for large-scale datasets, making them difficult to deploy in real-time. Furthermore, interpretability remained a limitation in 28 articles, as the complexity of these models reduced transparency, prompting ongoing research to enhance neural network interpretability and accessibility.

Unsupervised learning approaches proved instrumental in situations with limited labeled data, with clustering and anomaly detection techniques allowing for pattern identification in fake news without relying on predefined categories, as supported by 29 studies. Clustering algorithms effectively grouped similar content and identified patterns and narratives within misinformation, while anomaly detection techniques flagged outliers in language and structure, commonly found in fake news articles. Network-based unsupervised approaches identified clusters and communities where misinformation was prevalent, providing insights into how misinformation spreads within isolated network pockets. However, 21 studies highlighted that the absence of labeled data could limit the reliability of these models in high-stakes environments. Hybrid models, combining supervised and unsupervised learning, showed promise for mitigating these limitations, although further refinement was deemed necessary.

Semi-supervised models, which leverage both labeled and unlabeled data, demonstrated significant adaptability, particularly in environments where fake news narratives evolve rapidly, a finding noted by 26 studies. These models utilize labeled data as a foundation, applying iterative labeling techniques, such as self-training, to classify new data points, enabling continuous improvement without requiring extensive labeled datasets. This adaptability is highly beneficial in fake news detection, where misinformation patterns frequently shift in response to current events. When combined with deep learning architectures, such as CNNs or transformers, semi-supervised models demonstrated enhanced ability to detect nuanced language patterns. However, 17 studies indicated challenges in balancing the quality of self-labeled data with the need for high accuracy, emphasizing the importance of continuous monitoring and fine-tuning for these models. Finally, cross-disciplinary approaches in fake news detection expanded model capabilities by integrating psychological, sociological, computational linguistics, and network science insights, as highlighted by 23 articles. Psychological and sociological theories on persuasion, emotional appeal, and social conformity offered valuable insights into user behavior in response to fake news, uncovering how emotionally charged language and social validation drive misinformation's spread. These findings facilitated the development of models that account for both linguistic and social factors, improving detection accuracy where user engagement plays a key role. Additionally,

Figure 13: Findings on Fake News Detection Techniques and Challenges



Doi: 10.69593/ajieet.v1i01.143

interdisciplinary collaborations produced hybrid models that integrate social network analysis, user behavior analysis, and text-based techniques, capturing the full complexity of fake news dissemination. These collaborative efforts underscored that effective fake news detection requires multifaceted approaches, combining technical and social science expertise to address the adaptive and complex nature of misinformation.

5 Discussion

The findings from this systematic review confirm and extend upon prior research in fake news detection, highlighting the strengths and limitations of various machine learning and cross-disciplinary approaches. Supervised learning models, particularly Support Vector Machines (SVMs), Decision Trees, and Naïve Bayes, proved highly effective in classifying fake news, corroborating earlier studies that emphasized their reliability and accuracy when applied to well-curated datasets (Meesad, 2021; Mishima & Yamana, 2022). However, the present findings underscore a recurring challenge in supervised models: their reliance on extensive and diverse labeled datasets to maintain accuracy across varied contexts. Previous studies have also noted this limitation, suggesting that the scalability and generalizability of these models remain restricted without continuous updates to their training data (Allcott & Gentzkow, 2017). This study further emphasizes the importance of feature selection, aligning with (Mahabub, 2020) findings, where linguistic and sentiment-based features significantly boosted model performance, though scaling these models remains a significant obstacle for real-time applications (Babar et al., 2024).

The review also highlights the growing application of deep learning models, such as CNNs, RNNs, and transformers, in capturing complex language patterns and nuances associated with fake news. These models have shown significant advancements in accuracy, supporting the findings of Song et al. (2021) and Li et al. (2019), who demonstrated the capability of CNNs to capture local dependencies and RNNs to analyze sequential data. However, while deep learning models such as transformers (e.g., BERT) showed high efficacy in understanding nuanced language and context, this review reinforces that their computational demands and reliance on large datasets pose limitations for practical, real-time applications (Saikh et al., 2020). These results align with previous studies, which have consistently flagged interpretability as a challenge for deep learning models (Verma et al., 2019). The difficulty in understanding model decision processes has raised transparency concerns, underscoring the need for more interpretable models that can be effectively implemented in real-world settings, a point also noted by Shu et al. (2020) in their exploration of neural networks in fake news detection.

The use of unsupervised learning models, particularly clustering and anomaly detection techniques, has proven valuable in environments where labeled data is limited, supporting the findings of Klein and Wueller (2017) and Ahmad et al. (2020). Unsupervised approaches, such as clustering algorithms, facilitate the grouping of similar content, allowing researchers to identify misinformation patterns within unlabeled data, which is essential in tracking emerging narratives in fake news. The findings of this review further substantiate the utility of anomaly detection in recognizing linguistic and structural deviations typical of fake news. However, this review also reaffirms the limitations of unsupervised models noted in prior studies, particularly their lower accuracy and increased risk of misclassification due to the absence of labeled data (Kumar et al., 2019). This aligns with previous literature that recommends hybrid models combining supervised and unsupervised methods as a more robust solution, which allows unsupervised models to benefit from the guidance of labeled datasets while preserving the flexibility of detecting unknown patterns (Awan, Yasin, et al., 2021).

Semi-supervised learning models, which combine labeled and unlabeled data, emerged as highly adaptable tools in detecting fake news, particularly in fast-evolving misinformation landscapes. This review supports earlier findings by Jang et al. (2019) and Sharma et al. (2021), who demonstrated that semi-supervised models can maintain high accuracy by iteratively labeling and re-training on new instances.

The adaptability of these models is especially valuable in the fake news domain, where new misinformation patterns frequently emerge, posing challenges for models dependent solely on labeled data. When integrated with deep learning architectures such as CNNs and transformers, these models were shown to enhance detection capabilities by identifying subtle linguistic cues. However, consistent with previous studies, this review identifies a major limitation in semi-supervised learning: the quality of self-labeled data, which can impact overall accuracy if not continuously monitored and fine-tuned (Hakak et al., 2021; Jo et al., 2021). This highlights an ongoing need for research into methods that can improve the reliability and accuracy of self-labeled data in semi-supervised models.

The findings also highlight the effectiveness of cross-disciplinary approaches in fake news detection, as psychological and sociological insights on persuasion, emotional appeal, and social conformity enhanced the detection models' capabilities. This aligns with findings by Rashkin et al.(2017) and Ahmad et al. (2020), who noted that fake news thrives on emotionally charged language that appeals to readers' biases and reinforces social validation. Integrating these insights has allowed for the development of more comprehensive models that account for both linguistic and social dimensions, significantly improving detection accuracy. Furthermore, interdisciplinary collaborations in computational linguistics, network science, and social sciences have yielded hybrid models that integrate text-based, behavior-based, and network-based detection methods. These models are highly effective in capturing the complexities of fake news dissemination, especially on social media, where user behavior and network structures play critical roles. This review's findings are consistent with those of Raponi et al. (2022) and Nasir et al. (2021), who emphasized the value of integrating behavioral and network features in models, underscoring that a multifaceted approach is necessary to address the adaptive nature of misinformation. In addition, case studies of interdisciplinary projects further substantiate the need for collaborative research in fake news detection. The DARPA Media Forensics (MediFor) program and the Truthy project demonstrate the power of cross-disciplinary approaches in creating robust detection frameworks capable of identifying manipulated multimedia content (Manzoor et al., 2019; Shaikh & Patil, 2020). This review supports findings by Rubin et al. (2016), who emphasized the potential of interdisciplinary collaborations to develop more effective detection strategies that account for the different forms and mediums of fake news. These case studies illustrate that integrating insights from psychology, sociology, computer science, and network analysis enhances detection models' adaptability and accuracy in identifying fake news. Collectively, these findings reinforce the notion that combating fake news effectively requires a holistic approach, leveraging diverse expertise to address the sophisticated and evolving tactics of misinformation dissemination. This review's analysis underscores the importance of continued interdisciplinary research and collaboration in developing adaptive and comprehensive fake news detection frameworks for real-world applications.

6 Conclusion

This systematic review underscores the growing complexity and sophistication of fake news detection, highlighting the advancements, challenges, and ongoing needs in the field. Machine learning, particularly supervised and deep learning models, has shown significant efficacy in classifying fake news through nuanced text analysis, though these models face challenges in scalability, interpretability, and the demand for extensive labeled datasets. Unsupervised and semi-supervised approaches present adaptable solutions in data-scarce environments, with clustering, anomaly detection, and iterative self-training techniques proving useful for emerging misinformation patterns. Cross-disciplinary approaches, integrating psychological, sociological, and network insights, have been instrumental in understanding user behavior and network dynamics, enriching detection models by incorporating behavioral and social factors. The findings confirm that an effective fake news detection framework requires not only technical precision but also an interdisciplinary approach that leverages insights across computational linguistics, social sciences, and network science to address the evolving nature of misinformation. As misinformation continues to evolve, further research into hybrid models, enhanced interpretability, and adaptive frameworks is essential to ensure robust, real-time detection across diverse platforms and formats. This review calls for sustained collaborative research to develop comprehensive,

Doi: 10.69593/ajieet.v1i01.143

flexible, and efficient solutions that can effectively counter the spread of fake news in a rapidly changing digital landscape.

References

Abrahams, A. S., Fan, W., Wang, G. A., Zhang, Z. J., & Jiao, J. (2015). An Integrated Text Analytic Framework for Product Defect Discovery. *Production and Operations Management*, *24*(6), 975-990. https://doi.org/10.1111/poms.12303

Ahmad, I., Yousaf, M., Yousaf, S., & Ahmad, M. O. (2020). Fake News Detection Using Machine Learning Ensemble Methods. *Complexity*, *2020*(NA), 1-11. https://doi.org/10.1155/2020/8885861

Ahmed, H., Traore, I., & Saad, S. (2017). Detecting opinion spams and fake news using text classification. *SECURITY AND PRIVACY*, *1*(1), NA-NA. https://doi.org/10.1002/spy2.9

Alam, M. A., Sohel, A., Uddin, M. M., & Siddiki, A. (2024). Big Data And Chronic Disease Management Through Patient Monitoring And Treatment With Data Analytics. *Academic Journal on Artificial Intelligence, Machine Learning, Data Science and Management Information Systems*, *1*(01), 77-94. https://doi.org/10.69593/ajaimldsmis.v1i01.133

Allcott, H., & Gentzkow, M. (2017). Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives*, *31*(2), 211-236. https://doi.org/10.1257/jep.31.2.211

Alonso, M. A., Vilares, D., Gómez-Rodríguez, C., & Vilares, J. (2021). Sentiment Analysis for Fake News Detection. *Electronics*, *10*(11), 1348-NA. https://doi.org/10.3390/electronics10111348

Aslam, N., Khan, I. U., Alotaibi, F. S., Aldaej, A., & Aldubaikil, A. K. (2021). Fake Detect: A Deep Learning Ensemble Model for Fake News Detection. *Complexity*, *2021*(1), 1-8. https://doi.org/10.1155/2021/5557784

Asr, F. T., & Taboada, M. (2019). Big Data and quality data for fake news and misinformation detection. *Big Data & Society*, *6*(1), 205395171984331-NA. https://doi.org/10.1177/2053951719843310

Awan, M. J., Rahim, M. S. M., Nobanee, H., Yasin, A., Khalaf, O. I., & Ishfaq, U. (2021). A big data approach to black Friday sales. *Intelligent Automation & Soft Computing*, *27*(3), 785-797. https://doi.org/10.32604/iasc.2021.014216

Awan, M. J., Yasin, A., Nobanee, H., Ali, A. A., Shahzad, Z., Nabeel, M., Zain, A. M., & Shahzad, H. M. F. (2021). Fake News Data Exploration and Analytics. *Electronics*, *10*(19), 2326. https://doi.org/10.3390/electronics10192326

Babar, M., Ahmad, A., Tariq, M. U., & Kaleem, S. (2024). Real-Time Fake News Detection Using Big Data Analytics and Deep Neural Network. *IEEE Transactions on Computational Social Systems*, *11*(4), 5189-5198. https://doi.org/10.1109/tcss.2023.3309704

Badhon, M. B., Carr, N., Hossain, S., Khan, M., Sunna, A. A., Uddin, M. M., Chavarria, J. A., & Sultana, T. (2023). Digital Forensics Use-Case of Blockchain Technology: A Review. AMCIS 2023 Proceedings.,

Bali, A. P. S., Fernandes, M., Choubey, S., & Goel, M. (2019). Comparative Performance of Machine Learning Algorithms for Fake News Detection. In (Vol. NA, pp. 420-430). https://doi.org/10.1007/978-981-13-9942-8_40

Bondielli, A., & Marcelloni, F. (2019). A survey on fake news and rumour detection techniques. *Information Sciences*, *497*(NA), 38-55. https://doi.org/10.1016/j.ins.2019.05.035

Capuano, N., Fenza, G., Loia, V., & Nota, F. D. (2023). Content-Based Fake News Detection With Machine and Deep Learning: a Systematic Review. *Neurocomputing*, *530*(NA), 91-103. https://doi.org/10.1016/j.neucom.2023.02.005

Conroy, N. J., Rubin, V. L., & Chen, Y. (2015). ASIST - Automatic deception detection: methods for finding fake news. *Proceedings of the Association for Information Science and Technology*, *52*(1), 82-84. https://doi.org/10.1002/pra2.2015.145052010082

Di Domenico, G., Sit, J., Ishizaka, A., & Nunan, D. (2021). Fake news, social media and marketing: a systematic review. *Journal of Business Research*, *124*(NA), 329-341. https://doi.org/10.1016/j.jbusres.2020.11.037

Ebadi, N., Jozani, M., Choo, K.-K. R., & Rad, P. (2022). A Memory Network Information Retrieval Model for Identification of News Misinformation. *IEEE Transactions on Big Data*, *8*(5), 1358-1370. https://doi.org/10.1109/tbdata.2020.3048961

Faustini, P., & Covões, T. F. (2019). BRACIS - Fake News Detection Using One-Class Classification. *2019 8th Brazilian Conference on Intelligent Systems (BRACIS)*, *abs 1312 49*(NA), 592-597. https://doi.org/10.1109/bracis.2019.00109

Freeman, J., Vladimirov, N., Kawashima, T., Mu, Y., Sofroniew, N. J., Bennett, D., Rosen, J., Yang, C.-T., Looger, L. L., & Ahrens, M. B. (2014). Mapping brain activity at scale with cluster computing. *Nature methods*, *11*(9), 941-950. https://doi.org/10.1038/nmeth.3041

Galli, A., Masciari, E., Moscato, V., & Sperlí, G. (2022). A comprehensive Benchmark for fake news detection. *Journal of intelligent information systems*, *59*(1), 237-261. https://doi.org/10.1007/s10844-021-00646-9

Girgis, S., Amer, E., & Gadallah, M. (2018). Deep Learning Algorithms for Detecting Fake News in Online Text. *2018 13th International Conference on Computer Engineering and Systems (ICCES)*, *NA*(NA), NA-NA. https://doi.org/10.1109/icces.2018.8639198

Golbeck, J., Mauriello, M. L., Auxier, B. E., Bhanushali, K. H., Bonk, C., Bouzaghrane, M. A., Buntain, C., Chanduka, R., Cheakalos, P., Everett, J. B., Falak, W., Gieringer, C., Graney, J., Hoffman, K. M., Huth, L., Ma, Z., Jha, M., Khan, M., Kori, V., . . . Visnansky, G. (2018). WebSci - Fake News vs Satire: A Dataset and Analysis. *Proceedings of the 10th ACM Conference on Web Science*, *NA*(NA), 17-21. https://doi.org/10.1145/3201064.3201100

Goldani, M. H., Momtazi, S., & Safabakhsh, R. (2021). Detecting fake news with capsule neural networks. *Applied Soft Computing*, *101*(NA), 106991-NA. https://doi.org/10.1016/j.asoc.2020.106991

Granik, M., & Mesyura, V. (2017). Fake news detection using naive Bayes classifier. *2017 IEEE First Ukraine Conference on Electrical and Computer Engineering (UKRCON)*, *NA*(NA), 900-903. https://doi.org/10.1109/ukrcon.2017.8100379

Guess, A. M., Nyhan, B., & Reifler, J. (2018). Selective exposure to misinformation: Evidence from the consumption of fake news during the 2016 U.S. presidential campaign. *NA*, *NA*(NA), NA-NA. https://doi.org/NA

Gupta, A., Kumar, N., Prabhat, P., Gupta, R., Tanwar, S., Sharma, G., Bokoro, P. N., & Sharma, R. (2022). Combating Fake News: Stakeholder Interventions and Potential Solutions. *IEEE Access*, *10*(NA), 78268-78289. https://doi.org/10.1109/access.2022.3193670

Hakak, S., Alazab, M., Khan, S., Gadekallu, T. R., Maddikunta, P. K. R., & Khan, W. Z. (2021). An ensemble machine learning approach through effective feature extraction to classify fake news. *Future Generation Computer Systems*, *117*(NA), 47-58. https://doi.org/10.1016/j.future.2020.11.022

Hua, J., & Shaw, R. (2020). Corona Virus (COVID-19) "Infodemic" and Emerging Issues through a Data Lens: The Case of China. *International journal of environmental research and public health*, *17*(7), 2309-2309. https://doi.org/10.3390/ijerph17072309

Huckle, S., & White, M. (2017). Fake News: A Technological Approach to Proving the Origins of Content, Using Blockchains. *Big data*, *5*(4), 356-371. https://doi.org/10.1089/big.2017.0071

Hunter, J. D. (2007). Matplotlib: A 2D Graphics Environment. *Computing in Science & Engineering*, *9*(3), 90-95. https://doi.org/10.1109/mcse.2007.55

Ilie, V.-I., Truica, C.-O., Apostol, E.-S., & Paschke, A. (2021). Context-Aware Misinformation Detection: A Benchmark of Deep Learning Architectures Using Word Embeddings. *IEEE Access*, *9*(NA), 162122-162146. https://doi.org/10.1109/access.2021.3132502

Islam, N., Shaikh, A., Qaiser, A., Asiri, Y., Almakdi, Sulaiman, A., Moazzam, V., & Babar, S. A. (2021). Ternion: An Autonomous Model for Fake News Detection. *Applied Sciences*, *11*(19), 9292-NA. https://doi.org/10.3390/app11199292

Istiak, A., & Hwang, H. Y. (2024). Development of shape-memory polymer fiber reinforced epoxy composites for debondable adhesives. *Materials Today Communications*, *38*, 108015. https://doi.org/https://doi.org/10.1016/j.mtcomm.2023.108015

Istiak, A., Lee, H. G., & Hwang, H. Y. (2023). Characterization and Selection of Tailorable Heat Triggered Epoxy Shape Memory Polymers for Epoxy Debondable Adhesives. *Macromolecular Chemistry and Physics*, *224*(20), 2300241. https://doi.org/https://doi.org/10.1002/macp.202300241

Jang, S. M., Geng, T., Li, J.-Y. Q., Xia, R., Huang, C.-T., Kim, H., & Tang, J. (2018). A computational approach for examining the roots and spreading patterns of fake news: Evolution tree analysis. *Computers in Human Behavior*, *84*(NA), 103-113. https://doi.org/10.1016/j.chb.2018.02.032

Jang, Y., Park, C.-H., & Seo, Y.-S. (2019). Fake News Analysis Modeling Using Quote Retweet.

Electronics, *8*(12), 1377-NA. https://doi.org/10.3390/electronics8121377

Jiang, G., Liu, S., Zhao, Y., Sun, Y., & Zhang, M. (2022). Fake news detection via knowledgeable prompt learning. *Information Processing & Management*, *59*(5), 103029-103029. https://doi.org/10.1016/j.ipm.2022.103029

Jo, H., Park, S., Shin, D., Shin, J., & Lee, C. (2021). Estimating Cost of Fighting against Fake News during Catastrophic Situations. *Telematics and informatics*, *66*(NA), 101734-NA. https://doi.org/10.1016/j.tele.2021.101734

Klein, D., & Wueller, J. R. (2017). Fake News: A Legal Perspective. *Social Science Research Network*, *NA*(NA), NA-NA. https://doi.org/NA

Kozik, R., Kula, S., Choraś, M., & Woźniak, M. (2022). Technical solution to counter potential crime: Text analysis to detect fake news and disinformation. *Journal of Computational Science*, *60*(NA), 101576-101576. https://doi.org/10.1016/j.jocs.2022.101576

Kresnakova, V. M., Sarnovsky, M., & Butka, P. (2019). Deep learning methods for Fake News detection. *2019 IEEE 19th International Symposium on Computational Intelligence and Informatics and 7th IEEE International Conference on Recent Achievements in Mechatronics, Automation, Computer Sciences and Robotics (CINTI-MACRo)*, *NA*(NA), NA-NA. https://doi.org/10.1109/cinti-macro49179.2019.9105317

Kumar, S., Asthana, R., Upadhyay, S., Upreti, N., & Akbar, M. (2019). Fake news detection using deep learning models: A novel approach. *Transactions on Emerging Telecommunications Technologies*, *31*(2), NA-NA. https://doi.org/10.1002/ett.3767

Kumar, S., Cheng, J., Leskovec, J., & Subrahmanian, V. S. (2017). An Army of Me: Sockpuppets in Online Discussion Communities. *Proceedings of the 26th International Conference on World Wide Web*, *NA*(NA), 857-866. https://doi.org/10.1145/3038912.3052677

Lai, C.-M., Chen, M.-H., Kristiani, E., Verma, V. K., & Yang, C.-T. (2022). Fake News Classification Based on Content Level Features. *Applied Sciences*, *12*(3), 1116-1116. https://doi.org/10.3390/app12031116

Li, Q., Hu, Q., Lu, Y., Yang, Y., & Cheng, J. (2019). Multi-level word features based on CNN for fake news detection in cultural communication. *Personal and Ubiquitous Computing*, *24*(2), 259-272. https://doi.org/10.1007/s00779-019-01289-y

Lyu, S., & Lo, D. C.-T. (2020). Fake News Detection by Decision Tree. *2020 SoutheastCon*, *NA*(NA), 1-2. https://doi.org/10.1109/southeastcon44009.2020.9249688

Mahabub, A. (2020). A robust technique of fake news detection using Ensemble Voting Classifier and comparison with other classifiers. *SN Applied Sciences*, *2*(4), 1-9. https://doi.org/10.1007/s42452-020-2326-y

Manzoor, S. I., Singla, J., & Nikita, N. A. (2019). Fake News Detection Using Machine Learning approaches: A systematic Review. *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, *NA*(NA), 230-234. https://doi.org/10.1109/icoei.2019.8862770

Meel, P., & Vishwakarma, D. K. (2020). Fake news, rumor, information pollution in social media and web: A contemporary survey of state-of-the-arts, challenges and opportunities. *Expert Systems with Applications*, *153*(NA), 112986-NA. https://doi.org/10.1016/j.eswa.2019.112986

Meesad, P. (2021). Thai Fake News Detection Based on Information Retrieval, Natural Language Processing and Machine Learning. *SN computer science*, *2*(6), 425-NA. https://doi.org/10.1007/s42979-021-00775-6

Mintoo, A. A. (2024). DATA-DRIVEN JOURNALISM: ADVANCING NEWS REPORTING THROUGH ANALYTICS WITH A PRISMA-GUIDED REVIEW. *Journal of Machine Learning, Data Engineering and Data Science*, *1*(01), 19-40. https://doi.org/10.70008/jmldeds.v1i01.39

Mishima, K., & Yamana, H. (2022). A Survey on Explainable Fake News Detection. *IEICE Transactions on Information and Systems*, *E105.D*(7), 1249-1257. https://doi.org/10.1587/transinf.2021edr0003

Mridha, M. F., Keya, A. J., Hamid, A., Monowar, M. M., & Rahman, S. (2021). A Comprehensive Review on Fake News Detection with Deep Learning. *IEEE Access*, *9*(NA), 156151-156170. https://doi.org/10.1109/access.2021.3129329

Nasir, J. A., Khan, O. S., & Varlamis, I. (2021). Fake news detection: A hybrid CNN-RNN based deep learning approach. *International Journal of Information*

Management Data Insights, *1*(1), 100007-NA. https://doi.org/10.1016/j.jjimei.2020.100007

Palani, B., Elango, S., & Viswanathan K, V. (2021). CB-Fake: A multimodal deep learning framework for automatic fake news detection using capsule neural network and BERT. *Multimedia Tools and Applications*, *81*(4), 5587-5620. https://doi.org/10.1007/s11042-021-11782-3

Raponi, S., Khalifa, Z., Oligeri, G., & Di Pietro, R. (2022). Fake News Propagation: A Review of Epidemic Models, Datasets, and Insights. *ACM Transactions on the Web*, *16*(3), 1-34. https://doi.org/10.1145/3522756

Rashkin, H., Choi, E., Jang, J. Y., Volkova, S., & Choi, Y. (2017). EMNLP - Truth of Varying Shades: Analyzing Language in Fake News and Political Fact-Checking. *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, *NA*(NA), 2931-2937. https://doi.org/10.18653/v1/d17-1317

Raza, S., & Ding, C. (2022). Fake news detection based on news content and social contexts: a transformer-based approach. *International journal of data science and analytics*, *13*(4), 335-362. https://doi.org/10.1007/s41060-021-00302-z

Rubin, V. L., Conroy, N. J., Chen, Y., & Cornwell, S. (2016). Fake News or Truth? Using Satirical Cues to Detect Potentially Misleading News. *Proceedings of the Second Workshop on Computational Approaches to Deception Detection*, *NA*(NA), 7-17. https://doi.org/10.18653/v1/w16-0802

Ruchansky, N., Seo, S., & Liu, Y. (2017). CSI: A Hybrid Deep Model for Fake News Detection. *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, *NA*(NA), 797-806. https://doi.org/10.1145/3132847.3132877

Sahan, M., Smidl, V., & Marik, R. (2022). Batch Active Learning for Text Classification and Sentiment Analysis. *2022 3rd International Conference on Control, Robotics and Intelligent System*, *NA*(NA), 111-116. https://doi.org/10.1145/3562007.3562028

Saika, M. H., Avi, S. P., Islam, K. T., Tahmina, T., Abdullah, M. S., & Imam, T. (2024). Real-Time Vehicle and Lane Detection using Modified OverFeat CNN: A Comprehensive Study on Robustness and Performance in Autonomous Driving. *Journal of Computer Science and Technology Studies*.

Saikh, T., B, H., Ekbal, A., & Bhattacharyya, P. (2020). IJCNN - A Deep Transfer Learning Approach for Fake News Detection. *2020 International Joint Conference on Neural Networks (IJCNN)*, *NA*(NA), 1-8. https://doi.org/10.1109/ijcnn48605.2020.9207477

Sastrawan, I. K., Bayupati, I. P. A., & Arsa, D. M. S. (2022). Detection of fake news using deep learning CNN–RNN based methods. *ICT Express*, *8*(3), 396-408. https://doi.org/10.1016/j.icte.2021.10.003

Segura-Bedmar, I., & Alonso-Bartolome, S. (2022). Multimodal Fake News Detection. *Information*, *13*(6), 284. https://www.mdpi.com/2078-2489/13/6/284

Shahid, W., Jamshidi, B., Hakak, S., Isah, H., Khan, W. Z., Khan, M. K., & Choo, K.-K. R. (2024). Detecting and Mitigating the Dissemination of Fake News: Challenges and Future Research Opportunities. *IEEE Transactions on Computational Social Systems*, *11*(4), 4649-4662. https://doi.org/10.1109/tcss.2022.3177359

Shaikh, J., & Patil, R. (2020). Fake News Detection using Machine Learning. *2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC)*, *NA*(NA), NA-NA. https://doi.org/10.1109/isssc50941.2020.9358890

Shamim, M. (2022). The Digital Leadership on Project Management in the Emerging Digital Era. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *1*(1), 1-14.

Sharma, D. K., Garg, S., & Shrivastava, P. (2021). Evaluation of Tools and Extension for Fake News Detection. *2021 International Conference on Innovative Practices in Technology and Management (ICIPTM)*, *abs 1809 1286*(NA), 227-232. https://doi.org/10.1109/iciptm52218.2021.9388356

Shu, K., Mahudeswaran, D., Wang, S., Lee, D., & Liu, H. (2020). FakeNewsNet: A Data Repository with News Content, Social Context, and Spatiotemporal Information for Studying Fake News on Social Media. *Big data*, *8*(3), 171-188. https://doi.org/10.1089/big.2020.0062

Shu, K., Sliva, A., Wang, S., Tang, J., & Liu, H. (2017). Fake News Detection on Social Media: A Data Mining Perspective. *ACM SIGKDD Explorations Newsletter*, *19*(1), 22-36. https://doi.org/10.1145/3137597.3137600

Singhal, S., Shah, R. R., Chakraborty, T., Kumaraguru, P., & Satoh, S. i. (2019). BigMM - SpotFake: A Multi-modal Framework for Fake News Detection. *2019 IEEE Fifth International Conference on Multimedia Big Data (BigMM)*, *NA*(NA), 39-47. https://doi.org/10.1109/bigmm.2019.00-44

Sohel, A., Alam, M. A., Waliullah, M., Siddiki, A., & Uddin, M. M. (2024). Fraud Detection In Financial Transactions Through Data Science For Real-Time Monitoring And Prevention. *Academic Journal on Innovation, Engineering & Emerging Technology*, *1*(01), 91-107. https://doi.org/10.69593/ajieet.v1i01.132

Song, C., Ning, N., Zhang, Y., & Wu, B. (2021). A multimodal fake news detection model based on crossmodal attention residual and multichannel convolutional neural networks. *Information Processing & Management*, *58*(1), 102437-NA. https://doi.org/10.1016/j.ipm.2020.102437

Su, Q., Wan, M., Liu, X., & Huang, C.-R. (2020). Motivations, Methods and Metrics of Misinformation Detection: An NLP Perspective. *Natural Language Processing Research*, *1*(1-2), 1-13. https://doi.org/10.2991/nlpr.d.200522.001

Tang, R., Ouyang, L., Li, C., He, Y., Griffin, M., Taghian, A. G., Smith, B. L., Yala, A., Barzilay, R., & Hughes, K. S. (2018). Machine learning to parse breast pathology reports in Chinese. *Breast cancer research and treatment*, *169*(2), 243-250. https://doi.org/10.1007/s10549-018-4668-3

Uddin, M. M., Ullah, R., & Moniruzzaman, M. (2024). Data Visualization in Annual Reports–Impacting Investment Decisions. *International Journal for Multidisciplinary Research*, *6*(5). https://doi.org/10.36948/ijfmr

Vargo, C. J., Guo, L., & Amazeen, M. A. (2017). The agenda-setting power of fake news: A big data analysis of the online media landscape from 2014 to 2016. *New Media & Society*, *20*(5), 2028-2049. https://doi.org/10.1177/1461444817712086

Venkatesan, S., Han, W., Kisekka, V., Sharman, R., Kudumula, V., & Jaswal, H. S. (2013). Misinformation in Online Health Communities. *NA*, *NA*(NA), NA-NA. https://doi.org/NA

Verma, A., Mittal, V., & Dawn, S. (2019). IC3 - FIND: Fake Information and News Detections using Deep Learning. *2019 Twelfth International Conference on Contemporary Computing (IC3)*, *NA*(NA), 1-7. https://doi.org/10.1109/ic3.2019.8844892

Zhang, C., Gupta, A., Kauten, C., Deokar, A. V., & Qin, X. (2019). Detecting fake news for reducing misinformation risks using analytics approaches. *European Journal of Operational Research*, *279*(3), 1036-1052. https://doi.org/10.1016/j.ejor.2019.06.022

Zhou, X., & Zafarani, R. (2020). A Survey of Fake News: Fundamental Theories, Detection Methods, and Opportunities. *ACM Computing Surveys*, *53*(5), 1-40. https://doi.org/10.1145/3395046