**Deep-Learning-Based Fake News Detection for Afaan Oromo Language on Social Media Networks: *A Systematic Literature Review***

**Kedir Lemma Arega1,2, Kula Kekeba Tune**3**, Ayodeji Olalekan Salau4,Asrat Mulatu Beyene5, Wegderes Tariku6**

1Department of Information Technology, Ambo University, Ethiopia

2Department of Software Engineering Addis Ababa Science and Technology University, Ethiopia

3Department of Software Engineering Addis Ababa Science and Technology University, Ethiopia

4Department of Electrical/Electronics and Computer Engineering, Afe Babalola University, Ado-Ekiti, Nigeria

5Department of Software Engineering Addis Ababa Science and Technology University, Ethiopia

6Department of Information Systems, Mizan Tepi University, Tepi, Ethiopia

kedirnaw1999@gmail.com

# Abstract

Firms around the globe are confronted with the formidable task of discerning counterfeit information on the Internet, owing to the wide prevalence of misleading content. Deep learning-based systems have proven more efficacious than numerous machine learning techniques in detecting spurious news. Within the context of Ethiopian languages, deep learning (DL) methodologies have been advocated to improve assessment metrics derived from diverse social media platforms. By combining DL and machine learning approaches with a well-balanced dataset, the capacity for detection and counteraction can be significantly augmented. A systematic evaluation of the existing body of literature is a prescribed methodology employed to identify, select, appraise, and critically assess recent research endeavors aimed at addressing ongoing concerns and issues in the field of research. Specifically, the objective of this evaluation is to delve into the current challenges and shortcomings associated with the detection systems employed in identifying false information, specifically within the context of the Afan Oromo language, utilizing deep-learning algorithms. To establish a solid foundation for this evaluation, an elaborate review protocol was developed following meticulous analysis of the prevailing systematic evaluation methodologies and consultation with experts in the field. The protocol describes prospective research subjects, search techniques, sources, selection criteria, and the procedure. Boolean operators are employed to create search strings, which are then evaluated for false information detection. Primary studies are chosen to substantiate research topics. The inclusion criteria for this study encompassed research papers published between 2019 and 2023, assessments and evaluations of false information detection systems, and publications that specifically focused on the detection of false information in the Afan Oromo language. Furthermore, this study delves into key evaluative measures for identifying false information and proposes additional recommendations for enhancing detection techniques in future research.

**Keywords**: Fake news, machine learning, detection, Afan Oromo, social media, review deep learning.

# **Introduction**

A type of disinformation known as "fake news" disseminates incorrect information and influences public opinion for commercial, political, or financial advantages. It frequently uses dramatic headlines and false information to grab readers' attention and encourage clicks. Fake news may have major consequences for people and the community; including confusion, misunderstanding, and harm. Fake news must be detected and addressed to be combated. [1]. These obstacles include political polarization, limited media literacy, confirmation bias, quick propagation, difficulty recognizing the source, and legal issues. [2]. On social media, fake news may originate from a multitude of sources, including attention-seeking individuals, partisan websites, clickbait websites, social media bots, and foreign governments. Being aware of these sources is essential, as is critically assessing any information before taking it at face value. Fake news may have major implications, such as spreading misleading information, manipulating the public's perceptions, and undermining faith in established media sources. [3]. Fake news has been a major problem in recent years, especially since the introduction of social media and other online platforms.

Ethiopian social media platforms have benefited greatly from machine learning, yet these platforms can also spread misleading information. The Ethiopian government's control over social media decreased in the wake of political upheavals in 2018, which increased freedom of expression [4], [5]. On the other hand, the COVID-19 pandemic has increased the threat of hate speech and fake news, complicating response efforts and making it challenging for medical professionals to respond appropriately [6] [7]. To lessen these negative effects, governments, the technology sector, and researchers are collaborating. Facebook employs an independent verification expert service and will now be available in Ethiopia and other African nations, according to the “Hate Speech and Disinformation Prevention and Suppression Proclamation No. 1185/2020 issued by the Ethiopian government” [8] [9] [10]. However, the declaration is problematic in the context of equality and free expression, and this issue should be corrected immediately. Even though Ethiopians today have unparalleled civil and political rights, authorities continue to challenge the "freedom" of social media platforms [8]. Ethiopian laws aimed at preventing hate speech and disinformation have been challenged by fake news creators [11]. Despite the introduction of four additional working languages, Ethiopian spoken languages continue to be among the world's most endangered "low resources" due to a lack of resources for natural language processing applications [12]. Current advancements in natural language processing have enabled greater accuracy in detecting and counteracting fake news. The increasing power of online communication networks has led to a greater focus on combating fake news. The spread of fake news has impacted millions of lives, leading to school closures, business activities, and displacement. Ethiopia has introduced four additional working languages, namely, Afan Oromo, Afar, Somali, and Tigrigna, as official languages. Research has been conducted in Ethiopia and other foreign languages to identify and counter fake news in online communications [8]. This study reviews Ethiopian studies on fake news findings and recommends the best approach for future researchers to minimize the risk of widespread fake news in the country. Different techniques, such as content-based, social network-based, and hybrid approaches, are used to identify fake news. Content-based approaches use natural language processing (NLP) technologies to detect patterns of fakes while analyzing news items for bias, sensationalism, or inconsistency [13] [14]. Social network-based methods look for signs of manipulation in the social network activity, including automated posting or fake identities. For an in-depth analysis, hybrid techniques blend content-based and social network-based strategies. Advanced techniques encompass transfer learning, attention processes, and deep learning models [14]. While attention mechanisms concentrate on the most important parts of the narrative, deep learning algorithms use neural networks to examine massive amounts of data and spot deceptive trends. Transfer learning improves models' ability to identify false news items by training them on large datasets of related tasks [15]. Despite these advances, detecting false news remains a difficult task [16]. There is still [17]several ways for fake news to be transmitted and manipulated, and new techniques to avoid detection are continually being created. A proposed solution combines weighted feature sets with machine learning algorithms, integrating neural networks and support vector machines, to detect fake news on social networking platforms. This technique improves user experience and addresses real-world concerns related to fake news. However, it is believed that with further study and development, viable solutions to this expanding problem can be discovered.

1. **Literature Review**

## Overview of Fake News

False information, known as fake news, is disseminated through various media platforms with the intention of misleading audiences, harming the credibility of an individual or organization, or generating sensational interest. It is a serious challenge to democracy, free speech, and the Western system. Twitter and Facebook are rapidly spreading false news, with some pieces obtaining more views than direct media material. [18].

## The level of social media literacy in Ethiopia

Ethiopian smartphone users are rapidly utilizing major social media platforms such as Facebook for information and conversation. The nation's population of millions of individuals utilizes Facebook in a variety of languages, encompassing the official Amharic and Afan Oromo. However, due to an obvious knowledge gap in this virtual world, presuming that individuals are knowledgeable about the media is challenging. Many people are unaware of the influence of the media and struggle to handle information overload on social media sites. Furthermore, illogical and superficial conversations on online community sites suggest a lack of comprehension of the media's power, which leads to a lack of careful management of information on these platforms. [18]. There is still uncertainty regarding social media platforms' ability to close the digital divide between those who have access to information technology (IT) and people who do not, as well as the features that define online community users. Research indicates that social media draws users from a variety of demographic groups; however, this view is not definitive.

The Fojo Media Institute's paper investigates the influence of social media on Ethiopia's sustainable news publication, freedom of expression, and democracy. It emphasizes essential themes such as expanding internet access, publishing responsibility regulation, free speech, democracy, consumer protection, data privacy, platform data management, advertising, copyright, media financing, and media literacy. This paper investigates the reach of online media, stakeholders, and traditional media connections with social media platforms. It also investigates the government's influence on the media and its impact on the country's media landscape. The research also provides a worldwide perspective on data and social media legislation, consumer protection laws, and copyright laws. This finding suggests that Ethiopia enacts legislation and voluntary agreements comparable to those of the IT industry. Recommendations for the government, the media, and stakeholders are provided at the end of the study. It makes recommendations for generating income in a liberalized market, growing the telecommunications network, fostering transparency to increase confidence, and enabling Ethiopian news media firms to get paid for advertising. [19].

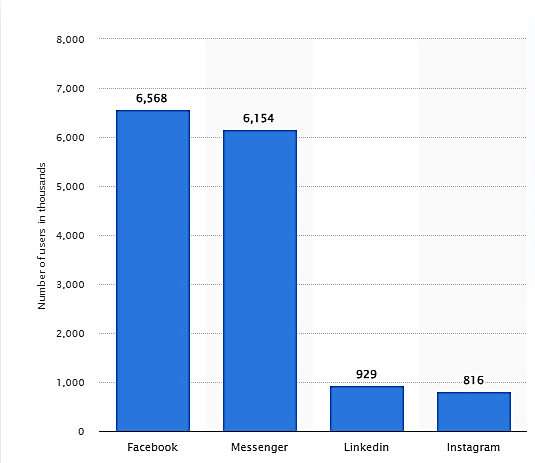


Figure 1 Number of social media users in Ethiopia as of May 2023, by platform ([© Statista 2023](https://www.statista.com/statistics/report-content/statistic/1312554)) [20]

## Social Media Metrics

The measurement of online network use is a fast-moving topic, with data embedded directly into sites such as YouTube and Flickr, blogging software, Facebook, Twitter, and other platforms. These platforms also provide other tools, such as Facebook Insights and YouTube Insights, for in-depth research. These tools assist users in determining the subjects in which their followers are interested.

Third-party programs like Google Analytics provide valuable insights into social media initiatives' effectiveness, allowing agencies to analyze visitor navigation, search engine terms, and preferences. These technologies help identify popular sites, locations, and visit durations. Link shorteners, which shorten lengthy site addresses for easier publication, are popular on Twitter due to their shorter posts. By tracking reader clicks on shortened links, these services help companies identify popular links. Social media use measurement science is constantly evolving.

## Methods for Detecting Fake News

Researchers are exploring indicators to determine if a piece of material is untrue. They are also exploring how computers can recognize characteristics from facts and simplify the likelihood of content being in a specific session. Approaches include identifying based on news content, using social context, and a combination of both. This is in addition to larger studies on Fake News [18].

### Knowledge-Based Method for Identifying False News

Knowledge graphs are effective tools for identifying and evaluating the veracity of false news. They can be generated from phony news article bases, open knowledge graphs, or real news article bases from reputable news sources using a variety of models, including single BTransE, binary TransE, and hybrid techniques. The process of fact-checking involves evaluating the veracity of news by contrasting the information gained from authenticated news sources with facts, including genuine knowledge [21]. The amount of freshly produced material is too high for traditional fact-checking techniques, especially those involving manual fact-checking, especially on social media. Automated fact-checking methods based on network/graph theory, natural language processing methods, and information retrieval have been developed to solve this problem. However, fact-checking strategies are frequently predicated on the idea that information can be independently verified through websites such as Snopes.com and FakeCheck.org, which are primarily focused on the political sphere. In response, knowledge-based fact-checking websites have been created; they allow more accurate analysis and detection of false information [22].

### Linguistics and Style-Based Method for Detecting Fake News

Linguistic approaches for detecting fake news have been created by extracting information from bogus news messages and studying linguistic patterns associated with fake news. To detect bogus opinions, researchers have utilized dictionary-based word counts and linguistic investigations. To detect false news, hybrid convolutional neural network models such as the LIAR model have been created. To detect near-duplicate and duplicated reviews, lexical models such as N-gram-based text classification models have been developed. The identification of clickbait has been studied using both textual and non-textual indicators. Two datasets for detecting false news have been suggested, one gathered by manual and crowdsourcing annotation methods and the other directly from the web [22]. This specific methodology is based on the application of linguistic-oriented attributes that are derived from documented content. The foundational attributes can be acquired from more minute components, such as characters and words, progressing up to the sentence and text scale. One of the most straightforward techniques for exploiting linguistic indications is to classify the text as a collection of words and n-grams [23]. Researchers use lexical and syntactic characteristics like part-of-speech, punctuation, and shallow parsing to identify dishonesty in news articles by analyzing their tone. The notion of employing computational science to examine writing style emerged from the field of psychology, and it was in a published document that the initial categorization of textual content based on style was put forth. Moreover, in addition to the aforementioned methodologies, linguistic indicators can also be acquired through an approach that relies on existing knowledge. In this particular strategy, dishonest material is extracted and scrutinized to ascertain its veracity through the process of inquiring about preexisting external knowledge [18].

### Visual Method-Based Approach

This particular methodology directs its focus toward the unique attributes of distortion that are extracted from visual content, encompassing both still images and moving pictures. Furthermore, the incorporation of specific statistical features has been shown to augment the authentication of news, as it enables the thorough examination of patterns in the distribution of images. By assimilating these statistical features in conjunction with the aforementioned qualities of distortion, a more comprehensive comprehension and evaluation of visual contents can be attained, thereby making a valuable contribution to the overall enhancement of news verification procedures [18].

### Propagation-based Technique

Researchers [24] have conducted studies on the propagation and evolution of news, focusing on collective structural signals. They tracked and analyzed large databases of both real and fake news within online social networks, providing a better understanding of the characteristics and dynamics of news dissemination. Fake news exhibits distinct characteristics that distinguish it from real news, even during the initial stages of propagation. The researchers discovered a propagation dynamic between real and fake news, revealing that false claims have a wider reach than the truth itself. This highlights the importance of developing effective strategies to combat the spread of fake news and promote accurate information dissemination [25]. Additionally, studies on news spreading patterns on Twitter have been conducted to distinguish between rumors and non-rumors using temporal, structural, and linguistic features. The temporal feature involved analyzing time series data to identify patterns and trends in news spread, while the structural feature examined network structure to uncover the role of social connections in news dissemination. The linguistic feature involved analyzing the language used in news posts to identify linguistic markers that may indicate the presence of rumors. This comprehensive approach contributed to the growing body of knowledge on the propagation of data in online social networks and provided useful insights for the creation of efficient tactics to prevent rumors and encourage the circulation of truthful information.

### Content-based Techniques

The identification of deception based on the content of a message can be achieved through the examination of linguistic characteristics that are evident within the message itself or by scrutinizing visual cues that are present in supplementary materials, such as images and videos. To carry out the process of discerning Fake News solely by analyzing its content, a substantial amount of data is required for training purposes, which consequently places a greater burden on the model being trained [18]. Nevertheless, this particular approach has shown considerable promise in effectively detecting misinformation and implementing necessary measures to hinder its dissemination, thereby mitigating its adverse effects on society as a whole [26].

## A Synopsis of the Languages

Afaan Oromo, a language belonging to the Cushitic branch of the Afro-Asiatic language phylum, is the official language of the Oromia regional state in Ethiopia. It is part of the East Cushitic group and is the third most widely spoken Afro-Asiatic language globally. The official script of Afaan Oromo is the Latin-based alphabet "Qubee," adopted in 1991 [27]. This system effectively represents vowels and consonants, making it a valuable tool for language. Ethiopia is a nation characterized by its cultural diversity, housing a plethora of ethnic groups, amounting to more than 80 people, each possessing distinct linguistic origins. Among these, Afaan Oromo is classified as belonging to the Lowland East Cushitic Group, which is part of the larger Cushitic family found within the Afro-Asiatic phylum [28]. It possesses numerous dialects, diverse variations, distinct alphabets, and a wide array of phonetics. Afaan Oromo, the language formally recognized as the primary means of communication in Oromia State, the most expansive regional state within Ethiopia's existing Federal States, is employed as the instructional medium for both elementary and high school levels [22].

## A deep learning model for detecting fake news

Machine learning methods are characterized as supervised, unsupervised, or semi-supervised. Supervised machine learning predicts future events using labeled examples, resulting in an inferred function that predicts output values. Unsupervised machine learning investigates the idea of inferring a function from unlabeled data to characterize hidden structures. When labeled data are rare and resources are scarce, semi-supervised machine learning, a combination of supervised and unsupervised approaches, is used. The supervised approach, which relies on the manual categorization of vast amounts of text, is often used for fraudulent account detection. In research studies, many classification algorithms are frequently utilized for computational purposes, comparison analysis, and identification of the best algorithm for the suggested detection model. The fields of speech recognition, computer vision, natural language processing, intelligent transportation, and communication have all undergone significant advancements due to the utilization of deep learning models [29]. In terms of detecting false information, these models exhibit enhanced accuracy and precision compared to traditional machine-learning methods. Although deep neural networks (DNNs) necessitate more memory than conventional classification methods, they are capable of rapidly acquiring concealed representations. Among sophisticated artificial neural networks, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are renowned models for deep learning [29].

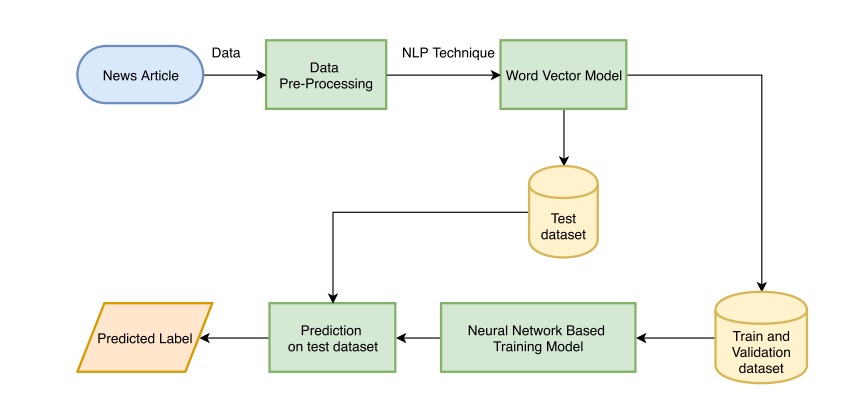


Figure 2. The diagram in the exposition illustrates the structure of deep learning-based architecture, which is widely used in academic fields such as computer science, artificial intelligence, and machine learning [29].

## Related Work

## 3.1. overview of related work

To comprehend the idea behind this study, a thorough examination of similar ideas and earlier research in this field was conducted [30]. Ethiopian local language fake news detection research is currently in its early stages [25], [31]. This chapter describes the use of the multinomial Nave Bayes algorithm with natural language processing algorithms for the identification of fake news in 752 Afan Oromo news texts [22] [31]. The term frequency-inverse document frequency (TF-IDF) was applied to unigrams and bigrams by the researchers, who utilized Facebook as the primary source of news articles. By considering the size of their data, they were able to achieve favorable outcomes, as indicated by the highest F1 score. Despite the satisfactory accuracy, it is important to note that the reliability of the information obtained from the dataset site's source is not absolute, and the attainment of the highest accuracy may have been influenced by the inclusion of unreliable news. A proposed approach for identifying fake news involves the utilization of machine learning techniques [22]. In terms of feature extraction, the researchers utilized the term frequency-inverse document frequency (TF-IDF) for a sample of words and n-grams, along with a support vector machine (SVM), as the classification method. Additionally, the authors recommend the use of a dataset consisting of both real and fake news for training the suggested system. The results obtained provide evidence of the effectiveness of the system. Employing various categorization algorithms, [32]we can identify fake news that is accurate. According to [32], the impact of fake news on social life is deleterious, with significant repercussions in the realms of politics and education. To construct their model, the authors employed classification techniques such as support vector machine (SVM), naive Bayes, and passive-aggressive classifier. The accuracy of the results yielded by their model, which utilizes feature extraction methods such as term frequency-inverted document frequency (TF-IDF) and support vector machine (SVM) classifiers, is 95.05%. By proposing a system that can effectively categorize fake news, the objective of this research is to expedite the process of identifying false information [33]. Machine learning methods such as naive Bayes, passive-aggressive classifiers, and deep neural networks were used for eight distinct datasets gathered from diverse sources. The analysis and results of each model are also included in the publication [34]. In this study, a repertoire of ten distinct machine learning and deep learning classifiers was used for classifying the fake news dataset within this classification. Four conventional approaches, namely, term frequency-inverse document frequency, count vector, character level vector, and N-Gram level vector, were adopted to extract features from the textual data. The findings revealed that counterfeit news stories containing textual elements can be distinguished, particularly when utilizing convolutional neural networks. By employing diverse classifiers, this research attained an accuracy ranging from 81% to 100%. The study used machine learning techniques such as naive Bayes, neural networks, and support vector machines to analyze hate speech on Ethiopian social media during the country's political transition. The naive Bayes method was 96.08% accurate, while the support vector and neural network techniques were 99.90% accurate. The study highlights the importance of social media during political shifts and the dynamics of hate speech. However, it has limitations such as sample selection restrictions and a need for a more comprehensive examination of contextual elements affecting hate speech. The article also addresses ethical issues and offers suggestions for reducing hate speech in Ethiopian political reform [5]. In particular, Afaan Oromo is the focus of the paper's discussion on the dissemination of false information in indigenous languages. For text classification problems, the multinomial naive Bayes method is applied. The strengths of this work include its unique addition to the field, its ability to address particular issues with Afaan Oromo false news identification, and its use of a content-based method for textual feature analysis to find patterns linked to fake news. Nevertheless, there are several limitations to consider, including the dataset utilized, possible biases, and performance measures applied to assess the efficacy of the multinomial naive Bayes model. To improve the overall quality and relevance of the study, the publication should address issues relating to dataset representativeness, possible biases, and assessment criteria. Its strengths include its novel contribution and methodology [31]. In this article, a decision tree classifier and support vector machine are used in a machine learning approach to classify news material written in Afaan Oromo. The system's goal is to classify news items into pre-established groups such as entertainment, sports, and politics. Researchers preprocessed Afaan Oromo news articles from various internet sources and trained a model using decision tree classifier and support vector machine techniques. Performance was assessed using F1 score, accuracy, precision, and recall measures. The support vector machine technique performed better than the decision tree classifier in terms of accuracy and other metrics. However, the study lacks reference to prior studies or the current literature on Afaan Oromo news text classification using machine learning algorithms, emphasizing a deficit in the literature review section. The report also failed to address the shortcomings of the suggested approach, such as dataset size and representativeness, generalizability to other languages and topics, and potential bias in the classification process, which might improve the study's validity and reliability.

The LDC-IL, an Indian language technology resource repository that offers lexicons, corpora, and annotated data for Indian languages, is discussed in the article. This highlights how crucial these resources are for applications using machine learning and natural language processing. However, the paper also covers the difficulties in setting up and keeping up the repository, including concerns with data collection, annotation, and copyright. The necessity of ongoing efforts to develop and enhance the LDC-IL is emphasized in the article's conclusion to support research in Indian language technology. The post emphasizes how important it is to continue working to improve the repository's features. However, given the content of the article, one potential drawback might be that it mostly concentrates on the significance and difficulties of developing and keeping up a linguistic resource repository for Indian languages without going into particular instances or case studies to illustrate the efficacy or significance of the LDC-IL. Furthermore, the paper does not discuss any potential objections or shortcomings of the LDC-IL, such as biases or errors in the data or restrictions on the range of resources that are accessible [35].

This study compares and contrasts deep learning models for detecting hate speech in Afaan Oromo, the Ethiopian language. Researchers have tested various models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM), on 5,000 Afaan Oromo tweets. The LSTM model outperformed the CNN and RNN models, with an accuracy of 89.4%. The study also revealed that politics, religion, and ethnicity are the most frequently mentioned hate speech issues in Afaan Oromo. These findings highlight the importance of creating language-specific models for detecting hate speech in Afaan Oromo and highlight the need for more effective methods [36]. The researchers used Facebook as the news source and used the TF-IDF of unigrams and bigrams for feature extraction. The results showed good accuracy, but the information from the dataset was not entirely reliable. The authors proposed a strategy using machine learning methods, including SVM, Nave Bayes, and Passive Aggressive Classifier, to identify accurate fake news. The study used ten different machine learning and deep learning classifiers to categorize the fake news dataset, with naive Bayes, neural network, and support vector machine classifiers achieving an accuracy ranging from 81 to 100%. The naive Bayes result was 96.08%, while the support vector and neural network achieved 99.90% accuracy.

## Summary of Related Work

This investigation examines the phenomenon of fabricated news in Ethiopia, underscoring the significance of being proficient in social media literacy. It delves into a range of techniques for classifying misinformation, encompassing linguistic and visual evidence, the social context, and interaction evidence. To extract features from textual data, deep learning models, bag-of-words models, and predictive models are employed. Moreover, the investigation delves into the idiosyncrasies of the target language and the obstacles that hinder automation. Researchers have developed designs for multiple languages to capture explicit or implicit attributes, thereby enabling models to make generalizations based on the input dataset. The identification of false news based on content, as opposed to social interaction data or dissemination channels, is a topic that is widely debated, with research focusing on approaches rooted in natural language processing and machine learning. The techniques employed encompass natural language processing, machine learning algorithms, and social network analysis to discern patterns and attributes that indicate false information. The study also investigated false information detection in other languages, such as Afan Oromo. Nonetheless, additional investigations are necessary to cultivate effective and dependable methods for the detection of false information in Afan Oromo and other languages. It should be noted, however, that there is currently no research available that attains a 100% accuracy rate in detecting false information.

# Result and discussion

## 4.1. Performance measures

The study focuses on evaluating language resources, examining quality standards, correctness, completeness, usability, accessibility, user input, data privacy, and ethical aspects. Researchers use various methods to evaluate linguistic resources, with user input and reviews crucial for improving quality. Linguistic resource repositories also provide data privacy and ethical information in construction and management.

Figure 3. A pie chart visually represents the number of articles published in a given year, along with their respective percentages.

Figure 4. The chart design depicts the primary research source and its spread.

Table 1. The presented table showcases the various perspectives, contributions, and an abridged version of the opening, methodology, or method employed, literature assessment, final deductions, results, and constraints

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| S. No | Title | Perceptions | Contributions | Approach/technique Used | Literature review | Conclusions | Outcomes | Limitations |
|  | Information Extraction Model for Afan Oromo News Text [37] | The paper explores the development and implementation of an Information Extraction model for identifying fake news in the Afan Oromo language. The aim is to improve the accessibility and comprehension of Afan Oromo news articles by extracting essential information. However, the paper lacks discourse on identifying fake news in Afan Oromo, a crucial aspect of news consumption and dissemination in the digital era. The paper suggests future research should explore methods for detecting and combating fabricated news in the Afan Oromo language, contributing to understanding and advancing effective measures to counter misinformation and disinformation, fostering a more informed and empowered society. | - AOTIE has 79.5% accuracy, 80.5% recall, and an F-measure of 80%.  - AOTIE's performance is heavily reliant on Afan Oromo's grammatical structure. | Preprocessing of documents, learning and extraction, and postprocessing  The creation of a gazetteer and the study of Afan Oromo grammatical structure | AOTIE performance is mostly dependent on the grammatical structure of Afan Oromo.  The influence of Afan Oromo's grammatical structure affects AOTIE performance. | AOTIE has 79.5% accuracy, 80.5% recall, and an F-measure of 80%.  AOTIE's performance is heavily reliant on Afan Oromo's grammatical structure. | AOTIE achieved 79.5% precision, 80.5% recall, and 80% F-measure.  AOTIE's performance is mostly dependent on the grammatical structure of Afan Oromo. | This article focuses on Information Extraction (IE) from news content written in Afan Oromo. Training and testing are done on a small dataset consisting of 3169 tokens. The model's performance is quantitatively assessed using evaluation measures including recall, accuracy, and F-measure; however, they ignore contextual relevance and semantic comprehension. Not every potential element affecting the model's performance is probably covered by the two experimental situations. The suggested model's scalability and generalizability to bigger datasets or other Afan Oromo language areas are not covered in the research. |
|  | Building a Dataset for Detecting Fake News in the Amharic Language [38] | The presented study concerns the establishment of a comprehensive collection of data and categorizers to identify fabricated news in the Amharic language. Nevertheless, the report does not address the identification of false news in the Afan Oromo language. | Development of machine learning classifiers for false news identification.  Creation of an Amharic fake news dataset | Researchers created an Amharic fake news dataset using data from trusted sources and social media accounts. They evaluated six machine learning classifiers, including Nave Bayes and Passive Aggressive Classifier, based on accuracy and F1-score. Nave Bayes and Passive Aggressive Classifier performed best, with accuracy over 96% and F1-score over 99%. The project aims to automate identifying bogus news in Amharic using machine learning techniques. | The study covers how to create a dataset for identifying fake news in Amharic using machine learning classifiers. The study emphasizes the increased use of social media platforms and the propagation of distorted information, particularly during the COVID-19 epidemic. Using six machine learning classifiers, the researchers constructed an Amharic fake news dataset from reputable sources and social media pages. With an F1-score of 99%, the Nave Bayes and Passive Aggressive Classifier performed the best. The findings might aid in the reduction of misinformation in Amharic and have implications for automated fake news identification in vernacular languages. | The work focuses on creating a dataset for identifying fake news in Amharic, a low-resource language.  The researchers compiled an Amharic false news dataset using verified news sources and social media pages.  Six different machine learning classifiers, including Nave Bayes, SVM, Logistic Regression, SGD, Random Forest, and Passive Aggressive Classifier, were created and tested.  The trial findings revealed that Nave Bayes and Passive Aggressive Classifier performed the best, with an accuracy of more than 96% and an F1 score greater than 99%.  The study makes an important contribution by lowering the rate of misinformation in the Amharic language. | The research used machine learning classifiers to detect and categorize bogus news in Amharic. Researchers collected verified sources and social media pages to develop an Amharic false news dataset. Six different classifiers were evaluated, with Nave Bayes and Passive Aggressive Classifier outperforming the others with accuracy greater than 96% and an F1-score greater than 99%. The findings have important implications for decreasing misinformation in Amharic and developing an automated method for recognizing and categorizing bogus news. | The paper lacks information on the size and representativeness of the Amharic fake news dataset, the specific features used in machine learning classifiers, potential biases or limitations of using verified news sources and social media pages, the challenges of detecting fake news in Amharic, and the impact of the chosen classifiers on computational resources and scalability for real-time fake news detection. These considerations may have an impact on the generalizability of the results and the model's dependability. |
|  | Deep Learning for Fake News Detection: Literature Review [39] | The research that has been presented does not provide any indication of the utilization of deep learning for identifying false information on social media in the Afaan Oromo language. | Deep learning algorithms for detecting fake news Investigation of word embedding models and attention processes | Deep learning techniques (RNNs, CNNs, multimodal approach) - Word embedding models for text-to-vector conversion | Deep learning approaches for detecting false news - Application of CNNs, RNNs, and word embedding models | Deep learning algorithms have shown potential in detecting bogus news - word embedding models and attention mechanisms are employed. | N/A | Manually detecting fake news is subjective and difficult. - An automated approach needs knowledge of complicated NLP and may struggle to produce correct results. |
|  | Deep Learning-Based Fake News Detection on social media [40] | The study "Fake News Detection on Social Media by Using Deep Learning for Afaan Oromo Language" is devoid of any discussion or information on the subject, raising concerns about its scope and emphasis. The report fails to address the rising concern about disinformation and fake news on social media platforms, and it makes no mention of the significance of deep learning techniques in addressing this issue. The absence of investigation into the Afaan Oromo language in the identification of fake news on social media is a key deficiency that requires additional attention. | The establishment of SOSYalan, the first real-world public dataset of Turkish false and legitimate news tweets. - The creation of deep learning-based methods for identifying bogus news in English and Turkish. | Recurrent neural networks-long short-term memory (RNN-LSTM) - Convolutional neural networks (CNN) | Existing FNDSs for the English language have been thoroughly researched. Few efforts have been made to develop FNDSs in Turkish. | Deep learning algorithms for English achieve better levels of accuracy. - Systems for Turkish are better than previous research. | When compared to previous studies, developed systems for the English language had greater accuracy rates. Few known research is outperformed by developed methods for the Turkish language. | Manually identifying fake news is subjective and difficult. - An automated approach needs knowledge of complicated NLP and may struggle to produce correct results. |
|  | Study of Fake News Detection Using Machine Learning and Deep Learning Classification Methods [41] | The research does not go into detail on "Fake News Detection on Social Media Using Deep Learning for Afaan Oromo Language." This lack of focus raises concerns about the research's thoroughness and the findings' possible limits. The authors' neglect of this area calls into question the completeness of their work and the relevance of their findings to the larger field of fake news identification and social media research. Future studies should fill this gap by investigating the possible applications and problems of deep learning approaches for detecting false news in Afaan Oromo. | When comparing the performance of Machine Learning and Deep Learning models for Fake News Detection on the FARN Dataset, Random Forest and Bag of Words outperformed with 98.8% accuracy. | Two Machine Learning and Deep Learning models are Random Forest and Bag of Words. | N/A | Random Forest and Bag of Words both had a 99.8% accuracy rate. - TF-IDF outperformed other feature extraction methods. | Random Forest and Bag of Words both scored 98.8% accuracy.  - TF-IDF outperformed other feature extraction approaches. | N/A |
|  | Tackling Fake News Detection by Interactively Learning Representations  using Graph Neural Networks [42] | The paper that has been provided unfortunately does not contain any information or discussion about the topic of "Fake News Detection on Social Media by Using Deep Learning for Afaan Oromo Language". | Proposing an interactive strategy that combines human understanding with the algorithmic system to improve the quality of social media representation.  Improving performance in this interactive context. | An interactive approach that combines human intuition with an automated mechanism - Supervised learning algorithms for detecting fake news | N/A | The interactive method improves the detection of fake information. - Human counsel may be regularly sought for better outcomes. | N/A | N/A |
|  | Combining Vagueness Detection with Deep Learning to Identify Fake News [43] | There is an absence of "Fake News Detection on Social Media by Using Deep Learning for Afaan Oromo Language" in the supplied article. The research discusses identifying bogus news on Twitter by combining the CNN approach with additional models. | For detecting fake news, a combination of VAGO and false-CLF detection algorithms is used.  A positive association exists between VAGO's vagueness and subjectivity measurements and FAKE-CLF's categorization of text as biased. | The VAGO algorithm measures ambiguity and subjectivity in text using semantic rules and NLP approaches.  To categorize texts as biased or authentic, the FAKE-CLF classifier uses Convolutional Neural Network classification and supervised deep learning. | N/A | A positive relationship between ambiguity and subjective measures - Additional strategies for detecting false news | Mutual positive aspects between VAGO and FAKE - Positive association between subjective and ambiguous measures and biased classification-CLF in elucidating and growing the database. | N/A |
|  | Fake news detection: A hybrid CNN-RNN-based deep learning approach [44] | The study introduces a brand-new hybrid deep learning model that combines recurrent and convolutional neural networks to classify bogus news. To stop the spread of false information, the research attempts to create automatic detection methods utilizing machine learning and artificial intelligence. Two false news datasets were used to effectively verify the model, and the findings show promise for more research. On the other hand, Afan Oromo's identification of bogus news on social media is not included in the supplied document. | Compared to existing baseline techniques, the hybrid deep learning model that was proposed for the classification of fake news produced improved detection results. | Deep learning model hybrid CNN-RNN  Artificial intelligence and machine learning approaches | N/A | A hybrid CNN-RNN model detects fake news more accurately. Promising findings for generalization across diverse datasets | Better fake news identification was attained by the hybrid model; promising generalization across other datasets | N/A |
|  | A Technique to Detect Fake News Using Machine Learning [45] | The important subject of "Fake News Detection on Social Media by Using Deep Learning for Afaan Oromo Language" is regrettably ignored in the offered article. This paper's failure to address the specific topic of misreporting and the methods used to identify false news that generally affects social media platforms is disappointing. Unfortunately, this paper lacks sufficient details about the previously described topic. | Presented a methodical methodology for identifying fake news.  94% classification accuracy and 97% recall were attained. | A systematic approach to detect fake news has been proposed. Employed a document-based corpus to gather datasets. | N/A | The proposed framework achieves 94% classification accuracy  The dataset was changed from a document-based format to an event-based representation. | 94% classification accuracy.  97% recall. | N/A |
|  | Deep Learning for Fake News Detection: Literature Review [46] | The paper that has been provided unfortunately neglects to include any discussion or mention regarding the crucial topic of "Fake News Detection on Social Media by Utilizing Deep Learning for the Afan Oromo Language". | Use of deep learning tools for detecting fake news. Investigating word embedding models and attention techniques | The use of deep learning techniques (CNNs, RNNs, and multimodal approaches)  Text-to-vector conversion word embedding models | Deep learning approaches for detecting false news - Application of CNNs, RNNs, and word embedding models | Algorithms using deep learning appear to be promising for spotting bogus news.  Attention mechanisms and word embedding models are employed. | N/A | Manually detecting fake news is subjective and difficult.  An automated approach needs knowledge of complicated NLP and may struggle to produce reliable results. |
|  | Study of Fake News Detection Using Machine Learning and Deep Learning Classification Methods [47] | The article given contains no material or discussion on the topic of "Fake News Detection on Social Media Using Deep Learning for Afaan Oromo Language." | We compared the performance of Machine Learning and Deep Learning models for detecting fake news.  Random Forest and Bag of Words outperformed with 98.8% accuracy on the FARN Dataset. | Machine Learning and Deep Learning models.  Random Forest with Bag of Words. | N/A | Random Forest and Bag of Words attained an accuracy of 98.8%.  TF-IDF performed better than other feature extraction approaches. | Random Forest and Bag of Words were both 99.8% accurate.  Other feature extraction approaches were outperformed by TF-IDF. | N/A |
|  | A Deep Learning-Based Approach for Fake News Detection [48] | The paper that has been given for analysis and examination, unfortunately, omits any discussion or mention of a crucial topic, namely, "Fake News Detection on Social Media by Using Deep Learning for Afaan Oromo Language", thereby neglecting to delve into the potential applications, methodologies, and advancements in the realm of utilizing deep learning algorithms for the identification and identification of fabricated or misleading information specifically within the context of the Afaan Oromo language. | A technique for detecting and eliminating fake news sites is used in this system.  XGBoost classifier evaluation metrics and ROC curve for tweet classification. | The XGBoost algorithm is used to identify user attributes.  Natural language processing algorithms, a sequential neural network, and the BERT transformer are used to classify Twitter text. | N/A | The algorithm known as XGBoost is used to classify user attributes.  The BERT transformer is used to classify Twitter text. | The XGBoost classifier identified tweets based on user and tweet properties using assessment metrics supplied in tabular form and the ROC curve displayed in a diagrammatic manner.  The BERT transformer achieved 98% accuracy in tweet text classification. | N/A |
|  | Combating Fake News in “Low-Resource” Languages: Amharic Fake News Detection Accompanied by Resource Crafting [49] | The study works to tackle misleading information in low-resource languages by establishing a cutting-edge algorithm for detecting fake news in Amharic. The model is predicted to be useful in detecting false information in Amharic text. The researchers also developed tools to aid in the detection of fake news in Amharic, such as a large Amharic corpus for training and testing algorithms and word embeddings that record semantic links between words. These contributions not only illustrate the difficulties in combatting false news in low-resource languages but also provide actual answers and tools to overcome these difficulties. The study, however, makes no mention of the Afan Oromo language. | - Model for detecting fake news in Amharic GPAC stands for General-Purpose Amharic Corpus. | Deep learning techniques  Embeddings of words | N/A | The study proposes a successful Amharic false news detection model.  In addition, the research presents a general-purpose Amharic corpus as well as a fresh Amharic false news detection dataset. | The Amharic false news detection algorithm outperformed the ETH\_FAKE dataset.  AMFTWE was employed as the detection model's word embedding. | The research emphasizes the difficulties in detecting fake news due to insufficient datasets and word embeddings, especially in low-resource African languages like Amharic. It also lacks a full description of the Amharic fake news detection model's weaknesses, such as potential biases or areas of struggle. The assessment is confined to the ETH\_FAKE dataset and the AMFTWE word embedding, with no additional datasets or embeddings being considered. |
|  | Fake News Detection: a comparison between available Deep Learning techniques in vector space [50] | However, there is no mention of "Fake News Detection on Social Media by Using Deep Learning for Afaan Oromo Language" in the supplied article. The study is about detecting false news using news articles and user participation in social networks. | Deep Learning Techniques for Detecting Fake News Comparison outcomes evaluation and study of the causes behind the outcomes | Deep Learning Techniques Comparison  In vector space, news occurrences are represented. | The research analyzes several deep-learning approaches for detecting fake news.  It examines the outcomes and assesses the causes underlying them. | Deep Learning approaches for detecting fake news are compared. The results analysis and rationale evaluation | Deep Learning technique comparison for fake news detection Analysis and assessment of the outcomes | The information provided contains no specified constraints.  N/A |
|  | Analysis of Text Feature Extractors Using Deep Learning on Fake News [51] | The paper that has been provided unfortunately neglects to include any information or discussion of the topic of "Fake News Detection on Social Media by Utilizing Deep Learning Specifically for the Afaan Oromo Language". | Analyzing the efficacy of a model for detecting bogus news.  Comparing various text feature extractors | - TD-IDF vectorizer - Glove embeddings - BERT embeddings | Fake news identification using NLP has gained popularity.  Various word transformation algorithms were investigated. | The best results were obtained with BERT embeddings.  TD-IDF outperformed glove embeddings. | BERT was 96% accurate on the first dataset and 99% accurate on the second.  On the first dataset, TD-IDF attained 93% accuracy and 96% accuracy on the second dataset. | The same sources may supply both phony and true news.  The terminology employed might be deceptive. |
|  | Deep Learning for Fake News Detection [52] | The paper does not address the topic of "Fake News Detection on Social Media Using Deep Learning for Afaan Oromo Language," which entails identifying false or misleading information on social media using advanced machine learning algorithms designed specifically for the Afaan Oromo language. This absence calls into question the research's comprehensiveness and breadth, needing more inquiry and analysis to understand the reasons for the exclusion and its consequences for the paper's conclusions. | A survey of deep learning techniques for detecting false news.  Evaluation criteria and datasets for detecting false news | Deep learning methods  A thorough examination of the literature and datasets used | The study does a thorough review of the current literature on fake news identification.  It emphasizes the application of deep learning models in the detection of fake news. | Deep learning algorithms are good at detecting fake news.  There are some promising research avenues for detecting fake news. | The study gives an in-depth examination of deep learning algorithms for detecting fake news.  The study offers possible research avenues for detecting fake news. mentioned. | N/A |
|  | Detecting Fake News Using Deep Learning and NLP [53] | Unfortunately, the paper that has been graciously provided for review fails to address or provide any relevant information on the highly significant and pertinent subject matter of "Fake News Detection on Social Media Using Deep Learning Techniques specifically catered for the Afaan Oromo Language." | Using deep learning to detect fake news.  Detection by natural language processing. | Deep learning technique  Natural language processing | N/A | Detecting fake news with deep learning and natural language processing  The importance of fact-checking and dependable information | The study describes a method for detecting false news using deep learning and natural language processing. By battling fake news, The Daily hopes to make every nation a safer place. | N/A |
|  | A Review of Web Infodemic Analysis and Detection Trends across  Multimodalities using Deep Neural Networks [54] | "Fake News Detection on Social Media by Using Deep Learning for Afaan Oromo Language" is not mentioned in the supplied article. The study compares Deep Learning approaches for generic Fake News Detection. | A comprehensive review of eighty papers  Identifying research needs and developing a research strategy | Machine learning and deep learning algorithms Techniques for detecting fake news in several modes | A review of 80 papers on multimodal fake news detecting strategies was conducted. - Identifies research gaps and lays the groundwork for future growth in the discipline. | Multimodal strategies for detecting fake news are successful.  There is a need for more study in this area. | The report includes an extensive literature review of eighty papers. The study outlines research gaps and provides a course for future progress in the field. | N/A |
|  | Fake News Detection Using Machine Learning: A Review [55] | "Fake News Detection on Social Media by Using Deep Learning for Afaan Oromo Language" is not mentioned in the supplied article. The research is about assessing and identifying bogus news across many modalities using deep neural networks. | Investigating various tactics and forms of discontent in the management of Internet news. A discussion of the characteristics of false news and the necessity for a mechanism to evaluate its possibility. | Natural language recognition techniques - Machine learning for fake news detection | The research investigates the use of natural language recognition algorithms for detecting false news. The research investigates several machine learning algorithms for discriminating between false and manufactured news. | The quantity of unnecessary and obsolete features in the fake news detection algorithm can be reduced.  In the function selection system, key qualities should be separated into discrete clusters. | Real-time tweet extraction and preprocessing Predictive accuracy and system variability calculation | The classifier's performance may be calculated. Prediction accuracy is quantified using precision, recall, and f1 scores. |
|  | FakeBERT: Fake news detection in social media with a BERT-based deep learning approach [56] | The paper provided fails to include any information regarding the identification of "Fake News" on social media through the utilization of deep learning techniques for the Afaan Oromo language. | Fake news identification using a BERT-based deep learning algorithm (FakeBERT). Combination of several parallel CNN blocks with BERT. | Deep learning technique based on BERT (FakeBERT) Combination of parallel 1D-CNN blocks with varying kernel sizes and filters | Kumar et al [21] did a thorough assessment of false news identification, including several categories, existing algorithms, and future implications. Shin et al [37] investigated key ideas to improve the multidisciplinary research of fake news, concentrating on erroneous information, writing styles, dissemination patterns, and producers' and spreaders' trustworthiness. | FakeBERT, a deep learning strategy based on BERT, surpasses current models with an accuracy of 98.90%. Future work will entail developing a hybrid technique for detecting multiclass fake news. | The suggested model (FakeBERT) performs better than current benchmarks. The proposed model's accuracy is 98.90%. | N/A |

Evaluating the output of a machine learning model is a critical stage in a predictive modeling pipeline. An evaluation matrix is a critical tool for planning and organizing an evaluation, and the confusion matrix displays a summary of model performance on the testing dataset [57]. The number of labels in most classification problems is fixed, so determining the score for each class and the loss from the ground truth is straightforward. In the case of NLP, even though the output format is predetermined, dimensions cannot be chosen because a single remark can be presented in a variety of ways without changing its intent or meaning. If we are attempting to solve two problems with one model, evaluation measures are critical for assessing its performance.

Various evaluation measures are utilized to assess the effectiveness of algorithms for identifying false news. The Afaan Oromo fake news dataset was used in this work to assess the efficacy of machine learning algorithms, with four potential categorization results represented by a confusion matrix. In our instance:

True Positives (TPs): The news item has been deemed false or fake.

False Positives (FPs): The news item has been mistakenly identified as true despite being false

False Negatives (FNs): The news item is accurate but has been labeled phony.

The news item has been evaluated as true and is true according to the true negative (TN)

We extract the following measures, which will be used to assess our models, from those measurements.

The ratio of accurate predictions to the total number of datasets reflects how accurately the data are measured.

Precision: the percentage of correctly identified positives that we corrected.

### Accuracy

The accuracy score, also known as the classification accuracy rating, is calculated as the proportion of correct predictions to total predictions generated by the model. The given formula in Equation (1) might illustrate the accuracy.

### Precision

The precision (P) was defined as the number of actual positive findings divided by the total number of positive results, including incorrectly recognized findings. The precision can be computed using Equation (2).

### Recall

When the total number of samples that should have been identified as positive is used for division, the number of true positive results is referred to as the recall (R). The recall can be computed using Equation (3):

## The Simple Bayesian Classifier

Academia has investigated different methods for detecting and categorizing bogus news in the Afan Oromo language, such as the bag of words, term frequency, and term frequency-inverse document frequency methods. They also tested different n-gram sizes and feature counts ranging from 6000 to 60,000. The multinomial naive Bayes classifier was found to be the best for discrete features such as word counts in text classification. The term frequency approach was used to measure document similarity by estimating the frequency of terms in the datasets. Each document was represented by a vector of equal length and word counts, which were then normalized to ensure equal sums. Based on word counts, the chance of each word occurring in the publications was computed.

## 4.2. K-Nearest Neighbor Classification System

The K-nearest neighbors (KNN) method uses a similarity metric to classify texts. It calculates the distance between each document in the training set. Within the K nearest neighbors set, the document is allocated to the category with the most papers. However, determining the optimum number of K might be difficult. In practice, an odd number is usually selected to avoid misunderstanding across data classes. The number N denotes the number of samples in the training dataset [58].

## Bidirectional LSTM

A bidirectional LSTM, commonly referred to as a BiLSTM, is a model for processing sequences that comprises two LSTMs. One LSTM network receives input in the forward direction, while the other receives input in the reverse direction. The author initially used the vanilla RNN in the initial experiment, then employed LSTM in the second part of the experiment, and ultimately utilized the Bi-LSTM technique in the final experiment. The pia chart shows the accuracy of each model.

Figure 5. The pia chart displays each model's accuracy.

### The Outcomes Contrasted with those of the Current Techniques

Within the domain of existing and proposed methods, support vector machines (SVMs) and neural networks provide two different results. It is important to compare the results gained from these two approaches with those derived from the current methods. Moreover, it becomes imperative to evaluate the characteristics and time needs of the current procedure relative to the hybrid strategy that is being presented. Furthermore, it is critical to assess the results obtained using the neural network and SVM in the proposed hybrid technique. These results should be examined alongside the accuracy rates that correlate with them. To fully understand the differences between the current/current approach and the proposed/novel methodology, we need to look at the diagram, which does a good job of illustrating the contrast indicated in the next figure presents a comparison between the suggested/new approach and the current/existing method.

Figure 6. Presents a comparison between the suggested/new approach and the current/existing method.

## An overview of the models' classification performance

Figure 7 A summary of the models' classification performance

# Challenges and Research Directions

## Consequences of fake news

The phenomenon of fake news and disinformation spreading rapidly across the internet can lead to significant and far-reaching consequences. In this digital age, individuals have the opportunity to access news and information online through a multitude of channels, enabling an unprecedented dissemination of both accurate and false news. However, it is important to acknowledge that the latter can proliferate at an alarming pace due to advancements in technology and the ever-evolving landscape of global media [59]. The detrimental impact of fake news on social stability and public trust necessitates an urgent and heightened demand for the identification and verification of such misinformation. Although the existence of fake news dates back to the very beginning of human civilization, its prevalence has experienced a substantial surge in recent years, primarily attributed to current technological advancements and sweeping transformations within the global media industry [29]. Fake news, or disinformation, may have serious ramifications for any language or culture, including Afaan Oromo. This can lead to increased hate speech and violent acts due to uncertainty, misconceptions, and distrust. Moreover, public trust in the media is undermined by discrediting trustworthy news sources [60]. This makes it harder for people to tell the difference between genuine and fake news, leaving them more vulnerable to manipulation and propaganda. Fake news has far-reaching consequences for Afaan Oromo and can cause severe harm. Individuals must check the authenticity of information before disseminating it, and media outlets must adhere to ethical standards in their reporting procedures. Fake news, or the dissemination of misleading information, has serious consequences for individuals, their well-being, and the financial system. During the 2016 American presidential election, the media focused on false news in particular, emphasizing its profound ramifications for society [61]. This tendency has the potential to weaken trust in institutions, leading to increasing division and a loss of faith in democratic processes. Fake news may disseminate false information on health and politics, causing uncertainty and even disastrous decisions. It has the potential to aggravate societal differences by perpetuating biases and prejudices. Fake news has the potential to influence political results and ruin the reputations of people and organizations. The pervasive repercussions of false news underline the importance of developing efficient methods for recognizing and countering this insidious problem. The pervasive repercussions of false news highlight the importance of developing effective techniques to detect and counteract this insidious problem.

### The source and the present fact of fake news

Fake news, which encompasses a type of misinformation deliberately disseminated across various social media platforms, arises from a multitude of sources, including but not limited to clickbait websites, partisan websites, social media bots, foreign governments, and individuals who crave attention. These aforementioned websites employ the tactic of crafting sensationalized headlines, enticing users to click, and generating revenue through advertisements, all while sacrificing accuracy and truth for their benefit. Partisan websites, on the other hand, cater to specific political ideologies and are inclined to publish stories that are either biased or false, thereby reinforcing the beliefs of their respective audiences. Moreover, social media bots, which are automated accounts, can be programmed to perpetuate the spread of fake news, thus manipulating public opinion. In a similar vein, foreign governments have been known to exploit social media as a tool for disseminating propaganda and disinformation, with the ultimate goal of influencing elections and fostering discord. Additionally, individuals who seek attention may resort to fabricating and disseminating fake news to gain the desired spotlight or advance their agendas. Given the ubiquity of these potential sources of fake news, it is of utmost importance to exercise caution and engage in critical evaluation before accepting any information as true. [29].

### Natural Language Processing in Fake News

The field of natural language processing (NLP) is experiencing rapid expansion, which in turn presents a host of new challenges. Addressing challenges like contextual usage of words, homonyms, sarcasm, irony, informal phrases, idioms, and culture-specific jargon is crucial for the widespread application of Natural Language Processing (NLP), as its effectiveness may vary. Despite advancements in autocorrect and grammar correction software, the presence of misspelled or misused phrases can still lead to complications. Consequently, it is essential to develop models that cater to the needs of all individuals rather than relying solely on specialized linguistic skills and technology for detecting fake news. Although deep learning-based methods have shown superior accuracy compared to conventional methods, there is still ample room for further improvement [62]. The selection of features and classifiers significantly impacts the efficiency of the model, an aspect that previous research has not adequately prioritized. Additionally, it is crucial to explore other features, such as user behaviors, profiles, and social network behaviors, to enhance the identification of fake news. By considering variables related to political or religious bias in profiles, as well as lexical, syntactic, and statistical factors, the detection rates can be significantly boosted. The utilization of metadata and other relevant information can further enhance the resilience of the system and minimize noise in evaluating individual textual claims. Furthermore, incorporating video and image features, along with real-time fake news detection methods, can potentially lead to improved outcomes in terms of detection accuracy. Data scarcity poses a significant challenge in the categorization of false news, necessitating a greater abundance of data. Compared with basic classifiers, ensemble approaches and models utilizing GRUs exhibit superior performance, while transformers have supplanted RNN models such as LSTM in the realm of NLP tasks. Deep learning-based techniques demonstrate greater accuracy than traditional methods, although further enhancement of these methods is needed. The selection of features and classifiers profoundly influences the effectiveness of the model, warranting researchers' attention toward identifying the optimal classifier for specific characteristics. Sequence models (RNNs) are essential for accommodating lengthy textual features, yet only a limited number of related research papers have done so. The concept of feature engineering is not commonly employed in deep learning-based investigations, and an amalgamation of deeply concealed textual features with other statistical attributes may aid in performance improvement. Network-based patterns of news propagation are not fully exploited for the identification of false news; thus, it is advisable to consider news dissemination when discerning spurious news [18]. The identification of fake news is a complex domain that necessitates the integration of characteristics derived from diverse origins. Scholars propose the utilization of visual data, encompassing videos and photographs, to construct a robust framework [63]. The amalgamation of pre-trained word embeddings with multimodal-driven methodologies could assist in the identification of deceitful articles [64]. The real-time acquisition of knowledge from newly published online articles could enhance the outcomes of detection. To enhance the performance of models, it is advisable to make more data regarding a greater number of false news items accessible to the public [63]. The implementation of ensemble techniques, such as deep learning (DL) and machine learning (ML) approaches, has the potential to enhance outcomes [65]. Scholars are encouraged to experiment with models such as sequential generative adversarial networks (SeqGANs) and deep belief networks (DBNs), as well as employ the generative pre-trained transformer (GPT) for natural language processing (NLP) tasks. The present algorithms make pivotal determinations without furnishing in-depth rationales for their decisions [66] [64] [67] [68].

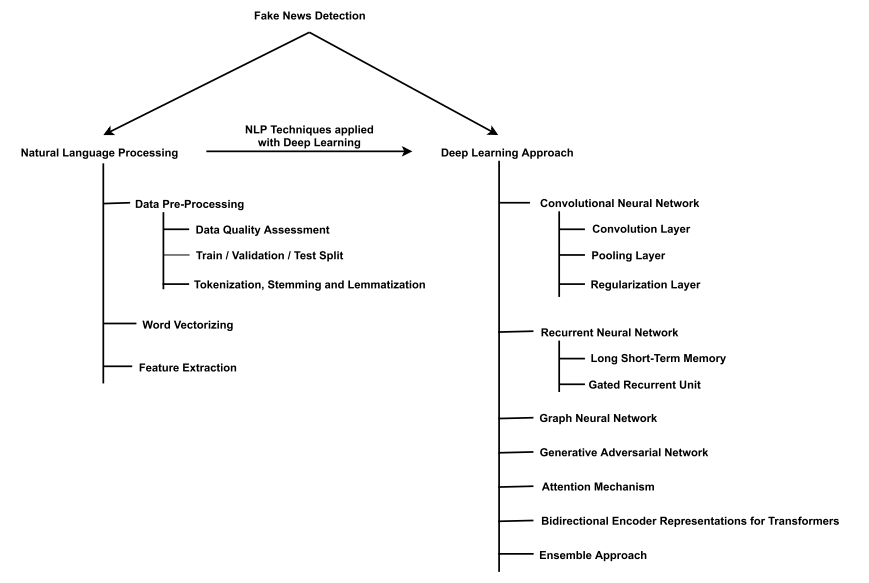


Figure 8 Categorization of fake news detection utilizing deep learning techniques [29].

# Conclusion

This study examines machine learning methodologies for detecting fake news in Ethiopia, focusing on deep learning techniques. The results show that deep learning significantly improves the performance of detection systems across all metrics. The study suggests that deep learning approaches should be employed in other Ethiopian languages to enhance the efficacy of these systems across various social media platforms. Combining deep learning and machine learning approaches and using a balanced dataset can greatly enhance the system's capabilities for detecting and combating fake news. The study also examines factors contributing to the spread of misinformation on social media, such as social, cognitive, political, financial, and malevolent aspects. Social variables like conformity, peer influence, and satire significantly impact the spread of erroneous information. Malicious causes like hate propaganda can also contribute to the propagation of incorrect information. Knowledge and education are critical in limiting the spread of misleading information. Fact-checking sites are often unknown and underutilized, but increased knowledge and education can raise users' awareness of potentially unregulated sources and prevent the spread of erroneous information. This research can serve as a valuable resource for further investigations into fake news identification and the development of new models or tools for early detection. Further studies using these criteria to detect and control the spread of erroneous information are advised.

**Declarations**

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**Competing interests**: The authors declare that they have no competing interests

**Conflicts of interest**: The authors declare that they have no conflict of interest

**Data availability**: The datasets generated and analyzed in this research study are not publicly accessible. However, they can be obtained from the corresponding author upon a reasonable request, even though they are not accessible to the general public.

**Code availability**: Not applicable

**Acknowledgments:** Not applicable

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