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Application of deep learning and machine learning techniques for the detection of misleading health reports

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ABSTRACT

In the current era of vast information availability, the dissemination of misleading health information poses a considerable obstacle, jeopardizing public health and overall well-being. To tackle this challenge, experts have utilized artificial intelligence methods, especially machine learning (ML) and deep learning (DL), to create automated systems that can identify misleading health-related information. This study thoroughly investigates ML and DL techniques for detecting fraudulent health news. The analysis delves into distinct methodologies, exploring their unique approaches, metrics, and challenges. This study explores various techniques utilized in feature engineering, model architecture, and evaluation metrics within the realms of machine learning and deep learning methodologies. Additionally, we analyze the consequences of our results on enhancing the efficacy of systems designed to detect counterfeit health news and propose possible avenues for future investigation in this vital area.

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1. INTRODUCTION

In today's digital landscape, where information is readily accessible and disseminated at remarkable speeds, the rise of misinformation, particularly in health-related matters, has emerged as a critical and challenging issue. Inaccurate health information encompasses a wide spectrum of misinformation, ranging from exaggerated claims about the efficacy of specific treatments to completely false data related to diseases and public health measures. The consumption of disinformation can lead to significant consequences, such as making erroneous health choices, endorsing hazardous practices, and eroding confidence in credible sources [1]. The rise of social media platforms, online forums, and instant messaging applications has enabled the swift spread of misleading health information, frequently outpacing the capacity of fact-checkers and health authorities to counter false claims. The coronavirus disease (COVID-19) pandemic has exacerbated the situation by facilitating the swift dissemination of misinformation regarding the virus, vaccines, and public health measures across digital platforms. This has led to tangible consequences, such as hesitancy towards vaccines and non-adherence to preventive strategies [2], [3]. In response to the growing issue of misleading health information, scholars and engineers have been investigating innovative approaches that leverage artificial intelligence (AI) techniques. Machine learning (ML) and deep learning (DL) are powerful tools for the automatic detection of fraudulent health-related information. Machine learning algorithms, encompassing traditional classifiers and ensemble methods, have been employed to analyze the textual, visual, and contextual features of health news articles and social media content. At the same time, deep learning algorithms, known for their capacity to comprehend complex patterns from large datasets, have shown promise in identifying nuanced signs of fake news [4]. This study aims to provide a comprehensive analysis of the techniques in ML and DL that are employed for the detection of fake health news. The focus is on conducting a comparative analysis of various methodologies, performance indicators, and challenges related to this task. By synthesizing and examining current research, we seek to provide a meaningful contribution to the advancement of artificial intelligence-driven solutions that could effectively address misinformation in the health sector [5]. This comparison study aims to analyze and comprehend the benefits and drawbacks of ML and DL techniques. Through this approach, we aim to acquire significant insights that can enhance the precision and dependability of systems designed to detect false health news.

In the following sections, we will review the literature on identifying fake health information. This will include an examination of machine learning and deep learning algorithms, training and evaluation datasets, feature generation strategies, and model performance indicators. We will also examine the difficulties of identifying bogus health information and suggest ways to improve AI-driven solutions to combat health misinformation [6]. Computer scientists, information scientists, and public health experts are interested in identifying fake health news. This section summarizes ML and DL studies on false health news detection. Key approaches, datasets, feature engineering methods, and evaluation measures from earlier works are highlighted [7]. Several research has used typical machine learning algorithms to detect fake health news. Zihan *et al.* used language features and user factors to categorize health-related tweets as real or deceptive using support vector machine (SVM). Their efforts identified deceptive smoking cessation tweets with potential results [8]. Castillo *et al.* detected health forum misinformation using naive Bayes classifiers. Textual attributes and user interaction patterns were used [9]. Along with the above methods, false health news detection has used random forests and gradient boosting. Olusola *et al.* used a random forest algorithm to evaluate COVID-19 related news stories as trustworthy or untrustworthy based on language and source reliability. Ensemble learning algorithms were accurate in identifying dubious news sources, reducing disinformation during public health crises [10]. Deep learning algorithms can find complex patterns in raw data, which might reveal fake health news. Text categorization, including fake news detection, is a common use of convolutional neural networks (CNNs). Wang *et al.* used a CNN to identify health-related tweets as trustworthy or untrustworthy. Their results showed that their strategy outperformed traditional machine learning [11].

Recurrent neural networks (RNNs), including long short-term memory (LSTM) and gated recurrent unit (GRU), have been used to predict sequences and detect false health news. Chen *et al.* used textual and contextual data to categorize health articles as trustworthy or untrustworthy using an LSTM-based model. Their method identified counterfeit health news stories better than machine learning methods, showing that deep learning can recognize temporal linkages and complex linguistic clues. Multi-dataset models have been trained and evaluated to identify bogus health news. The datasets include publicly available collections like HealthMisinfo and proprietary datasets based on online forum and social media data. Models that recognize bogus health news are evaluated using accuracy, precision, recall, and F1-score. In these jobs, eliminating false positives and negatives must be balanced [12]. Identifying fraudulent health information has improved, but many obstacles remain. The growth of disinformation across various platforms, malicious actors' ever-changing methods, and the lack of labeled data for exact detection models are major hurdles in this sector. Scholars, professionals, and decision-makers from different fields must collaborate to solve these problems. Additionally, breakthrough AI-powered solutions that can adapt to changing information environments and stop the spread of incorrect health information are needed. The following sections will compare ML and DL methods for detecting bogus health news [13], [14]. Their strengths, shortcomings, and performance measures will be analyzed using standard datasets. We will also examine how our findings may affect future health sector misinformation studies and applications.

2. METHOD

Identifying false health news can be achieved through machine learning by employing a range of algorithms and feature engineering methods. This discussion focuses on various performance metrics, feature engineering strategies, and machine learning techniques aimed at identifying fraudulent health news articles [15]. One method to detect misleading health information involves the application of support vector machines, naive bayes, decision trees, or random forests. Given its strong performance in high-dimensional feature spaces, SVM has been utilized to classify health-related text by taking into account lexical, syntactic, and semantic factors. Naive Bayes classifiers demonstrate an impressive capability to differentiate between authentic and fraudulent health records, even with minimal training data, highlighting their effectiveness despite an appearance of simplicity [16]. Decision trees and random forests excel at managing nonlinear relationships and feature interactions, enabling them to identify nuanced signs of misleading health information. Ensemble methods like random forests improve generalization and reduce overfitting by combining the predictions of multiple base learners [17]. Feature engineering transforms raw text into significant representations for classification, helping machine learning identify bogus health news. Term frequency-inverse document frequency (TF-IDF) weights, word embeddings, bag-of-words representations, and syntactic or semantic linguistic analysis features are used [18]. Bag-of-words approaches ignore text structure and order when estimating word frequency. TF-IDF weighting highlights valuable traits while downplaying common phrases by boosting discriminative terms throughout documents. Word2Vec and GloVe use continuous vector space to densely represent words, capturing contextual nuances and semantic commonalities [19]. Machine learning algorithms leverage user engagement indicators like likes, shares, and comments, publication timeliness, and source credibility to detect fake health news. These metadata characteristics improve classification model discrimination using contextual information [20].

Machine learning systems that recognize bogus health news are evaluated using accuracy, precision, recall, and F1-score. The ratio of correctly categorized occurrences determines model accuracy [21]. Precision measures the percentage of real positives to total positives, while recall measures model accuracy. In imbalanced class distributions, the F1-score—the harmonic mean of recall and precision—improves model performance [22]. Area under the receiver operating characteristic curve (AUC-ROC) and area under the precision-recall curve (AUC-PR) are used to evaluate machine learning models' discriminative capability and robustness at different classification thresholds [23]. Machine learning evaluates health news stories using algorithms, feature engineering, and performance indicators. These algorithms are effective, but they may struggle to recognize minor language variations and adapt to evil people's deception. The pros and cons of using machine learning and deep learning to identify fake health news will be examined [24]. Deep learning systems can automatically understand complex patterns in sequential, visual, and textual data, identifying bogus health news. Techniques, model designs, and performance measures for recognizing fake health information are covered here. Advanced techniques use sequential or textual neural network designs to recognize deceptive health information. Text categorization often uses CNNs. Convolutional neural networks build hierarchical text representations using convolutional and pooling layers. CNN-based models can capture local and global text trends using word embeddings as dense vectors [25]. Figure 1 shows how deep learning and machine learning are used to create models using material and recommended attributes. False news models are produced only from content, while feature-based models are built using content and readability features. We compare their performance.

LSTM and GRU excel at sequential data modeling and long-range relationships. Traditional RNNs struggle with vanishing gradients, whereas LSTM and GRU variations preserve text sequence context and temporal dynamics [26]. The context and word order of online discussions, news stories, and social media updates greatly affect believability. These models help evaluate such content. Transformer-based models like bidirectional encoder representations from transformers (BERT) and its variants have identified fake health news. BERT models use self-attention processes to gather bidirectional contextual information from input sequences to understand complicated textual representations without sequential processing. Pre-trained BERT embeddings fine-tuned using domain-specific datasets perform well at identifying bogus health news. Deep learning algorithms emphasize linguistic nuances, contextual signals, and semantic links to identify deceptive health news. Word2Vec, GloVe, and FastText capture contextual nuances and semantic similarities by representing words as dense vectors using continuous vector spaces. Dynamic relevance focusing uses word embeddings and attention mechanisms to reduce irrelevant data and emphasize relevant input sequences in deep learning models. Giving informative words and phrases more weight helps the computer discern factual from false content. Deep learning models that recognize bogus health news are assessed using accuracy, precision, recall, and F1-score. AUC-ROC and AUC-PR are additional measures for assessing deep learning models' discriminative power and robustness across classification criteria. Deep learning models are trained on large labeled datasets and evaluated on distinct test sets to ensure generalization. By dividing data into smaller sets, cross-validation can check model stability and variability. DL-based false health news detection systems can be assessed qualitatively for error analysis and model interpretability [27]. Deep learning uses transformers, RNNs, and CNNs to detect health news misinformation in textual or sequential data. These models generate complex representations of incoming information via assimilation of semantic links and contextual cues of dishonesty. Traditional metrics and qualitative assessments are used to evaluate deep learning models. Following sections will examine the pros and cons of using deep learning and machine learning to detect fake health news.

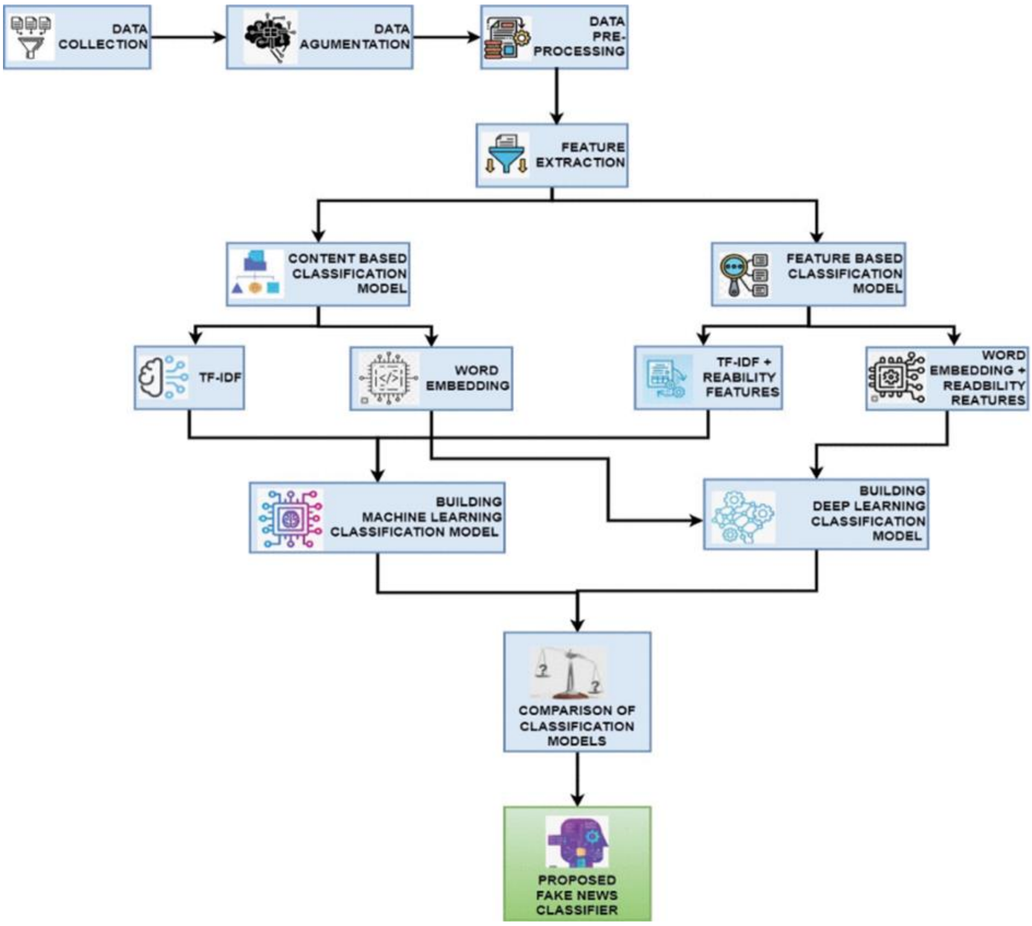

Figure 1. Methodology proposed

2.1. Comparative analysis

A comparison of machine learning and deep learning methods for identifying false health news is presented, including an analysis of their performance measures and associated challenges. An analysis of the advantages and limitations of both techniques is conducted to assess their effectiveness in mitigating health misinformation. In machine learning techniques, handcrafted characteristics and classical algorithms are employed to classify health content as either authentic or false. These methods require significant feature engineering and domain knowledge to derive valuable features from unprocessed textual data. Machine learning models have the potential to rival well-constructed features and ensemble methods; however, they often face challenges in identifying intricate patterns and advanced linguistic cues associated with misleading health news [28]. Rather than relying on feature engineering, deep learning techniques employ neural network architectures to autonomously learn representations of input data. Deep learning models, particularly those based on transformer architectures such as BERT, are capable of capturing intricate semantic connections and contextual details from textual data, thereby enhancing the detection of false health news. Deep learning models often require extensive labeled datasets and significant computational power for training, which can limit their use in environments with limited resources. Metrics such as accuracy, precision, recall, and F1-score are employed to assess machine learning and deep learning models in the context of identifying fake health news. With carefully crafted features and finely tuned hyperparameters, machine learning models can perform competitively on benchmark datasets. There is a possibility that they will not be able to generalize to new information or adjust to the deceptive strategies employed by adversarial entities. Deep learning models have the capability to identify intricate patterns within unprocessed data, surpassing traditional machine learning approaches in the detection of false health news. Transformer architectures leverage pre-trained embeddings and self-attention mechanisms to identify subtle linguistic cues associated with fraudulent or deceptive content, demonstrating strong performance on benchmark datasets. Deep learning models can exhibit overfitting tendencies, particularly when trained on limited datasets, necessitating fine-tuning with domain-specific data to achieve optimal performance.

3. RESULTS AND DISCUSSION

The accessibility of GPUs for intensive computations enables condition-based maintenance (CBM) and failure-based maintenance (FBM) to implement machine learning and deep learning techniques within the Google Colab framework. The code was developed using several Python packages, including Matplotlib, Scikit-learn, NumPy, pandas, and Keras. The deep learning models employed a 100-dimensional GloVe word embedding. A sequential model featuring multiple layers of neurons, available in Keras, was utilized to build the models that depend on deep learning. To evaluate the precision of false news classification, CBM employed five machine learning algorithms: decision tree, random forest, support vector machine, AdaBoost-decision tree, and AdaBoost-random forest. The results are illustrated in Figure 2. We conducted an analysis of the performances of five machine learning algorithms using FBM. Figure 3 presents the results, incorporating the readability features in conjunction with the content. The performances of CNN-LSTM and CNN-BiLSTM were analyzed for both the CBM and the proposed FBM. The materials are analyzed through a sophisticated methodology for the FBM, utilizing state-of-the-art techniques including the GloVe embedding approach, SMOG score, and TTR. These techniques are utilized to produce exact and reliable input vectors. Figures 4 and 5 illustrate a comparative analysis of the performance between CNN-LSTM and CNN-BiLSTM for both CBM and FBM. The figures are organized according to their performance metrics.

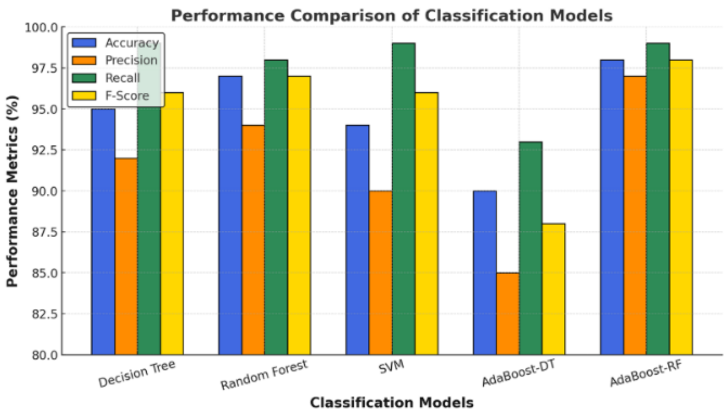

Figure 2. An evaluation of the efficacy of conventional machine learning models in comparison to content-based models

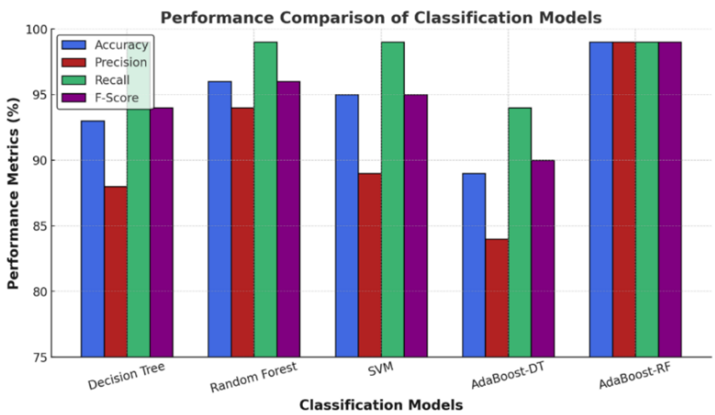

Figure 3. A comparison of how well traditional machine learning models work in the area of feature-based learning

The F1-score serves as an important metric for assessing the performance of the model, as it takes into account both Precision and Recall. The model's capability to predict and identify genuine instances is crucial for recognizing false news. The top-performing model in each category was identified according to its F1-score. Figure 6 presents the top model in each category, accompanied by its performance metrics. The experiments indicate that feature-based models demonstrate superior performance compared to traditional models. The findings indicate that AdaBoost-RF stands out as the leading performer among the content and feature based models. Upon examination of both groups, it is clear that AdaBoost-RF attained the highest F1-score. In the comparison between AdaBoost-RF and feature based AdaBoost-RF, it is notable that the former reaches an F1-score of 98.5% in CBM, whereas the latter surpasses this with a score of 98.9%. The AdaBoost-random forest model, well-respected in its domain, is affiliated with the FBM group and is frequently employed for the classification of false news.

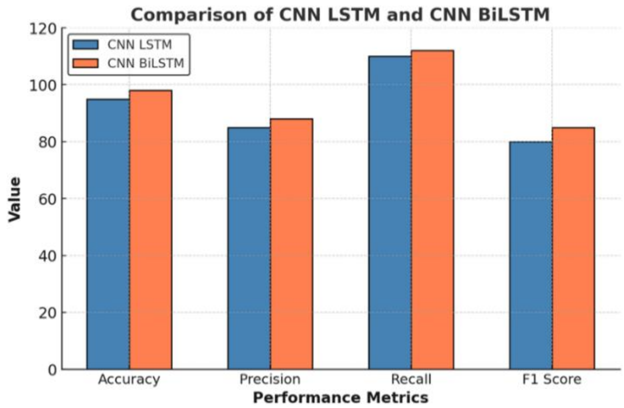

Figure 4. The proposed deep learning models' performance is compared under the content-based category

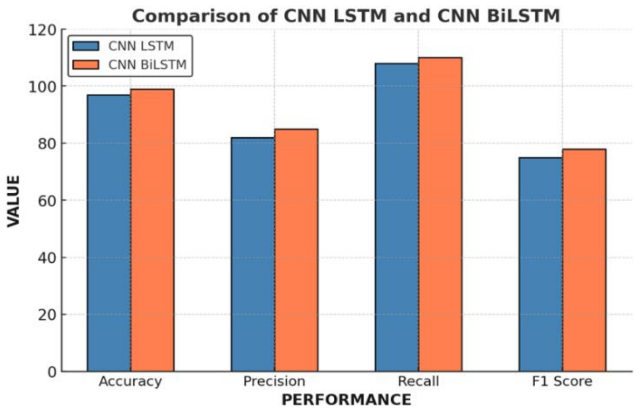

Figure 5. Feature-based performance comparison of suggested deep learning models

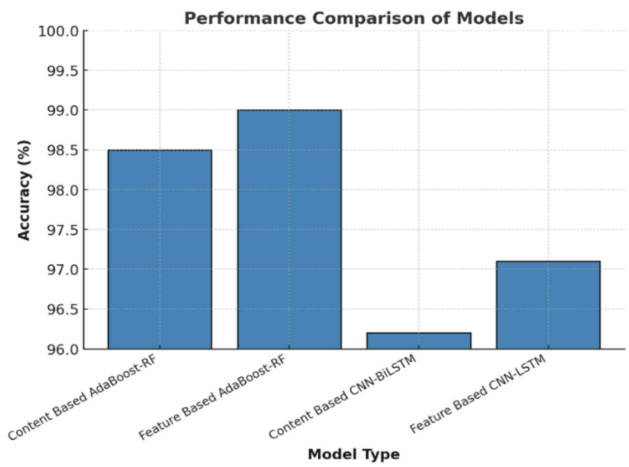

Figure 6. The top models in each category are compared

4. CONCLUSION

The spread of inaccurate health information occurs swiftly on social media and online platforms, presenting a significant risk to public health. Experts have utilized machine learning and deep learning techniques to create automated systems capable of identifying and addressing misleading health information. This investigation examines the approaches, obstacles, and prospective concepts for identifying fraudulent health information. In resource-constrained environments, it is possible to achieve interpretable machine learning solutions by employing traditional methodologies and handcrafted features. These methods might face challenges in identifying complex patterns and nuanced linguistic signals associated with deceptive health news. Nonetheless, advanced methodologies like convolutional neural networks, recurrent neural networks, and transformer-based models demonstrate exceptional capability in uncovering subtle semantic relationships and contextual details from raw textual data. Deep learning models demonstrate considerable effectiveness; however, their application is often limited by the requirement for large labeled datasets and substantial computational resources during the training process. Recognizing misleading health information moving forward necessitates cooperation among various fields, the application of cutting-edge research techniques, and the establishment of stringent assessment frameworks. Future studies should concentrate on creating models that withstand adversarial attacks, with the ability to identify and counteract these threats. Furthermore, it is essential to investigate the application of multimodal content analysis for assessing various forms of information. Additionally, it is essential to improve the clarity and understanding of detection models. The compilation of comprehensive collections of categorized datasets from various fabricated health news sources will facilitate the advancement of scalable, efficient, and real-time detection algorithms.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known financial or personal conflicts of interest that could have influenced the work reported in this paper. All authors confirm that there are no competing interests related to the research, authorship, or publication of this study.

ETHICAL APPROVAL

This study does not involve human participants, animals, or sensitive personal data requiring institutional ethical clearance. All datasets used in this research are publicly available or anonymized prior to use. Therefore, formal ethical approval was not required for the conduct of this study.

DATA AVAILABILITY

The datasets used and analyzed in this study are publicly available and can be accessed from the respective online repositories cited within the paper. Any additional data generated during the research are available from the corresponding author upon reasonable request.

REFERENCES

[1] H. Luo, M. Cai, and Y. Cui, "Spread of misinformation in social networks: Analysis based on Weibo tweets," *Security and Communication Networks*, vol. 2021, pp. 1–23, 2021, doi: 10.1155/2021/7999760.
[2] M. Sayeed, "COVID-19-related social media fake news in India," *Journalism and Media*, vol. 2, no. 1, pp. 100–114, 2021, doi: 10.3390/journalmedia2010007.
[3] M. Ittefaq, "'It frustrates me beyond words that I can't fix that': Health misinformation correction on Facebook during COVID-19," *Health Communication*, 2023, doi: 10.1080/10410236.2023.2282279.
[4] P. Akhtar, A. M. Ghouri, H. U. R. Khan, and Others, "Detecting fake news and disinformation using artificial intelligence and machine learning to avoid supply chain disruptions," *Annals of Operations Research*, vol. 327, pp. 633–657, 2023, doi: 10.1007/s10479-022-05015-5.
[5] E. A. Alikhashashneh, K. M. O. Nahar, M. Abual-Rub, and H. M. Alkhaldy, "A robust method for detecting fake news using both machine and deep learning algorithms," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 36, no. 3, pp. 1816–1826, Dec. 2024, doi: 10.11591/ijeecs.v36.i3.pp1816-1826.
[6] H. Najadat, M. Tawalbeh, and R. Awawdeh, "Fake news detection for Arabic headlines-articles news data using deep learning," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 4, pp. 3951–3959, Aug. 2022, doi: 10.11591/ijece.v12i4.pp3951-3959.
[7] M. F. Mridha, A. J. Keya, M. A. Hamid, M. M. Monowar, and M. S. Rahman, "A comprehensive review on fake news detection with deep learning," *IEEE Access*, vol. 9, pp. 156151–156170, 2021, doi: 10.1109/ACCESS.2021.3129329.
[8] Z. Zihan, L. Xiaosheng, W. Lijun, and H. Guangqiu, "Prediction of blast-induced ground vibration using eight new intelligent models," *IAENG International Journal of Computer Science*, vol. 51, no. 6, pp. 642–649, 2024.
[9] G. Castillo, "Territory as a sociopolitical appropriation of space. Between deterritorialization and multiterritoriality (in Spanish)," *Investigaciones Geográficas*, no. 103, Nov. 2020, doi: 10.14350/rig.60127.
[10] O. Olusola, R. Damaševičius, R. Maskeliūnas, and S. Misra, "An ensemble learning model for COVID-19 detection from blood test samples," *Sensors*, vol. 22, no. 6, p. 2224, 2022, doi: 10.3390/s22062224.
[11] Y. Wang, M. McKee, A. Torbica, and D. Stuckler, "Systematic literature review on the spread of health-related misinformation on social media," *Social Science & Medicine*, vol. 240, p. 112552, Nov. 2019, doi: 10.1016/j.socscimed.2019.112552.
[12] S. Chen, L. Xiao, and J. Mao, "Persuasion strategies of misinformation-containing posts in the social media," *Information Processing & Management*, vol. 58, no. 5, p. 102665, Sep. 2021, doi: 10.1016/j.ipm.2021.102665.
[13] E. Aïmeur, S. Amri, and G. Brassard, "Fake news, disinformation and misinformation in social media: A review," *Social Network Analysis and Mining*, vol. 13, no. 30, 2023, doi: 10.1007/s13278-023-01028-5.
[14] J. Alghamdi, S. Luo, and Y. Lin, "A comprehensive survey on machine learning approaches for fake news detection," *Multimedia Tools and Applications*, pp. 1–59, 2023, doi: 10.1007/s11042-023-17470-8.
[15] L. Hu, S. Wei, Z. Zhao, and B. Wu, "Deep learning for fake news detection: A comprehensive survey," *AI Open*, vol. 3, pp. 133–155, 2022, doi: 10.1016/j.aiopen.2022.09.001.
[16] I. H. Sarker, A. S. Kayes, and P. Watters, "Effectiveness analysis of machine learning classification models for predicting personalized context-aware smartphone usage," *Journal of Big Data*, vol. 6, no. 1, pp. 1–28, 2019, doi: 10.1186/s40537-019-0219-y.
[17] S. Hegelich, "Decision trees and random forests: Machine learning techniques to classify rare events," *European Policy Analysis*, vol. 2, no. 1, 2016, doi: 10.18278/epa.2.1.7.
[18] F. Alarfaj and J. Khan, "Deep dive into fake news detection: Feature-centric classification with ensemble and deep learning methods," *Algorithms*, vol. 16, no. 11, p. 507, 2023, doi: 10.3390/a16110507.
[19] Y. Li and T. Yang, "Word embedding for understanding natural language: A survey," in *Deep Learning in Internet of Things*, Springer, 2018. doi: 10.1007/978-3-319-53817-4_4.
[20] M. A. Alonso, D. Vilares, C. Gómez-Rodríguez, and J. Vilares, "Sentiment analysis for fake news detection," *Electronics*, vol. 10, no. 11, p. 1348, 2021, doi: 10.3390/electronics10111348.
[21] A. N. Ramkissoon and W. Goodridge, "Enhancing the predictive performance of credibility-based fake news detection using ensemble learning," *Review of Socionetwork Strategies*, vol. 16, pp. 259–289, 2022, doi: 10.1007/s12626-022-00127-7.
[22] P. Thölke and Others, "Class imbalance should not throw you off balance: Choosing the right classifiers and performance metrics for brain decoding with imbalanced data," *NeuroImage*, vol. 277, p. 120253, 2023, doi: 10.1016/j.neuroimage.2023.120253.
[23] K. Boyd, V. Costa, J. Davis, and C. Page, "Unachievable region in precision-recall space and its effect on empirical evaluation," 2012. doi: 10.5555/3042573.3042622.

[24] A. Gotmare, G. Thite, and L. Bewoor, “A multimodal machine learning approach to generate news articles from geo-tagged images,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 3, pp. 3434–3442, Jun. 2024, doi: 10.11591/ijece.v14i3.pp3434-3442.

[25] M. R. Islam, S. Liu, X. Wang, and Others, “Deep learning for misinformation detection on online social networks: a survey and new perspectives,” *Social Network Analysis and Mining*, vol. 10, no. 82, 2020, doi: 10.1007/s13278-020-00696-x.

[26] H. Sak, A. Senior, and F. Beaufays, “Long short-term memory recurrent neural network architectures for large scale acoustic modeling,” in *Proceedings of the Annual Conference of the International Speech Communication Association (INTERSPEECH)*, 2014, pp. 338–342. doi: 10.21437/Interspeech.2014-80.

[27] S. F. Ahmed, M. S. B. Alam, M. Hassan, and Others, “Deep learning modelling techniques: current progress, applications, advantages, and challenges,” *Artificial Intelligence Review*, vol. 56, pp. 13521–13617, 2023, doi: 10.1007/s10462-023-10466-8.

[28] R. Archana and P. S. E. Jeevaraj, “Deep learning models for digital image processing: a review,” *Artificial Intelligence Review*, vol. 57, no. 11, 2024, doi: 10.1007/s10462-023-10631-z.

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