

Fake News Detection Model Basing on Machine Learning Algorithms

Mohammed A. Taha*¹  , Haider D. A. Jabar²  , Widad K. Mohammed²  

¹Ministry of Education, Babylon Education Directorates, Babylon, Iraq.

²Ministry of Education, Baghdad, Iraq.

*Corresponding Author.

Received 07/03/2023, Revised 14/07/2023, Accepted 16/07/2023, Published Online First 20/01/2024,
Published 01/08/2024



© 2022 The Author(s). Published by College of Science for Women, University of Baghdad.

This is an open-access article distributed under the terms of the [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Abstract

The rapid growth of the internet and easy communication has made it quick and simple to create and spread news. Social media users now generate and share more information than before, but some of it is false and unrelated to reality. Detecting false information in text is challenging, even for experts who need to consider multiple factors to determine authenticity. Malicious misinformation on social media negatively affects societies, especially during crises like terrorist attacks, riots, and natural disasters. To minimize the harmful impact, it is crucial to identify rumors quickly. This study aims to build a learning model for detecting fake news. This research paper relies on finding and analyzing the characteristics of the text, then the words are converted into features using TF-IDF technology, after that the highest-ranking features are identified for the purpose of studying and distinguishing the spread of news, whether it is real or fake using machine learning techniques. Finally, the Logistic Regression, Decision Tree, Gradient Boosting and Random Forest algorithm has been adapted. The accuracy of Logistic Regression is 0.985, Random Forest (0.989) whereas the accuracy of Decision Tree is 0.994 and Gradient Boosting (0.9949), respectively.

Keywords: Classification, Decision Tree, Gradient Boosting, Logistic Regression, Random Forest.

Introduction

The internet and communication technologies have revolutionized communication, making it faster and more accessible. Popular social networks like Facebook have played a key role in spreading news rapidly, replacing traditional print media. For example, Facebook referral traffic accounts for 70% of all traffic to news websites¹. In the era of fast and efficient information flow through online platforms, people are susceptible to deception and manipulation, leading to lasting consequences. The popularity of social networking websites has enabled global information sharing and

consumption, making news readily accessible. The way that information is disseminated around the world and on the web has changed recently as a result of web-based media². The mass distribution of false information has detrimental effects on people and society. It disrupts social authenticity, promotes biased opinions, particularly through political propaganda, and hampers the comprehension and response to real news³. Text categorization is the technique of organizing and classifying texts based on their content. It plays a crucial role in natural language processing (NLP),

especially in tasks like subject labelling, spam detection, and sentiment analysis. NLP enables the automatic detection of relevant medical research documents, journals, and other sources worldwide by selecting specific labels or categories. However, evaluating the similarity of training dataset inputs remains important even after categorization. By employing NLP, machine learning, and data mining, patterns in electronic texts are automatically discovered and uncovered⁴. The technology's main goal is to make it possible for people to handle tasks involving text mining and information extraction from textual tools. Technologies for information extraction (IE) aim to extract exact information from text-based materials. This is the first method that shows that the terms "text mining" and "data extraction" can be used synonymously⁵. Many researches have concentrated on identifying and categorizing fake news on social media platforms, including in web content and social media⁶.

In⁷, the authors employed the vectorizers Count-Vectorizer (CV), Hashing-Vectorizer(HV), and Term Frequency-Inverse Document Frequency (TF-IDF) to categorize fake news, a multi-level voting ensemble model was deployed. The study in⁸ acknowledged the detection of false content in an effective method. The proposed methodology for identifying fake news was divided into four stages: data pre-processing, feature reduction, feature extraction, and classification. Data pre-processing involves tokenization, stop-word elimination, and stemming to pre-process the input data. In order to increase accuracy, the characteristics are decreased in the second stage using PPCA. For the extraction of text features, many techniques were used⁹. The authors advised creating text word embedding for the titles of the Reddit submissions using InferSent and BERT. In order to extract the features from the Reddit submission thumbnails, VGG16, EfficientNet, and ResNet50 were used. The research in¹⁰ suggested an upgraded deep neural networks for false news detection. Two deep learning methods are The Updated (one to three layers) as well as the improved GRU (one to three layers). Researchers investigated a sizable sample of tweets that contain information about COVID-19 in particular. The automated technique in¹¹, motivated

by natural human behaviours to detect bogus news. Humans naturally double-check new knowledge with reputable sources. A machine learning (ML) framework that automates the act of cross-checking fresh information with a collection of predetermined reputable sources is built using natural language processing (NLP), checks whether the wording of the tweet is consistent with reliable news using a Random Forest model. Optimization by particle swarms (PSO), the genetic algorithm (GA), and the Slap swarm algorithm were used in the suggested method in¹² to implement three wrapper feature selections for evolutionary classifications in order to limit the number of symmetrical features and achieve high accuracy (SSA).

The main objective of this work is designing, implementing, and evaluating a proposed system with classifiers from Logistic Regression, Random Forest, Decision Tree, and Gradient Boosting, assuming it is successful, in order to assist reduce the harm that fake news causes to the general public and the media ecosystem. It is vital that to create tools to detect fake news on social media automatically. Social bots are one of the most common ways to contribute fake news. Social media bots automatically create material and disseminate it to users of social media. Although the technologies used by social media have been carefully updated, they are still not effective in filtering fake news or disseminating critical information. More work is required before the news can reach the world at large.

Significant contributions have been made in this field, and the key features of proposed technique can be summarized as follows:

- These research studies gain their originality by using different classification models, such as logistic regression, random forest classifier, decision tree classifier, and gradient boosting classifier, to select the best fit model for the current data set since there is no standard data set for identifying fake news.
- Different textual properties that could be utilized to differentiate fake contents from real are explored in proposed study. By employing those properties, a combination of different

machine learning algorithms is trained, which has not been thoroughly explored in the current literature.

- Extensive experiments were conducted on publicly available real-world datasets in our study. The results validate the improved performance of our proposed technique, as measured by commonly used performance metrics such as accuracy, precision, recall, and F-1 score.
- Comparing the performance of machine learning classifiers and deep learning models in identifying and detecting fake news.

The rest of this article is structured as follows. Section 2 presents many false news terms, and Section 3 reviews the technique and outlines the various machine-learning methods utilized to develop the categorization model. Section 4 provides the classification findings. Final thoughts are offered in Section 6, which concludes the article.

Fake News Terminology

Fake news is any information that pertains to society and makes statements or descriptions about anything specific in speeches, bulletins, articles, headlines, postings, microblogs, or tweets¹³. Although the quantity of fake news, there are mostly two categories: partly false news which a crucial piece of information was missing, and totally fake news, with some or all of the news being made up to give it a completely new meaning or merely to make it more interesting. The world of fake news is very broad, fleeting, and its paths somewhat blurred, even if there are occasions when many forms of disinformation are transformed into fake news. To do this, one must be aware of the many forms of fake news¹⁴. On the basis of distribution channels and content, fake news can be divided into a number of sub-categories. Among them are:

Content Based Fake News

Based on content, fake news categorizes the news according to the type of content it contains. People

may misinterpret news that is satirical or contains material that was meant to be a joke for actual news¹⁵. A commentary on something may be personal thoughts or opinions that are not well educated, but the person or group delivering it may have a large number of followers who value their comments for whatever they are delivering⁶. Content based fake news can be further classified to the following types¹⁵:

- Fabricated stories: Stories that are completely fake that are spread to trick people, frequently for political or economic gain.
- Misleading headlines: Headlines that are intended to attract more attention but are not totally true or representational of the story's content¹⁶.
- Satire or parody: Stories that are meant to be humorous but are often mistaken for real news.
- Propaganda: Information that is disseminated to advance a specific political agenda, frequently by misrepresenting or presenting the facts in a biased way¹⁶.
- Hoaxes: Stories that are circulated with the intention of misleading others, frequently in order to cause harm or sow fear¹⁷.
- Clickbait: Headlines that often offer little real information or content but are intended to tempt readers to click on a story. It is a trap meant to generate advertising revenue or spread malware; when a user interacts with it while online, they are then sent to an advertisement or a dangerous page¹⁵.

Propagation-Based Fake News

Propagation-based fake news focuses on the origin and spread of false information. When someone or an organization spreads false information, they are misled since they don't understand if what they are saying is factually accurate or true to the point. When someone or a group is disseminating information, they are aware that what they are saying is false and that their motive for doing so is financial gain¹⁶.

Materials and Methods

Using a supervised classifier, the fake news detection problem has been approached as a classification problem. A significant, labelled dataset was required for supervised classification. It is the job of categorization to give a certain unlabelled location a name or class. A classifier is formally defined as a model or function that assigns a class to the class label point of an input. A training data set with precisely class-labeled points is required to build the supervised classifier. The model is ready to predict the class or label for any new point after it has been constructed and may

then be evaluated on a test data set. Following a description of the proposed framework, descriptions of the algorithms, datasets, and performance assessment indicators are provided. The suggested approach employed a binary supervised classifier to detect the bogus news. The association between independent factors and a dependent variable may be established using classification techniques and models. The classification models often depict traits, patterns, or principles of categorization that are concealed in the material. The proposed system model for detection is shown in Fig. 1.

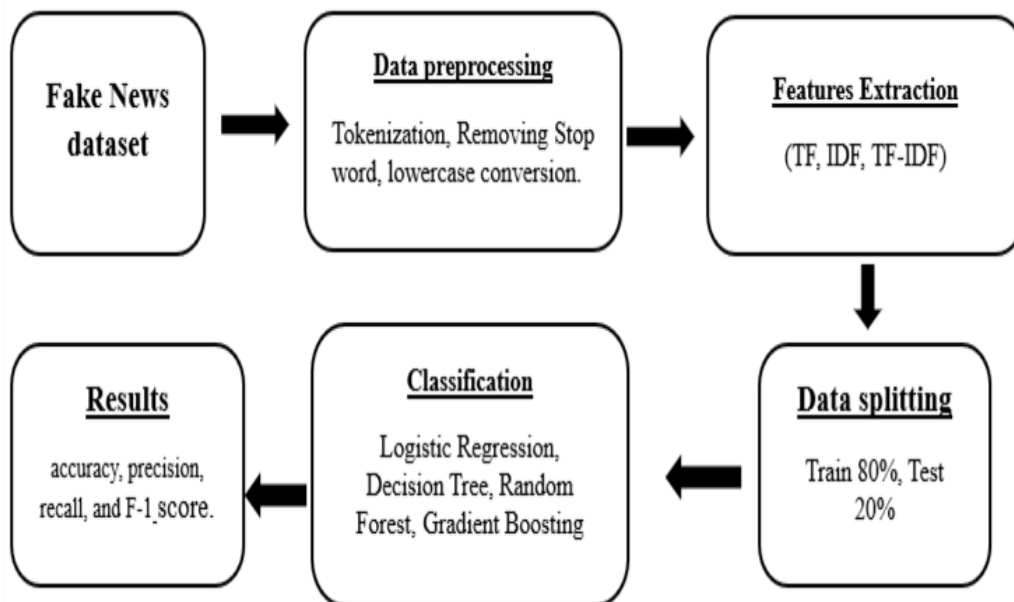


Figure 1. Fake news detection model

Data Source

The dataset was obtained from the Kaggle website. It possesses the following qualities: Id: a special identifier for a news story, title: the headline, subject: a description of the article's subject, and text: the article's content. 23524 news articles make up the data set for training and testing.

Data Pre-processing

The data needs to be pre-processed before being used in the training, testing, and modelling procedures. The real and fake news are combined before proceeding to subsequent phases. Tokenization describes interpreting and grouping isolated tokens to generate higher-level tokens in

addition to dividing strings into fundamental processing units. Word tokenization includes pre-processed raw texts are divided into textual units^{18,19}. During the dataset cleaning stage, the columns from the datasets that weren't needed for processing were removed. The punctuation and stop words were also taken off. Stop-words, such as "I," "are," "will," "shall," and "is it," are words that often appear in sentences. URLs are removed, because the URLs in the articles have no significance. Pre-processing data is regarded as an essential stage in natural language processing applications like key word extraction and search engine optimization, uppercase letters were changed into lowercase. To transform the information

collection into the proper organization, pre-processing is required. All NAN values were instantly removed from the dataset. The dataset appeared fine after cleaning, and the next step would be exploration.

Feature Extraction

Information extraction and natural languages processing employ the statistical measure TF-IDF (Term Frequency-Inverse Document Frequency) to assess the significance of a word in a document. With TF-IDF, a word's significance in a text is intended to be reflected in connection to the corpus of documents as a whole²⁰. Term Frequency (TF), which is the frequency at which a term appears in a document, is multiplied by the overall number of words contained in the document to produce Term Frequency-IDF. Inverse Document Frequency (IDF), on the other hand, is a value that indicates how uncommon a word is within the corpus of texts. It is determined by dividing the total number of documents by the number of papers containing the word in logarithmic form²¹. A word's significance in a document is shown by the resulting TF-IDF value, with higher values reflecting a word's greater significance. In addition to feature extraction and dimensionality reduction in machine learning models, TF-IDF is frequently employed in document classification, information retrieval, and text mining applications. Scikit learn, a Python library, was utilized. When utilizing the TF-IDF vectorizer model, this library is ideal. Tasks involving topic modelling, NLP, and machine learning all profit tremendously from TF-IDF. It makes it easier for algorithms to forecast outcomes using word importance. In Eq. 1, the formula for determining the TF is displayed²⁰:

$$TF(t, d) = \frac{\text{Number of times } t \text{ occurs in a document } \textit{d}}{\text{Total word count of document } \textit{d}}$$

1

The IDF, or inverse document frequency, is the next factor that must be determined to make sure the model functions effectively. It is employed to evaluate how significant a term is across the board in the dataset. The IDF formula is displayed in Eq. 2:

$$IDF(t) = \log_e \left(\frac{\text{Total number of documents}}{\text{Number of documents with term } t \text{ in it}} \right)$$

2

The TF-IDF should then be determined as the next step. Eq. 3 depicts the formula for the inverse document frequency integrated into term frequency¹⁸:

$$TF - IDF(t, d) = TF(t, d) * IDF(t)$$

3

The TF-IDF algorithm retrieved the feature engineering from the real and false news in used dataset and counted the most pertinent terms.

Classification

In data mining and machine learning, the process of classification involves training a model to identify a given input's class or category based on a collection of attributes. It is a supervised learning technique in which the model has been trained on a labelled dataset with the intention of discovering the link between the features and the target class¹. The proposed system uses more than one method of classification, including:

Logistic Regression: Machine learning's use of logistic regression makes it necessary to establish a link between the likelihood and highlights (outcome) of a given result²². When a categorical value is being predicted, a logistic regression classifier is used²³. Logistic regression is a method used in supervised learning. It is employed to ascertain or predict the probability that a binary (yes/no) event will take place. Making use of machine learning to predict whether or not news is likely to be fake could serve as an example of logistic regression. For instance, it will respond with true or false when anticipating the value. The likelihood (outcome) and highlights (probability) of a particular result can be connected using logistic regression. Considering its ease of use, effectiveness, and interpretability, logistic regression is a well-liked and frequently applied technique²³.

Random Forest Classifier: A random forest classifier, is a method for creating various decision trees and combining them to provide a more precise and reliable prediction²⁴. A decision tree or sacking classifier's hyperparameters are essentially identical

to those of the random forest. While creating the trees, this method increases the model's arbitrariness^{25,26}. There are diverse arbitrary trees that provide worth, and worth with more votes is the genuine aftereffect of this classifier.

Decision Tree Classifier: A decision tree or binary classifier have nearly same hyperparameters to the random forest. Through the development of the trees, this method increases the model's arbitrariness. The non-parametric supervised learning techniques that decision trees are known for can be applied to tasks like classification and regression. It functions as intended²⁵. Order trees are tree models where the goal variable can assume a discrete arrangement of attributes. Based on the Gini index, decision trees perform well and may be made rapidly. The decision tree classifier will be our final machine learning algorithm. Non-parametric supervised learning techniques for both processes, such as classification and regression

Results and Discussion

Various criteria were employed to assess the performance of the algorithms. The bulk of them are built on the confusion matrix²⁹. The classification model's performance on the test set is tabulated as a confusion matrix, which includes the four parameters true positive, false positive, true negative, and false negative Table 1.

Table 1. Confusion matrix

	Predicted true		Predicted false	
Actual true	True (TP)	positive	False (FN)	negative
Actual false	False (FP)	positive	True (TN)	negative

Accuracy: The most often used measure of accurately predicted observations, whether true or wrong, is accuracy³⁰. To assess a model's accuracy, use the Eq. 4 as below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad 4$$

In this scenario, a classification model is being created, and unfavorable effects may result from

problems, are well known for decision trees. A decision tree might also work well for detecting false news.

Gradient Boosting Classifiers: is a kind of ensemble learning algorithm applied to classification and regression tasks in supervised machine learning. To build a stronger, more precise model, it pools several weak learners (like decision trees). The fundamental principle behind gradient boosting is to train several models in succession, with each model attempting to fix the mistakes made by the model before it²⁷. To reduce a loss function that represents the model's error, the gradient boosting approach optimizes the weak learners' parameters²⁸. Through a weighted sum or voting method, the predictions of all the weak learners are combined to create the final prediction. High accuracy and robustness of Gradient Boosting Classifiers are well-known characteristics.

false positives or false negatives. A strong model is implied by a high accuracy score under most circumstances. Similarly, if accurate facts were present in a report that was considered fraudulent, the same could be said. To account for incorrectly categorized observations, three additional measures have been included: precision, recall, and F1-score.

Recall: is the total number of classifications outside of the genuine class that were correctly created. In our case, it represents the percentage of items that were accurately predicted out of all the articles that were successfully predicted, recall can be computed in Eq. 5 can be seen below³¹:

$$Recall = \frac{TP}{TP+FN} \quad 5$$

F1-Score: The F1-score illustrates the compromise between recall and accuracy. Between each pair, it calculates the harmonic mean. As a result, it takes into consideration observations that are both falsely positive and falsely negative. To determine the F1-score, apply the formula below. The following Eq. 6 can be used to calculate F1-score^{31,32}:

$$F1 - score = 2 \frac{Precision * Recall}{Precision + Recall} \quad 6$$

The recall, precision, and F1 scores of each algorithm on the dataset used for the false news detection model are summarized in Fig. 2.



Figure 2. Proposed System Results

The performance results for each method on the used datasets are summarized in Fig. 2. It is clear that the Gradient Boosting classifier has a maximum accuracy of 99%. After considering the observations and analyses presented above, it has been concluded that the suggested fake news detection model has been successful in achieving a notable increase in accuracy, precision, recall, and F-score with a very low value of false-positive rate. A recall value of 0.98 or 0.99 signifies that these models have a high ability to identify actual instances of fake news, minimizing the chances of false negatives (misclassifying real fake news as genuine). This high recall implies that the models have a low rate of missing or overlooking fake news articles.

A precision value of 0.99 or 1 implies that these models have a high ability to correctly classify

instances as fake news, minimizing the chances of false positives (misclassifying genuine news as fake). This high precision suggests that the models have a low rate of incorrectly labeling real news articles as fake.

The F1 score values of 0.99 for all four models—Logistic Regression, Random Forest, Decision Tree, and Gradient Boosting—suggest that they exhibit strong performance in accurately classifying instances as fake news. This implies that these models have a high ability to correctly detect fake news while minimizing misclassifications of genuine news.

The main factor leading to the superior performance of Gradient Boosting is the working principle which efficiently identifies errors and minimizes them in each iteration. The basic intuition behind the working of Gradient Boosting is to use multiple classification which combine multiple weak learners to assign higher weights to misclassified data points. The gradient boosting algorithm optimizes the parameters of the weak learners to minimize a loss function that represents the error of the model. The final prediction is made by combining the predictions of all the weak learners through a weighted sum or voting mechanism. Therefore, during each subsequent iteration, the model is able to correctly identify the misclassified points whereas regularization parameters are used to reduce the overfitting problem.

A Comparison with Existing Works

In order to prove the effectiveness of the proposed model, it is necessary to compare it and show its strengths and weaknesses with the previous used techniques. Table 2 shows a brief comparison between the methods used to diagnose and identify fake news.

Table 2. Fake News detection methods comparison

Classification Methods	Advantages	Disadvantages	accuracy
BERT ¹⁰	Captures contextual information effectively. Ability to handle long-range dependencies in text.	High computational requirements. Large memory footprint,	76%

	Pre-trained models provide a strong foundation.	Training time can be lengthy.	
VGG16⁹	Good at capturing visual features in images. Pre-trained models readily available.	Limited to image-based fake news detection. Difficulty in handling textual information.	86.5 %
EfficientNet¹⁰	Simplicity in architecture and implementation. Achieves high accuracy with fewer parameters. Balances model size and computational efficiency. Scalable to different image resolutions and sizes.	May require additional text processing for hybrid models. Training may be computationally expensive. Requires a large amount of training data.	86%
Proposed System	Decision Tree -Easy to interpret and understand. Gradient boosting Automatic feature selection and importance estimation. Random Forest robust to noise and outliers. Logistic Regression simple and interpretable model.	Prone to overfitting without proper regularization. Requires careful hyperparameter tuning. May require longer training times due to ensemble. Sensitive to outliers and noise in the data.	99.4 %

Based on variables including the dataset, feature representation, tuning of the hyperparameters, and the needs of the false news detection task, the actual performance and restrictions of these algorithms can differ. The choice of method depends on the specific requirements of the fake news detection

task, the available dataset, the interpretability desired, computational constraints, and the trade-off between accuracy and efficiency^{33,34}. It is essential to evaluate and compare these methods using appropriate metrics and techniques to identify the most suitable approach for a given application³⁵⁻³⁷.

Conclusion

Fake news spreads incredibly quickly. It might not be possible to tell it apart from truthful reporting. Nowadays, users download the data and share it with others. They don't even verify it to see if it's real, and by the end of the day, the false information has gone so far from its origin that it is no longer recognizable. Researchers suggested a practical method for identifying misleading information and

fake news using machine learning algorithms. Using Logistic Regression, Random Forest, Decision Trees, and Gradient Boosting a technique to identify bogus news. Fake news identification has a number of open issues that need to be researched. For instance, a vital first step in limiting the spread of false news is recognizing the essential elements involved in the distribution of news.

Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for

- re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at Ministry of Education\ Babylon Education Directorates.

Authors' Contribution Statement

M.A.T.: conceptualization, data collection, analysis, writing, review, and final approval. H.D.A.: literature review, methodology development, data

analysis, writing, visualization, and final approval. W.K.M.: supervision, funding acquisition, writing, project administration, and final approval.

References

1. Ahmad I, Yousaf M, Yousaf S, Ahmad MO. Fake News Detection Using Machine Learning Ensemble Methods. *Complexity*. 2020; 1-11. <https://doi.org/10.1155/2020/8885861>.
2. Awan MJ, Yasin A, Nobanee H, Ali AA, Shahzad Z, Nabeel M, et al. Fake news data exploration and analytics. *Electron*. 2021; 10, 19: 2326. <https://doi.org/10.3390/electronics10192326>.
3. Shu K, Sliva A, Wang S, Tang J, Liu H. Fake News Detection on Social Media. *Int J Inf Secur*. 2023; 22: 177–212. <https://doi.org/10.1007/s10207-022-00625-3>.
4. Khanam Z, Alwasel BN, Sirafi H, Rashid M. Fake News Detection Using Machine Learning Approaches. *IOP Conf Ser Mater Sci Eng*. 2021, 012040 IOP <https://doi.org/10.1088/1757-899X/1099/1/012040>
5. Ali I, Ayub MN Bin, Shivakumara P, Noor NFBM. Fake News Detection Techniques on Social Media: A Survey. *Wirel Commun Mob Comput*. 2022, Article ID 6072084,2022. <https://doi.org/10.1155/2022/6072084>.
6. Haque S, Eberhart Z, Bansal A, McMillan C. The Future of Misinformation Detection: New Perspectives and Trends. *IEEE Int Conf Progr Compr*. 2022; 36–47. <https://doi.org/10.48550/arXiv.1909.03654>.
7. Kaur S, Kumar P, Kumaraguru P. Automating fake news detection system using multi-level voting model. *Soft Comput*. 2020; 24(12): 9049–69. <https://doi.org/10.1007/s00500-019-04436-y>
8. Dixit DK, Bhagat A, Dangi D. Automating fake news detection using PPCA and levy flight-based LSTM. *Soft Comput*. 2022; 26(22): 12545–57. <https://doi.org/10.1007/s00500-022-07215-4>
9. Nakamura K, Levy S, Wang WY. r/Fakeddit: A new multimodal benchmark dataset for fine-grained fake news detection. *Lr 2020 - 12th Int Conf Lang Resour Eval Conf Proc*. 2020; 6149–57.
10. Abdelminaam DS, Ismail FH, Taha M, Taha A, Houssein EH, Nabil A. CoAID-DEEP: An Optimized Intelligent Framework for Automated Detecting COVID-19 Misleading Information on Twitter. *IEEE Access*. 2021; 27840–67. <https://doi.org/10.1109/ACCESS.2021.3058066>
11. Ghadiri Z, Ranjbar M, Ghanbarnejad F, Raeisi S. Automated Fake News Detection using cross-checking with reliable sources. *arXiv*. 2021; 1–12. <https://doi.org/10.48550/arXiv.2201.00083>
12. Al-Ahmad B, Al-Zoubi AM, Ruba AK, Ibrahim A. An Evolutionary Fake News Detection Method for COVID-19. *Symmetry (Basel)*. 2021; 1–16. <https://doi.org/10.3390/sym13061091>
13. Islam MR, Liu S, Wang X, Xu G. Deep learning for misinformation detection on online social networks: a survey and new perspectives. *Soc Netw Anal Min*. 2020; 10(1): 1–20. <https://doi.org/10.1007/s13278-020-00696-x>
14. Sharma S, Sharma DK. Fake News Detection: A long way to go. 2019 4th Int Conf Inf Syst Comput Netw, 2019; 816–21. <https://doi.org/10.1109/ISCON47742.2019.9036221>
15. Stitini O, Kaloun S, Bencharef O. Towards the Detection of Fake News on Social Networks Contributing to the Improvement of Trust and Transparency in Recommendation Systems: Trends and Challenges. *Info*. 2022; 13(3): 128. <https://doi.org/10.3390/info13030128>
16. Rastogi S, Bansal D. A review on fake news detection 3T's: typology, time of detection, taxonomies. *Int J Inf Secur*. 2023; 22(1): 177–212. <https://doi.org/10.1007/s10207-022-00625-3>
17. Rani N, Das P, Bhardwaj AK. Rumor, misinformation among web: A contemporary review of rumor detection techniques during different web waves. *Concurr Comput Pract Exp*. 2022; 34(1): 1–21. <https://doi.org/10.1002/cpe.6479>
18. Ismael Kadhim A, Cheah Y-N, Abbas Hieder I, Ahmed Ali R. Improving TF-IDF with Singular Value Decomposition (SVD) for Feature Extraction on Twitter. *Int Eng Conf*. 2017; 144–52. <https://doi.org/10.23918/iec2017.16>
19. Wotaifi TA, Dhannoon BN. Improving Prediction of Arabic Fake News Using Fuzzy Logic and Modified Random Forest Model. *Karbala Int J Mod Sci*. 2022; 8(3): 477–85. <https://doi.org/10.33640/2405-609x.3241>
20. Das B, Chakraborty S. An Improved Text Sentiment Classification Model Using TF-IDF and Next Word Negation. *arXiv*. 2018; 1-6. <https://doi.org/10.48550/arXiv.1806.06407>

21. Utsha RS, Keya M, Hasan MA, Islam MS. Qword at CheckThat! 2021: An extreme gradient boosting approach for multiclass fake news detection. CEUR Workshop Procding. 2021; 2936: 619–27. CEUR.org.
22. Poreba J, Baranowski J. Functional Logistic Regression for Motor Fault Classification Using Acoustic Data in Frequency Domain. Energies. 2022; 15(15). <https://doi.org/10.3390/en15155535>
23. Boateng EY, Abaye DA. A Review of the Logistic Regression Model with Emphasis on Medical Research. J Data Anal Inf Process. 2019; 07(04): 190–207. <https://doi.org/10.4236/jdaip.2019.74012>
24. Sievering AW, Wohlmuth P, Geßler N, Gunawardene MA, Herrlinger K, Bein B, et al. Comparison of machine learning methods with logistic regression analysis in creating predictive models for risk of critical in-hospital events in COVID-19 patients on hospital admission. BMC Med Inform Decis Mak . 2022; 22(1): 1–14. <https://doi.org/10.1186/s12911-022-02057-4>
25. Ong AKS, Prasetyo YT, Yuduang N, Nadlifatin R, Persada SF, Robas KPE, et al. Utilization of Random Forest Classifier and Artificial Neural Network for Predicting Factors Influencing the Perceived Usability of COVID-19 Contact Tracing “MorChana” in Thailand. Int J Environ Res Public Health. 2022; 19(13): 1-28. <https://doi.org/10.3390/ijerph19137979>
26. Popuri SK. An Approximation Method for Fitted Random Forests. Arxiv. 2022; 2207: [02184v1](https://doi.org/10.48550/arXiv.2207.02184). <https://doi.org/10.48550/arXiv.2207.02184>
27. Lacrois D, Bonnell TR, Shukla A, Chion C. The Gradient-Boosting Method for Tackling High Computing Demand in Underwater Acoustic Propagation Modeling. J Mar Sci Eng. 2022; 10(7): 899, <https://doi.org/10.3390/jmse10070899>
28. Adler AI, Painsky A. Feature Importance in Gradient Boosting Trees with Cross-Validation Feature Selection. Entropy. 2022; 24(5): 687. <https://doi.org/10.3390/e24050687>
29. Meshoul S, Batouche A, Shaiba H, AlBinali S. Explainable Multi-Class Classification Based on Integrative Feature Selection for Breast Cancer Subtyping. Math. 2022; 10(22). <https://doi.org/10.3390/math10224271>
30. Palaniappan M, Desingu K, Bharathi H, Chodisetty EA, Bhaskar A. Deep Learning and Gradient Boosting Ensembles for Classification of Snake Species. CEUR Workshop Procding. 2022; 3180: 2175–88.
31. Heydarian M, Doyle TE, Samavi R. MLCM: Multi-Label Confusion Matrix. IEEE Access. 2022; 10: 19083–95. <https://doi.org/10.1109/ACCESS.2022.3151048>
32. TAW, Dhannoon BN. An Effective Hybrid Deep Neural Network for Arabic Fake News Detection. Baghdad Sci J. 2023; 20(2) <https://dx.doi.org/10.21123/bsj.2023.7427>
33. Al-Shareeda, M.A.; Manickam, S. Man-in-the-Middle Attacks in Mobile Ad Hoc Networks (MANETs): Analysis and Evaluation. Symmetry 2022; 14: 1543. <https://doi.org/10.3390/sym14081543>
34. Baideia A Mohammed, Selvakumar Manickam, Zeyad Ghaleb, Abdulrahman Alreshaid, Meshari Alazam, Jalwal Sulaimani, et al. FC-PA: Fog Computing-Based Pseudonym Authentication Scheme in 5G-Enabled Vehicular Networks. IEEE Access. 2023. 11: 3-12. 18571-18581. <https://doi.org/10.1109/ACCESS.2023.3247222>
35. Taha MA, Ahmed HM. A fuzzy vault development based on iris images. EUREKA Phys Eng g. 2021; 5: 3-12. <https://doi.org/10.21303/2461-4262.2021.001997>.
36. Saha S, Dasgupta S, Anam A, Saha R, Nath S, Dutta S. An Investigation of Suicidal Ideation from Social Media Using Machine Learning Approach. Baghdad Sci J. 2023; 20(3(Suppl.)) :1164. <https://doi.org/10.21123/bsj.2023.8515>
37. Kareem AK, AL-Ani MM, Nafea AA. Detection of Autism Spectrum Disorder Using A 1-Dimensional Convolutional Neural Network. Baghdad Sci J. 2023; 20(3(Suppl.):) 1182. <https://doi.org/10.21123/bsj.2023.8564>

نموذج الكشف عن الأخبار المزيفة استناداً إلى خوارزميات التعلم الآلي

محمد عبدالله طه¹، حيدر ضياء عبدالجبار²، و داد كاظم محمد²

¹وزارة التربية، مديرية تربية بابل، بابل، العراق.
²وزارة التربية، بغداد، العراق.

الخلاصة

نظراً للتطور السريع والهائل لشبكة الويب العالمية وسهولة الاتصال بالعالم الخارجي، فقد أصبح من السهولة إنشاء الأخبار ونشرها بشكل أسرع من أي فترة أخرى. نتيجة للاستخدام المتزايد للشبكات الاجتماعية، يقوم المستخدمون بإنتاج ونشر معلومات أكثر من أي وقت مضى، وبعضها واقع خاطئ وغير ذي صلة. من الصعب اكتشاف المعلومات الخاطئة أو المضللة تلقائياً في المحتوى النصي. حتى المتخصص في الموضوع يجب أن يأخذ في الاعتبار عدداً من العناصر قبل تحديد مصداقية المقالة. المعلومات المضللة على وسائل التواصل الاجتماعي والكيدية والمنشورة عن قصد لها تأثير سلبي على المجتمعات والأشخاص، لا سيما في المواقف التي توجد فيها كوارث فعلية مثل الهجمات الإرهابية وأعمال الشغب والزلازل والفيضانات والحروب. لذلك من الأفضل التعرف على الشائعات في أسرع وقت ممكن للحد من أثارها السلبية على المجتمع. تهدف هذه الدراسة إلى بناء نموذج تعليمي للكشف عن الأخبار المزيفة. تعتمد هذه الورقة البحثية على البحث عن خصائص النص وتحليلها، ثم يتم تحويل الكلمات إلى ميزات باستخدام تقنية TF-IDF، وبعد ذلك يتم تحديد الميزات الأعلى مرتبة لغرض دراسة وتمييز انتشار الأخبار، سواء كان ذلك حقيقي أو مزيف باستخدام تقنيات التعلم الآلي. أخيراً، تم تكييف خوارزمية الانحدار اللوجستي، وشجرة القرار، وتعزيز التدرج، وخوارزمية الغابة العشوائية. تبلغ دقة الانحدار اللوجستي (0.985)، والغابة العشوائية (0.989)، بينما تبلغ دقة شجرة القرار (0.994) وتعزيز التدرج (0.9949) على التوالي.

الكلمات المفتاحية: التصنيف، شجرة القرار، تعزيز التدرج، الانحدار اللوجستي، الغابة العشوائية.