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FAKE NEWS DETECTION IN MOLDOVA'S INFORMATION SPACE

Maria Smarcevscaia *, ORCID: 0009-0008-7204-7963,
Victoria Bobicev *, ORCID: 0000-0003-4450-3964

Technical University of Moldova, 168, Stefan cel Mare Blvd., Chisinau, Republic of Moldova
* Corresponding author: Victoria Bobicev, *victoria.bobicev@ia.utm.md*

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Abstract. This work is devoted to the development of a system for automatic detection of fake news in Russian, relevant for the region of the Republic of Moldova and its neighboring countries. Initially, a representative dataset of fake and real news was collected from the news sites. Several machine learning models were applied for fake news detection, including Naive Bayes classifier, logistic regression, nearest neighbors, support vector machines, and random forest. The results demonstrated that support vector machines and random forest provide the highest accuracy of classification, reaching 91%, which is an impressive result for such difficult task. The developed system helps protecting society from disinformation, which is especially important in the modern world, where the information warfare and political manipulation have become commonplace.

Keywords: *natural language processing, automatic fake news detection, corpus of annotated news, machine learning.*

Rezumat. Această lucrare este dedicată dezvoltării unui sistem de detectare automată a știrilor false în limba rusă relevante pentru regiunea Republicii Moldova și țările vecine. Inițial, a fost colectat un set reprezentativ de știri false și reale de pe site-urile de noutăți. Mai multe modele de învățare automată au fost aplicate pentru detectarea știrilor false, inclusiv clasificatorul Naive Bayes, regresia logistică, metoda vecinilor celor mai apropiați, mașinile cu vectori de suport și pădure aleatorie de arbori decizionali. Rezultatele au demonstrat că mașinile cu vectori de suport și pădure aleatorie de arbori decizionali oferă cea mai mare precizie de clasificare, ajungând la 91%, ceea ce reprezintă un rezultat impresionant pentru o sarcină atât de dificilă. Sistemul dezvoltat ajută la protejarea societății de dezinformare, ceea ce este deosebit de important în lumea modernă, unde războiul informațional și manipularea politică au devenit o realitate zilnică.

Cuvinte-cheie: *procesarea limbajului natural, detectarea automată a știrilor false, corpus de știri adnotate, învățare automată.*

1. Introduction

The described research is dedicated to the development of an automatic fake news detection system. Fake news, also known as disinformation or misinformation, poses a significant threat to society. Fake news can erode trust in traditional media outlets, leading

people to question credible sources, they can also undermine trust in government institutions and democratic processes. Emotionally written fake news can exacerbate social divisions by spreading false or misleading information to reinforce existing prejudices [1]. Disinformation can damage the reputation of individuals, organizations, and even entire countries; they can influence elections by spreading false or misleading information about candidates or policies disrupting democratic processes by sowing confusion and distrust [2].

To combat the problem of fake news, it is essential to promote critical thinking, media literacy, and fact-checking. Additionally, platforms and governments need to work together to address the spread of misinformation and disinformation [3].

Fact-checking organizations around the world are tirelessly fighting for the truth, debunking fake news and disinformation. However, due to today's political events, their efforts may not be enough, as there is a constant information war. It is clear that in order to protect people from fake news, the process of identifying fakes must be automated. Machine learning algorithms trained on the reliable data can be a powerful tool in this fight.

Despite the existence of similar research, there is no adequate system for detecting fake news in Russian for the Republic of Moldova and neighboring regions. The complexity of developing such a system lies in the need to create a representative dataset, which involves identifying reliable sources that do not publish fake news and finding the fake news itself [4]. The creation of such a dataset is included in this work.

The paper includes an analysis of the concept of "fake news" and its impact on society and politics, and the development of a system for automatic detection of fake news, starting from data collection and ending with machine learning experiments, analysis of their results and conclusion.

2. Related Work

2.1 Fake News

The Cambridge Dictionary defines fake news as false or distorted stories that are spread online or in the media and created to influence political opinion or as a joke.

The term “fake news” in its modern sense first appeared in the 1890s, when newspapers often published sensational stories that had no basis in fact. The term has been used to describe false information in a variety of contexts, including political propaganda and disinformation [5].

Lately, the phenomenon of fake news in the modern online environment is investigated intensively in marketing, psychology, political and social studies. The review of the term "fake news" definition in previous studies is presented in [6] and a typology created in this study included news satire, parody, fabrication, manipulation, advertising, and propaganda, based on levels of facticity and deception. The cases of "fake news" when the author desires to manipulate the readers with the information that is not even truthful are considered the worst. In [7], the concept of "fake news" is studied as well, expanding it beyond false information; an introduced taxonomy identifies seven types of this phenomenon. The paper contains detailed lists of distinctive features for all seven types of news, tables of their comparison and a decision tree for news classification. In [8], the author concentrated on the "political fake news" and explored their historical specifics for different geographical region (Russian, Chinese and Western approaches). In [1], 25 types of fake news were identified; all types are evaluated for truthfulness, intention to deceive, ability to harm and humor. The paper is mostly concentrated on the problem of fake news in marketing. As it was pointed

out in [9], detection of the types of fake news is an essential criterion for their qualitative classification.

Important decisions, such as choosing a political candidate or determining a treatment for a disease, often depend on information from the news, making its accuracy critical. When people are unable to distinguish between real and fake news, confusion and misunderstandings arise around key issues. As a result, people distrust everything they read online, which in turn weakens trust in reliable news sources. This phenomenon is studied in [10]; the authors name this "fake news label", namely, the instrumentalization of the term to delegitimize news media. In [11], a broad classification of fake news is proposed, based on Ukrainian online media news, stydying ten types of deceptive content proposed in [12]: fake news, manipulation, deep fakes, puppet news, phishing, spreading rumors, bots, disinformation, clickbait, satire and parody. The authors emphasized the need for adaptable classifications while analyzing fake news for various geographical areas, political and social event.

Misinformation about treatments for diseases such as acquired immune deficiency syndrome (AIDS) or cancer leads people to make poor health choices [13].

Numerous fake news stories aim to increase social conflict. Since each side in a dispute has its own "facts," this contributes to increasing social polarization and can influence the outcome of elections or even the outbreak of war [14].

2.2 Fact Checking Organisations

Fact-checking websites are specialized online resources aimed at verifying the veracity of information, debunking false claims and disinformation. They play an important role in the modern media space, especially in the context of the dissemination of fake news and manipulative information. An overview of several sites of online fact-checking systems, such as FactCheck.org (https://www.factcheck.org/) and PolitiFact.com (https://www.politifact.com/) was presented in [15]. These systems are based on manual detection approaches performed by professionals. In the Republic of Moldova, fact-checking is carried out by the **stopfals.md** platform (Figure 1). This platform, developed by the Association of Independent Press (API), continues the campaign against disinformation **STOP FALS!**, launched in 2015-2017 together with the Center for Independent Journalism and the Association of Independent Television Journalists of Moldova.

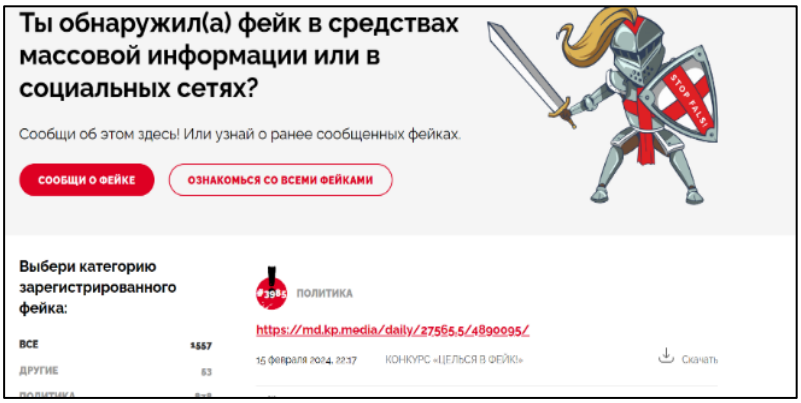

Figure 1. Screenshot of the web page semnale.stopfals.md.

The project is supported by the FHI 360 program "Partnership for a Sustainable Civil Society in Moldova". This initiative aims to combat propaganda and manipulation that is spread through the media and politically controlled structures, raising citizens' awareness of this and forcing them to objectively evaluate information.

Fact-checking sites fight for the truth on the Internet all over the world. For example, the organization Veridica (veridica.ro) monitors media and social networks in Romania and the Republic of Moldova.

The StopFake (stopfake.org) website fights fakes about Ukraine. The Factcheck (factcheck.kz) project is the first fact-checking resource in Kazakhstan and Central Asia, created by professional journalists from the International Journalism Center "MediaNet".

The Snopes (snopes.com) from the US, formerly known as Urban Legends Reference Pages, is engaged in checking the veracity of any controversial information. The site was founded in 1994 by Chris Richardson and Drew Schuntrup and has become one of the most authoritative sources of information on fake news.

The International Fact-Checking Network (IFCN), founded by Poynter (poynter.org) in 2015, brings together a growing global community of fact-checkers and advocates to combat misinformation on a global level. IFCN supports fact-checkers by building networks, expanding capacity, and facilitating collaboration

2.3 Automate Fake News Detection

Fake news detection is one of the tasks of Natural Language Processing (NLP) and is becoming an increasingly important and challenging problem today.

The main task is to analyze texts for their credibility. Usually, fake news is identified through a binary classification, where they are labeled as fake or real [16]. The effectiveness of such systems depends on the quality and quantity of training data, which leads to the exploration of semi-automated and manual methods. In [17], a series of experiments of fine-grained classification were conducted using a taxonomy of news that included factual and fake news. The importance of the feature selection is emphasized in multiple research. A number of various lexical resources such as sentiment lexicons, personal pronouns, modal and subjective verbs, strong adjectives, etc. were explored in [18] to define which are more prominent in unreliable and truthful news. In [19], the traditional token-based classification features such as named entities, headlines, subjectivity and sentiment of the text are used, but also the credibility history for the text author, sharing, and the comments for the post. The patterns of sentences interaction across different kind of news articles were studied in [20]. The authors encoded each document as a graph of sentences connected by their similarity, and demonstrated that such encoding was helpful in better detection of the false news. A complex onion-shaped graph that contains four major components of a false news: Creator/Spreader, Target Victims, News Content, and Social Context was presented in [21] along with the exhaustive analysis of every aspect of these components. A combination of bag-of-n-grams, bag of Rhetorical Structure Theory features, and BERT embeddings was used in [22] for the detection of two classes: satire and fake news for Russian texts; these features helped to reach 0.889 F1-score in distinguishing fake news from satire. Fine-grained modeling of subtle clues aimed to replicate human's information processing was described in [16]. Selection and analysis of such information as author's features, post's characteristics and text's key words was considered similar to user's treatment of news.

The role of manually annotated benchmark datasets was explored in various papers. A crowd-sourcing of fake news dataset was described in [23]. While simply collecting legitimate news from various USA news agencies, the authors used Amazon Mechanical Turk [24] to obtain fake news. A huge benchmark dataset named LIAR was presented in [25]. The paper describes the collection of 12.8K manually labeled short statements in various contexts

from politifact.com. Each statement was labelled for truthfulness, subject, context/venue, speaker, state, party, and prior history. A list of nine datasets is analyzed in a comprehensive review [4]. Only three of them had two classes: true or false. Others have three [26], four, six [24] and even ten classes. Vectors of 30 annotation elements are associated with every tweet of CredBank corpus [27]. The corpus comprises more than 60 million tweets; every tweet is labelled for credibility by 30 annotators. Creation of another dataset named PROPANEWS, with 2,256 examples is described in [28]. The authors of the paper used an original method: they did not collected data; they automatically generated more realistic disinformation with specific propaganda techniques. A new multi-domain knowledge-enhanced benchmark with fine-grained manual annotations that contains 16,909 data samples on six topics from eight platforms created in the framework of FineFake project was presented in [19].

Traditional machine learning methods are often applied in this area [29, 30], including support vector machines (SVM), naive Bayes classifiers (NBC), logistic regression (LR), and random forest classifiers (RFC).

Scientists from the Polytechnic University of Bucharest conducted a study to create a machine learning system for identifying fake news [31]. Their system is based on the Romanian news corpus, which contains 25,841 true news items and 13,064 fake news items. They used neural networks, language models, and classic machine learning methods. When identifying fake Romanian news items, the SVM method achieved 94% accuracy, the Naive Bayes classifier achieved 0.97%. Neural networks language models reached 98% of accuracy [32].

Deep learning methods have great potential in fake news detection tasks. Various experiments with classical BERT model and different combinations of features are presented in [33] demonstrating its effectiveness for this task. Bidirectional LSTM-GRU proposed in [34] demonstrated excellent results on huge Fake News Corpus (https://github.com/several27/FakeNewsCorpus). It is worth noting that neural networks are relevant for large data sets and there are various parameters that affect the performance of a neural network, such as the initialization of weights and biases, the activation functions used at each level, the optimizer and the loss function. A completely automated DeClarE (Debunking Claims with Interpretable Evidence) end-to-end neural network model [35] is working on the whole articles without complex text preprocessing. Transfer Learning (TL) is used in [36] to overcome the problem of massive data necessity for the neural network models obtaining over 90% accuracy on Filipino news dataset.

Most of the systems accessible via Internet that address the problem of fake news are created for the English texts. For example, Fake News Detection [37] by Discourse Processing Lab is a project by researchers from Simon Fraser University (SFU) in Canada, which is dedicated to detecting and combating fake news. Fake News Detector [38] of the Center for Brains, Minds and Machines (Massachusetts) uses deep neural networks to detect subtle differences in the language of real and fake news. Google's Fact Check Explorer is a tool designed to help journalists, fact-checkers, and anyone who wants to dig deeper into a topic or image. It lets you search for fact checks conducted by independent organizations around the world.

3. Corpus Creation

The study required the creation of a high-quality and representative dataset that would include both fake and reliable news materials. For this purpose, web parsing of reliable sources and manual collection of fakes were performed, Figure 2.

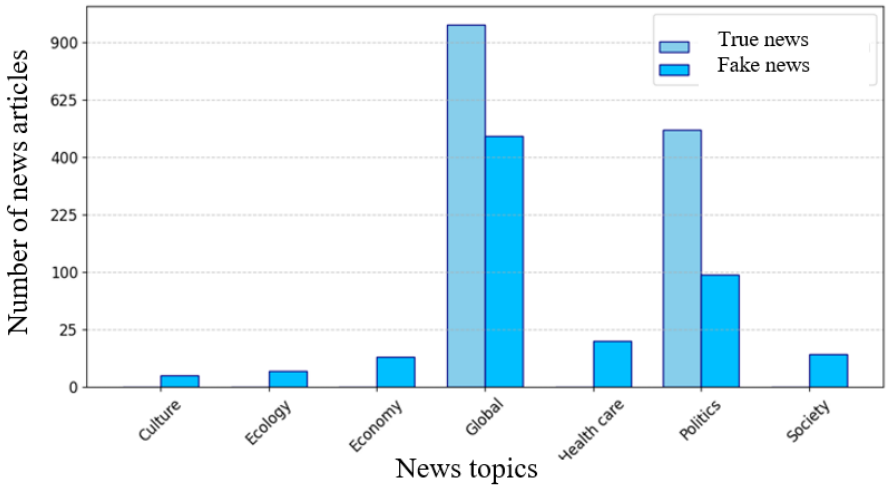

Figure 2. Topic Distribution in the Dataset.

The following sites specializing in fact-checking in Russian were selected as sources of fake news: stopfals.md, stopfake.org, factcheck.kz, veridica.ro, provereno.media, factcheck.kg, stopfake.kz. These sites regularly publish materials that verify the reliability of information.

To collect reliable news, two websites have been selected that are members of the Independent Press Association: "SP" and "Ziarul de Gardă". The choice of these sources was due to their reputation and strict standards in fact-checking. "SP" is a regional news agency that has been active in the city of Bălți (Moldova) since 1994. This publication is one of the largest local media outlets on the Internet, oriented not only to residents of the north of the country, but also to other regions of Moldova. The mission of "SP" is to provide honest information, protect human rights and freedoms, solve their problems and create a platform for exchanging opinions in its region.

”Ziarul de Gardă” is a Moldovan news outlet that has been promoting transparency and human rights through investigative journalism and objective reporting since 2004. The publication is dedicated to fighting corruption; it has won numerous awards for its work, which has led to resignations, sanctions and even criminal cases against those exposed.

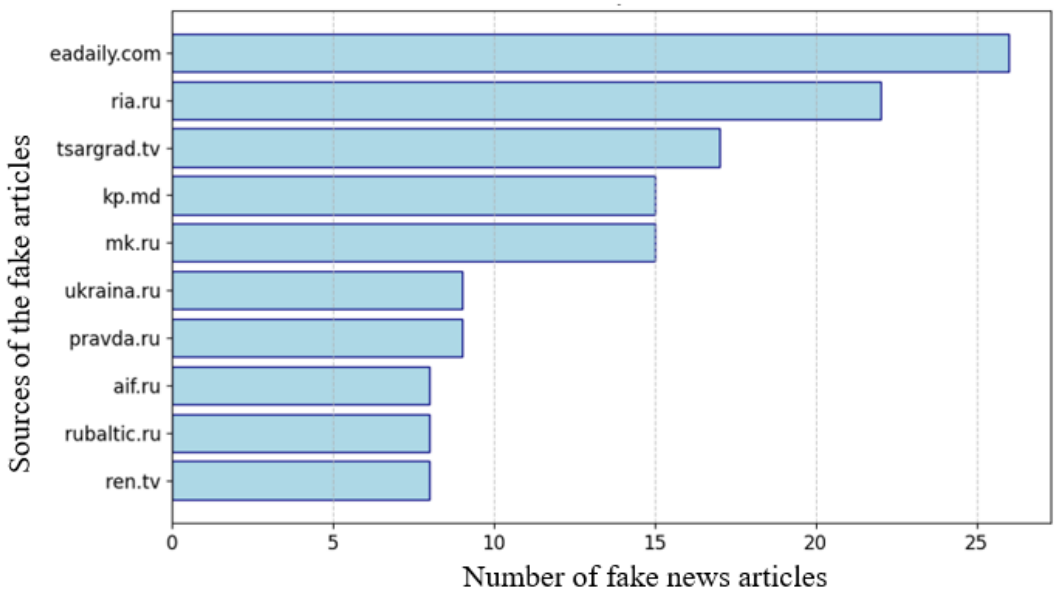

Figure 3. Sources of unreliable materials that are most often found in the dataset.

During the collection of information from reliable sources, BeautifulSoup library was used to parse web pages and extract news articles. As a result, a dataset was formed containing 2108 news articles, of which 614 are fake and 1494 are reliable

The largest number of fake texts were obtained about local political (Politics) and international (Global) topics: about the war in Ukraine, about Moldovan political figures, about relations between the Republic of Moldova and other countries. There are also many fakes about coronavirus and vaccination, the global economy, biological weapons and radiation. The full distribution of topics can be seen in Figure 2.

Fake news articles have been collected from 338 different sources. Many sites that published fakes are blocked in Moldova: kp.md, kp.ru, tsargrad.tv, aif.md, eadaily.com, pravda.ru and some others. These sites had to be accessed using a proxy server. The sources of unreliable materials that are most often found in the dataset are shown in Figure 3.

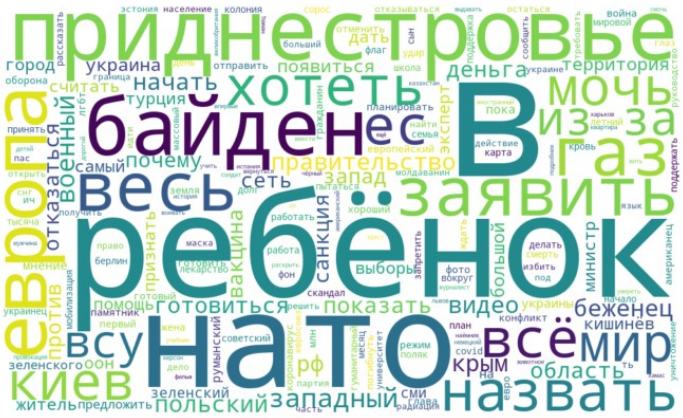

Figure 4. Word cloud based on fake headlines.

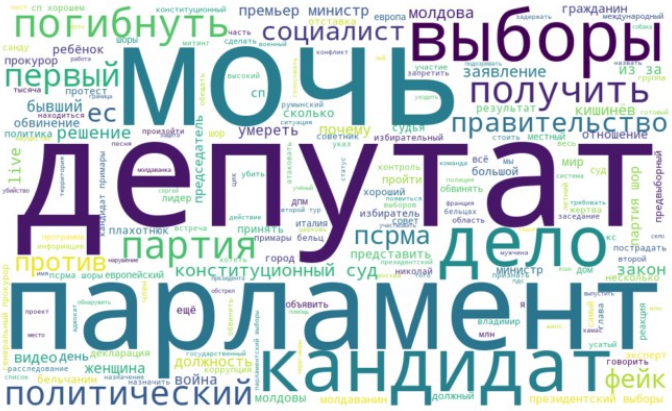

Figure 5. Word cloud based on credible headlines.

The word clouds for the fake and non-fake news headlines (Figures 4 and 5) had been generated using Python library.

4. Machine Learning Experiments

For the experiments, the texts were preprocessed: the texts were cleaned, tokenized, stop words were removed and other words were lemmatized. Term Frequency–Inverse Document Frequency weighting was used as a vectorization technique.

A balanced collection of 614 fake and 614 reliable news articles has been used in the machine learning experiments. The preprocessed texts were split in train-test parts in proportion 70%-30%.

Algorithms that demonstrated their ability to obtain good results in binary classification tasks and can work with vectorized texts were selected [39], namely:

- Naive Bayes classifier (NB),
- logistic regression,
- k-nearest neighbors method (KNN),
- SVM,
- random forest.

Precision, Recall and F-measure have been used as the evaluation metrics. When evaluating the models, we noted that all models were "prone" to depend on specific names and locations, which can lead to biased results in data analysis. As a result, a model may show good results on training data, but generalize poorly to new, previously unseen data.

This became a problem when training models, as they latch on to such unique identifiers instead of focusing on the overall structure and words used to create fake news. To improve the performance of the models, we decided to remove named entities from the text dataset, for example, names of countries, cities, organizations, and politicians such as “Ukraine”, “Moldova”, “Russia”, “Romania”, “Zelensky”, “Sandu”, “Shor”, “NATO”, etc. were excluded from the texts. This allows the models to focus on more general characteristics of the text, such as lexical features, syntactic structures, and thematic content, which in turn helps to increase their stability while working with new texts.

Next experiment has been performed with additional pre-processing, namely, lemmatization. This is a process of transformation of words by their reduction to their base form, which helps the model to better generalize information from the text. Lemmatization was done using pymorphy2 function of the NLTK library.

Next experiment used stemming (SnowballStemmer for Russian from nltk.stem), which, unlike lemmatization, cuts words to their root form. This also could reduce the number of unique features and made the models more efficient. Next, bigrams of words have been used in vectorization, taking into account word pairs rather than just single words, to improve the understanding of context and relationships between words. These changes are aimed at improving classification accuracy and the generalization ability of the model. To achieve this, the ngram_range parameter in CountVectorizer was modified. This parameter specifies the minimum and maximum length of n-grams that is taken into account during vectorization

5. Results and Discussion

For the experiments, the classification_report module from the sklearn.metrics library was used to evaluate the results.

First metric used to evaluate the algorithms was accuracy. It shows the proportion of correctly classified objects from the total number of objects in the test dataset. The naive Bayes classifier and logistic regression achieved an accuracy of 88%, the nearest neighbor method showed the lowest results at 84%, while the support vector machine and random forest algorithm showed the best results, achieving an accuracy of 90% and 91%, respectively.

Model accuracy at 88%-91% is relatively high for this type of classification task, considering the criterion of classification, which is often difficult to analyze.

The other metrics were Precision, Recall and F-measure. Tables 1 and 2 contain Precision, Recall and F-measure for reliable news and for the fake news respectively.

Table 1

Metrics for the class of reliable news

Model	Precision	Recall	F-score
Naive Bayes	0.91	0.84	0.88
Logistic Regression	0.87	0.87	0.87
k-nearest neighbors (k=5)	0.88	0.78	0.83
support vector machine	0.89	**0.91**	**0.90**
Random Forest	**0.92**	0.88	**0.90**

Table 2

Metrics for the class of reliable news

Model	Precision	Recall	F-score
Naive Bayes	0.86	0.92	0.89
Logistic Regression	0.88	0.88	0.88
k-nearest neighbors (k=5)	0.81	0.89	0.85
support vector machine	**0.91**	0.89	0.9
Random Forest	0.89	**0.93**	**0.91**

SVM and Random Forest show high Precision for the fake news class (Table 2), with scores of 0.91 and 0.89 respectively, indicating a high probability of correctly identifying fake news. In terms of Recall, Random Forest and Naive Bayes lead with scores of 0.93 and 0.92, indicating their ability to detect most fake news. The F1-score of Random Forest is 0.91, making it the best-in-class model for detecting fake news.

Table 3 contains results for the texts in which named entities had been removed. In comparison with Tables 1 and II, we see that the results are slightly lower. This demonstrated that the algorithms used named entities as markers for the classification. However, we believe that the models, created on texts without named entities are more general and robust while working on new texts.

Table 4 contains the results of the experiments with several word preprocessing methods: lemmatization, stemming and bi-grams.

Table 3

Results on the Texts without Named Entities

Model	Precision	Recall	F-score
Naive Bayes	0.88	0.89	0.88
Logistic Regression	0.88	0.88	0.88
k-nearest neighbors (k=5)	0.84	0.83	0.84
Support vector machine	0.90	**0.91**	0.90
Random Forest	**0.91**	0.87	**0.91**

Table 4

Results on the Texts without Named Entities

Model	Initial Accuracy	Lemmatization	Stemming	Bi-grams
Naive Bayes	0.89	0.90	0.90	0.89
Logistic Regression	0.88	0.88	0.88	0.88
k-nearest neighbors (k=5)	0.83	0.83	0.83	0.81
Support vector machine	**0.91**	**0.92**	**0.91**	**0.89**
Random Forest	0.87	**0.92**	0.88	0.85

Logistic regression showed a stable accuracy of 0.89 regardless of the used preprocessing methods. Naive Bayes increased its accuracy to 90% with lemmatization and stemming, while it remained 89% with bigrams. K-nearest neighbors also remained at 83% with lemmatization and stemming, but its accuracy decreased to 81% with bigrams. Support vector machines remained unchanged (91%) with stemming, but increased to 92% with lemmatization and decreased to 89% with bigrams. Random forest showed differences in accuracy: it increased from 87% to 92% with lemmatization and to 88% with stemming, but decreased to 85% with bigrams, indicating a potential deterioration in model performance in this case.

Of all the text preprocessing methods applied, the stemming method showed the best results. This method increased the accuracy of the naive Bayes classifier, support vector machine, and random forest. The accuracy of the random forest increased by as much as 5%. In conclusion, only stemming definitely improves the classification results.

In the experiments, we found several cases where all five machine learning models made errors in classifying news texts as fake or reliable. The causes of the errors were identified using Local Interpretable Model-agnostic Explanations (LIME) [5]. LIME is a library for interpreting machine learning models, namely, for explaining model predictions at the level of individual predictions. This method allowed us to understand which features were the most important for the model while making a specific decision.

When evaluating the models, it was noted that all models were "prone" to depend on specific names and places, which could lead to biased results in data analysis.

It was noted that negation ("not") has a huge weight in identifying fake news, which causes errors in identifying real news that contained negations. When analyzing the dataset, it was found that the particle "not" is mentioned 5615 times in real news and 7828 times in fake news.

Another important note is that the use of personal pronouns is also more common in fake news than in real news. This can be explained by the fact that in real news such pronouns are used only in quotes, while fake news articles are written in more personalized style.

Also, an experiment was conducted with a couple of new articles that were not in the used dataset. A real news story from the esp.md website titled “Winners of the German Language Republican Olympiad has been Awarded” was fed to the machine learning models to evaluate their ability to classify the text. Almost all models, except for the random forest, identified it as reliable, which shows their effectiveness in recognizing real news.

Then a fake news story from the telegram channel “Gagauznews - News of Gagauzia” was fed under the title “What was the next NATO hawk looking out for in Chisinau?” As a result, all 5 models classified it as fake

5. Conclusions

This work was devoted to the development of a system for automatic detection of fake news in Russian, relevant for the region of the Republic of Moldova and its neighboring countries.

Initially, a representative dataset of fake and real news was collected from the news sites.

Several machine learning models were developed and tested, including a naive Bayes classifier, logistic regression, nearest neighbors, support vector machines, and random forest. The results demonstrated that support vector machines and random forest provide the highest accuracy of classification, reaching 91%, which is an impressive result for such difficult task.

During further experimenting, biases caused by named entities were eliminated which increased the generalization ability of the models and made them more robust to the new texts. Lemmatization and stemming were also used in order to increase the accuracy of classification.

Error analysis allowed us to study in detail classification issues and improve the quality and robustness of the models for the new texts.

The developed system helps protecting society from disinformation, which is especially important in the modern world, where information warfare and political manipulation have become commonplace. Protecting people from fakes is vital to ensure a safe, healthy and prosperous environment free from deception, discrimination, bad decisions and economic losses.

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Conflicts of Interest: The authors declare no conflict of interest.

References

1. Rahmanian, E. Fake news: a classification proposal and a future research agenda. *Spanish Journal of Marketing-ESIC* 2023, 1, pp. 60-78.
2. Ognyanova, K.; Lazer, D.; Robertson, R. E.; Wilson, C. Misinformation in action: Fake news exposure is linked to lower trust in media, higher trust in government when your side is in power. *The Harvard Kennedy School Misinformation Review* 2020, 1(4), 19 p.
3. Reglitz, M. Fake News and Democracy. *Journal of Ethics and Social Philosophy* 2022, 22(2), pp. 162-187.
4. Oshikawa, R.; Qian, J.; Yang Wang, W. A Survey on Natural Language Processing for Fake News Detection. In: *Proceedings of the Twelfth Language Resources and Evaluation Conference*, Marseille, France, 2020, pp. 6086–6093.
5. Davletbacov, S.K. The term "fake news" in history and modern times. *Questions of student science* 2022, 9 (73), pp. 121-124.
6. Tandoc, E.; Lim, Z.; Ling, R. Defining "Fake News": A typology of scholarly definitions. *Digital Journalism* 2017, 6, pp 1-17.
7. Molina, M. D.; Sundar, S.; Le, T.; Lee, D. "Fake News" Is Not Simply False Information: A Concept Explication and Taxonomy of Online Content. *American Behavioral Scientist* 2019, 65, pp. 180 - 212.
8. Pozdnyakov, E. On the Problems of Theoretical Understanding of the Term "Fake News". *Istoriya* 2023, 14 (12), 134.
9. Collins, B.; Hoang, D.T.; Nguyen, N.T.; Hwang, D. Fake News Types and Detection Models on Social Media A State-of-the-Art Survey. In: *Intelligent Information and Database Systems*. Sitek, P.; Pietranik, M.; Krótkiewicz, M.; Srinilta, C. (eds); Springer, Singapore, 2020, 1178, pp 562–573.

10. Egelhofer, J.; Lecheler, S. Fake news as a two-dimensional phenomenon: a framework and research agenda. *Annals of the International Communication Association* 2019, 43, pp 97-116.
11. Kitsa, M. Classification of Fake News in Ukraine and Abroad. *State and Regions Series: Social Communications* 2023, 1(53), pp. 57-62.
12. Lazer, D.; Baum, M.; Benkler, Y.; Berinsky, A.; Greenhill, K.; Menczer, F.; Metzger, M.; Nyhan, B.; Pennycook, G.; Rothschild, D.; Schudson, M.; Sloman, S.; Sunstein, C.; Thorson, E.; Watts, D.; Zittrain, J. The science of fake news. *Science* 2018, 359, pp. 1094-1096.
13. Borges do Nascimento I. J.; Pizzaro A.B.; Almedia J.M.; Azzopardi-Muscat N.; Goncalves M.A.; Bjorklund M.; Novillo-Ortoz D. Infodemics and health misinformation: a systematic review of reviews. *Bull World Health Organ* 2022, 9, pp. 544-561.
14. Aimeur E.; Amri S.; Brassard G. Fake news, disinformation and misinformation in social media: a review. *Soc Netw Anal Min.* 2023, 13(1), 30
15. Zhang, X.; Ghorbani, A. An overview of online fake news: Characterization, detection, and discussion. *Information Processing and Management: an International Journal* 2020, 57(2), 102025.
16. Yiqiao, J.; Wang, X.; Yang, R.; Sun, Y.; Wang, W.; Liao, H.; Xie, X. Towards Fine-Grained Reasoning for Fake News Detection. In: *Proceedings of the AAAI Conference on Artificial Intelligence* 2022, 36, pp. 5746-5754.
17. Wang, L.; Wang, Y.; Melo, G.; Weikum, G. Understanding archetypes of fake news via fine-grained classification. *Social Network Analysis and Mining* 2019, 9, pp. 1-17.
18. Rashkin, H.; Choi, E.; Jang, J. Y.; Volkova, S.; Choi, Y. Truth of Varying Shades: Analyzing Language in Fake News and Political Fact-Checking. In: *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, Copenhagen, Denmark, 2017, pp. 2931-2937.
19. Zhou, Z., Zhang, X., Zhang, L., Liu, J., Zhang, X., Li, C. FineFake: A Knowledge-Enriched Dataset for Fine-Grained Multi-Domain Fake News Detection. *ArXiv, abs/2404.01336*.
20. Vaibhav, V.; Mandyam, R.; Hovy, E. Do sentence interactions matter? Leveraging sentence level representations for fake news classification. In: *Proceedings of the 13th Workshop Graph-Based Methods Natural Lang* 2019, pp. 134–139.
21. Sahu, L.; Narain, B. Use of Implicit and Explicit Features of Fake News Detection. Available online: https://sciforum.net/manuscripts/12647/manuscript.pdf (accessed on 13.09.2024).
22. Kuzmin, G.; Larionov, D.; Pisarevskaya, D.; Smirnov, I. Fake news detection for the Russian language. In: *Proceedings of the 3rd International Workshop on Rumours and Deception in Social Media (RDSM)*, Barcelona, Spain, 2020, pp. 45–57.
23. Pérez-Rosas, V.; Kleinberg, B.; Lefevre, A.; Mihalcea, R. Automatic Detection of Fake News. In: *Proceedings of the 27th International Conference on Computational Linguistics*, Santa Fe, New Mexico, USA, 2018, pp. 3391–3401.
24. Amazon Mechanical Turk. Available online: https://www.mturk.com (accessed on 07 July 2025)
25. Yang Wang, W. "Liar, Liar Pants on Fire": A New Benchmark Dataset for Fake News Detection. In: *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*, Vancouver, Canada, 2017, 2, pp. 422–426.
26. Thorne, J.; Vlachos, A.; Christodoulopoulos, C.; Mittal, A. FEVER: a Large-scale Dataset for Fact Extraction and VERification. In: *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 2018, 1, pp. 809–819.
27. Mitra, T.; Gilbert, E. CREDBANK: A Large-Scale Social Media Corpus with Associated Credibility Annotations. In *Proceedings of the International AAAI Conference on Web and Social Media*, 2021, 9(1), pp. 258-267.
28. Huang, K.-H.; McKeown, K.; Nakov, P.; Choi, Y.; Ji, H. Faking Fake News for Real Fake News Detection: Propaganda-Loaded Training Data Generation. In: *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics,* Toronto, Canada, 2023, 1, pp. 14571–14589.
29. Volkova, S.; Shaffer, K.; Jang, J. Y.; Hodas, N. Separating Facts from Fiction: Linguistic Models to Classify Suspicious and Trusted News Posts on Twitter. In: *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*, Vancouver, Canada, 2017, 2, pp. 647–653.
30. Ahmed, H., Traore, I., Saad, S.: Detecting opinion spams and fake news using text classification. *Secur. Priv.* 2018, 1(1), e9.
31. Buzea, M.C.; Trausan-Matu, S.; Rebedea, T. Automatic Fake News Detection for Romanian Online News. *B: Information.*2022, 13(3), 151.
32. Jamal Abdul, N.; Osama Subhani, K.; Iraklis, V. Fake news detection: A hybrid CNN-RNN based deep learning approach. *International Journal of Information Management Data Insight* 2021, 13 p,

33. Mehta, D.; Dwivedi, A.; Patra, A.; Anand Kumar, A. A transformer-based architecture for fake news classification. *Social Network Analysis and Mining,* 2021, 13 p,
34. Alzaidi, M.; Alshammari, A.; Hassan, A. Q. A.; Yousafzai, S. N.; Thaljaoui, A.; Fitriyani, N. L.; Kim, C.; Syafrudin, M. An Efficient Fusion Network for Fake News Classification. *Mathematics* 2024, 12(20), 3294.
35. Popat, K.; Mukherjee, S.; Yates, A.; Weikum, G. DeClarE: Debunking Fake News and False Claims using Evidence-Aware Deep Learning. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, 2018, pp. 22–32.
36. Blaise Cruz, J. C.; Tan, J. A.; Cheng, C. Localization of Fake News Detection via Multitask Transfer Learning. In: *Proceedings of the Twelfth Language Resources and Evaluation Conference*, Marseille, France, 2020, pp. 2596–2604.
37. Discourse Processing Lab, Our Battle against Fake News. Available online: fakenews.research.sfu.ca (accessed on 07 July 2025).
38. Fake News Detector. Available online: fakenews.research.sfu.ca (accessed on 07 July 2025).
39. Molnar, C. Interpretable Machine Learning. A Guide for Making Black Box Models Explainable. Available online: https://originalstatic.aminer.cn/misc/pdf/Molnar-interpretable-machine-learning_compressed.pdf. (accessed on 25 June 2025)

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Submission of manuscripts: jes@meridian.utm.md