Information Technology for Referencing Ukrainian-Language News at Detecting Disinformation in Cybersecurity*

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Abstract

The paper describes the analysis of existing approaches to the abstracting of English-language texts. The research results also include software development and the implementation of an abstract method based on machine learning for Ukrainian-language news abstracting to detect disinformation. The study object is the process of automatic referencing of Ukrainian-language news text. The methods and algorithms of automatic abstracting of Ukrainian-language news texts are studied. They are capable of automatically abbreviating natural language texts and providing the user with a secondary document containing the main content of the document. The scientific novelty of this work consists of the application of byte pair coding in the preliminary processing of Ukrainian texts and the proposed abstracting algorithm. The practical results obtained value in the work by using the developed methods in the system of referencing of Ukrainian-language news text. Currently, the model accuracy based on the Naive Bayesian classifier is 83%, which is a good indicator, but it needs to be increased in the future.

Keywords

referencing texts, Ukrainian text analysis, text rubrication, text abstracting, abstract method, machine learning, Naive Bayes classifier, NLP, TensorFlow, PyTorch, Gensim 1

1. Introduction

Modern people live in conditions of constant information load. With the development of information technologies, more and more people use the Internet, which in turn gives them unlimited access to the distribution and consumption of information [1-3]. A person is unable to comprehend the entire amount of available information without directly studying it. In such cases, an automatic news abstracting program could become a helpful assistant, help overcome information overload and quickly make a decision about which information is worth further consideration [4-7]. Referencing is reducing the volume of the text by highlighting the main theses. The main goal is to take raw natural language data and, using linguistics and algorithms to transform or enrich the text, process it in such a way that it provides more value. There are two general approaches to solving this problem: extractive and abstract [8-10]. There is also an approach that combines the previous ones (hybrid). In the extractive approach, the most critical parts of the input document (mostly sentences) are selected based on their preliminary assessment of informativeness. After that, they are combined to form an essay. An internal semantic representation of the original content is built and then used to create a short representation closer to what a human can express. This method can transform the extracted content by paraphrasing it to compress the text more than just extraction. It makes it possible to use words that were not in the input data set. The annotations generated by this approach should be very close to what people write in contrast. The basis of this research is the process of information

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dissemination and consumption in global media spaces - a vast and multifaceted canvas on which dynamic and often contradictory information flows unfold. In the era of digital technologies, this process has become especially significant due to its impact on the formation of public opinion, political sentiments, and socio-cultural trends. The speed and volume of information dissemination create unique challenges for information verification and analysis. The focus of our research is on the methods and tools used to identify, analyse and neutralize disinformation, fake news and propaganda messages in the media space. We investigate modern technological approaches, such as machine learning and natural language processing algorithms, to determine their effectiveness in detecting distorted content. We also analyse how these techniques can be integrated into everyday media consumption, providing users with powerful tools for self-assessment of the veracity of the information they consume. This two-dimensional approach allows us to delve deeply into the mechanisms of information influence and identify strategies for developing practical tools that could resist manipulation and distortion in the media, thereby ensuring a higher level of information transparency and trust in society.

This project opens up new horizons in the application of machine learning by adapting advanced algorithms to the specifics of the Ukrainian language. The uniqueness lies in the creation of new methods of deep semantic analysis, which allow us to approach the structural and contextual features of Ukrainian vocabulary and syntax with understanding. These developments provide more accurate and effective detection of information distortions, offering algorithmic innovations that can become the foundation for future research in the field of natural language processing (NLP). The project has a significant practical impact, as it provides Ukrainian society with reliable and accessible tools for detecting and analysing disinformation. These tools allow users not only to identify false content but also to understand its sources and potential targets, thereby strengthening society's information immunity. As a result, the project contributes to enhancing the information independence and sovereignty of Ukraine, increasing the level of information transparency and trust, which is key to the stability of democratic institutions and national security.

2. Related Work

2.1. Approaches to referencing Ukrainian-language news

Several products on the market offer automatic reporting of Ukrainian News, each of which has its features and advantages. Summarizer.ua uses machine learning (ML) algorithms to generate short descriptions of news articles [8]. It offers a free plan with limited features and paid plans with advanced features, including adjusting the length of essays, defining keywords, and translating them into other languages. QuickText is an automated referencing text platform that offers automatic News abstracting [9]. This product uses proprietary machine learning algorithms and provides integration with other platforms, personalization, and analytics that help users track essay performance. NewsBreak is a mobile app that offers short descriptions of news articles [10]. The app uses machine learning algorithms, offers personalized news feeds and offline access, and allows users to share essays with friends and followers. Abstracting Ukrainian-language news, for example, referencing Ukrainian-language news to detect disinformation, can be a valuable tool for saving time and increasing productivity [11-12]. However, it is essential to remember that these products are not always accurate and reliable [13-15]. Further research and development in this area are needed to improve the accuracy and reliability of automatic referencing and to make it more accessible to a broader range of users. There are several ways to solve the problem of accuracy and reliability of automatic referencing of Ukrainian-language news [16-21]:

1. Improving ML algorithms is necessary to continue the research and ML algorithms-based NLP development that better understand the Ukrainian language and can generate more accurate and reliable essays.

2. Human review may be used to review and edit automated abstracts to ensure accuracy and objectivity.

3. Provide users with more context in abstracts, such as links to full texts of news articles or additional information about the topic of the article.

4. Develop more accessible products for automatic referencing to make them available to a broader range of users.

5. Simplify implementation is necessary to simplify the automatic referencing products implementation to make them more accessible to smaller organizations and companies with limited budgets.

3. Main Part

3.1. Methods for automatic referencing

Various machine learning algorithms can be used to generate abstracts of Ukrainian news articles. Keyword extraction methods identify keywords and phrases that describe the content of a news article and use them to create an abstract. Classification-based methods classify the sentences of a news article as important or unimportant and then generate an abstract from the critical sentences. Neural network-based methods use artificial neural networks to train on large data sets of news articles and abstracts and then generate abstracts for new articles.

3.2. Tools for automatic referencing

Many machine learning tools can be used to develop an automatic referencing system. TensorFlow is an open-source machine-learning platform that offers extensive capabilities for developing and training machine-learning models. PyTorch is another open-source machine learning platform that is similar to TensorFlow but offers some advantages, such as flexibility and ease of use. Gensim is a Python library for NLP that offers tools for tasks such as topic modelling, sentiment analysis, and keyword extraction.

Process modelling of news abstract generating

Product development for Ukrainian-language news abstracting, which will generate short descriptions of news articles containing the most critical information. The product should be accurate, reliable, easy to use and accessible to a wide range of users. It is necessary to define the goals of the development, the target audience, functional requirements and non-functional requirements. Development goals are saving users' time, productivity improvement, improving news articles' content understanding, News accessibility for people with reading disabilities and news content personalization. The target audience is the following subjects as users who need to quickly familiarize themselves with the News, people with reading disabilities, organizations that need to process large volumes of text data and software developers who want to integrate automatic referencing into their products. Functional requirements are the following items as generating short descriptions of news articles, defining keywords and phrases, selecting the most critical information, adjusting the length of essays, translation of essays into other languages, integration with other platforms, personalization of essays and providing analytics. Non-functional requirements are accuracy and reliability, Ease of use, Availability, Scalability and Security, and Speed of work. Consider the sequence diagram for the process of generating an abstract of a news article (Fig. 1). Actors are User, System and ML Algorithm. The user is the person who uses the system to generate abstracts of news articles. The system is software that produces abstracts of news articles. ML Algorithm is an algorithm used to create abstracts for news articles based on NLP and Naive Bayes classifier.

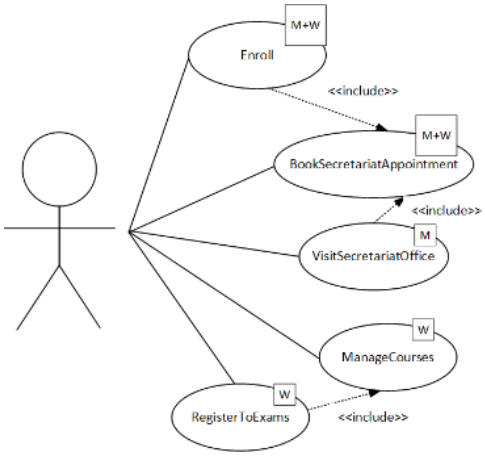

Figure 1: UML sequence diagram

This flow chart describes the process of generating an abstract for a news article. The user provides the system with a link to the news article he wants to refer to. The system downloads a news article from the Internet and sends it to an ML algorithm. It analyses a news article and generates an abstract and text rubrication (classification). The system sends an abstract to the user.

3.3. Testing and evaluation

For research, ua_datasets are used, which is a collection of datasets in the Ukrainian language with articles that will be classified. This library is provided by FIdo.ai (ML research department of the FIdo non-profit student organization of the Kyiv-Mohyla Academy National University) for research purposes in the field of data analysis (classification, clustering, keyword extraction, etc.). Ukrainian News has been selected from the collection of datasets. Ukrainian News is a collection of more than 150,000 news articles collected from more than 20 news resources. Sample datasets are divided into five categories: Policy, Sports, News, Business and Technologies. The number of records of the training sample is 120417, of the test sample – 30105:

from ua_datasets import NewsClassificationDataset

train_data = NewsClassificationDataset(root = 'data/', split = 'train', return_tags = True)

test_data = NewsClassificationDataset(root = 'data/', split = 'test', return_tags = True)

1. Import the Pandas library and write data into variables:

import pandas as pd
train_data = pd.read_csv('data/train.csv')
test_data = pd.read_csv('data/test.csv')

2. Convert text files into numeric feature vectors based on words bag and CountVectorizer from sklearn.feature_extraction.text.

count_vector = CountVectorizer()

X_train_counts = count_vector.fit_transform(train_data.text)

X_train_counts.shape

3. TF-IDF can reduce the weight of more common words that appear in all documents.

X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)
X_train_tfidf.shape

4. Different algorithms can be used to classify text, for example, Naive Bayes classifier:

from sklearn.naive_bayes import MultinomialNB

clf = MultinomialNB().fit(X_train_tfidf, train_data.target)

5. A text analysis pipeline construction:

text_clf = Pipeline([('vect', CountVectorizer()), ('tfidf', TfidfTransformer()),

('clf', MultinomialNB()),])

text_clf = text_clf.fit(train_data.text, train_data.target)

6. The system has learned to determine the heading of the text (Fig. 2). Derivation of matrix dimension is X_train_tfidf.shape. The execution result is (120417, 494590). A few records (172, 2324 and 3 elements) from the test sample (Fig. 3-5) are taken to determine its rubric.

test_data.text[A]

text_clf.predict([test_data.text[A]])

Next, an arbitrary text from the Internet is taken to define its rubric (Fig. 6): test_clf.predict ([any_text]).

	title	text	tags	target
0	ВЕРНИДУБ: «Нанесимо 25 ударів, 15 у ворота, а ...	Головний тренер сопгорського «Шахтаря» Юрій В...	Футбол|нші новини|Шахтар Сопгорськ|Юрій Верн...	спорт
1	У "Київстар" заявляють, що їх обшукала ДФС	Про це на своїй сторінці у Facebook написав пр...	|Київстар|Новини|податкова|ДФС|обшук|	новини
2	В 2016 році 1% найзаможніших людей вперше ста...	Про це повідомляється в доповіді некомерційної...	|багатство|найбагатші люди світу|Новини|Бідність|	новини
3	Шакіл О'Ніл продав шикарний маєток у Флориді в...	Легенда НБА Шакіл О'Ніл продав свій маєток у ...	США|Баскетбол|Флорида|Фото	спорт
4	У «заблокованій» СБУ B2B Jewelry заявили, що п...	Засновник фінансової піраміди B2B Jewelry Мик...	Служба безпеки України (СБУ)|Фінансова пірами...	бізнес

The first five records as the head() method request result

'Компанія Microsoft продовжує натякати на те, що найближчим часом користувачі побачать нову операційну
s 10, яка по надійності, швидкодії й безпеці значно перевершила будь-яку з попередніх операційних сист
пуватися, підвищуючи стабільність системи, швидкість і захищеність від злонів і вірусів. Оновлення тр
MI запрошення на захід, і на самому запрошенні можна побачити новий логотип ОС, що відкидає тінь: він
oi версії до одинадцятої. і. якщо так. то чи можна буде Windows 11 завантажити через оболонку "десятки

```
array(['технології'], dtype='<U10')
```

Text from the test sample (172 items) and text analysis result - Technology

'Про це заявив начальник департаменту патрульної поліції Євген Жуков, передає Еспресо.TV. "За
АТО можу порівняти: за 2016 рік у зоні АТО загинули 763 наших захисника. Водночас у мирних мі
2016 році в ДТП загинули 3187 людей. Читайте також: Українці тисячами вбивають один одного в
3 млн порушень водіями правил дорожнього руху. "Лише цього року поліцейські зафіксували понад
ерування транспортом у стані сп\'яніння", - додав Жуков. Нагадаємо, ...'

```
array(['новини'], dtype='<U10')
```

Text from the test sample (2324 elements) and text analysis result - News

' Курс російського рубля на торгах на Московській біржі впав до 80 руб. за долар вперше з 2016
б. за євро. На курсі рубля негативно позначилися падіння світових фондових ринків і розрив уго
овила мінімум з 2003 року, опустившись до $ 27 за барель.'

```
array(['бізнес'], dtype='<U10')
```

Text from the test sample (3 elements) and analysis result - Business

Форвард «Ювентуса» та збірної Аргентини **Пауло Дібала**, швидше за все, продовжить кар'єру в «Інтері».

30 червня 28-річний гравець стане вільним агентом.

Як повідомляє Football Italia, Дібала погодив із міланським клубом 4-річний контракт із зарплатою 6 млн євро на рік. Разом із бонусами оклад аргентинця становитиме 8 мільйонів.

Футболісту залишилося лише пройти медогляд в «Інтері» та підписати угоду.

У сезоні 2021/22 на рахунку Дібали 15 голів та 6 асистів у 38 матчах.

```
array(['спорт'], dtype='<U10')
```

Free text from the Internet and text analysis result - Sport

Determine the system accuracy after executing the code:

predicted = text_clf.predict(test_data.text) np.mean(predicted == test_data.target)

The execution result is 0.8301278857332669. All of the above results turned out to be correct, which means that the accuracy is 83% true.

4. Building a system to detect fake messages from chat users

We load a dataset to determine fake or true news.

	A	B	C	D	E	F	G	H	I	J	K	L
1	№	дата	час	текст повідомлень	мітки	Pos1/Repos1	Автор/Group	Джерело	Мова	Like	Поширення	веб-адреса
13	12	01.03.2022	18:42:00	комендантської години у Львові - фейк!	0	Pos1	новий у країни				0	https://t.me/andriysadovyi
14	13	24.10.2022	18:41:00	«Аферисти і бандерівці Стерненко і Притула починають збір грошей на брудну бомбу», – солов'йов	0	Pos1	TATIANA TKACHENKO	Google	Russian		0	prostranyaet_fejki_o_tom_chto_ukraina_izgotovila_gryaznuyu_bombu
15	14	19.10.2023	10:50:00	Друзі, новина Фокуса про те, що військовозобов'язаним можуть блокувати банківські картки за неявку в військомат	0	Pos1	Олександра Шараєвська	Google	Ukrainian		0	https://focus.ua/uk/voennye-novosti/600167-mobilizaciya-v-ukrajini-chi-mozhut-zablokuvati-bankivsku-kartu-za-neyavku-do-tck
16	15	25.02.2024	18:41:00	рф поширюють відеопровокацію з так званим «сином Сирського».	0	Pos1	УНІАН	YouTube	Russian		0	https://youtu.be/4kO9dNlAing
17	16	01.06.2024	18:37:00	Львівським випускникам видали стрічки з картою України без Криму	0	Pos1	AIF	Google	Russian		0	https://aif.ru/society/vo-lvove-vypusknikam-vydali-povyazki-s-kartoy-ukrainy-bez-kryma
18	17	10.02.2025	11:35:00	Пілот розніс на новому літаку базу рф	0	Pos1	Повітряний простір України	Telegram	Ukrainian		0	тг - Повітряний простір України
19	18	17.09.2024	20:49:00	Мер Одеси Труханов заперечує наявність в нього російського паспорта	0	Pos1	Радіо Свобода	Google	Ukrainian		0	https://www.radiosvoboda.org/a/news-trukhanov-stemenko-rosiyskyy-pasport/33123893.html
20	19	01.05.2024	18:42:00	Володимир Зеленський танцював танець живота	0	Pos1	okadamokta	TikTok	Russian		0	https://www.tiktok.com/@okadamokta/video/7320698627515501857
21	20	20.11.2024	14:41:00	рф проводить масовану інформаційно-пс	0	Pos1	Суспільне Новини	Google	Ukrainian		0	gur-mo-nazvali-fejkom-povidomlenna-pro-zagrozu-osoblivo-masovanogo-raketnogo-udaru-rosieu-po-ukraini/

Figure 2: An overview of the dataset developed by the authors

The dataset is preprocessed through the removal of redundant lines, unnecessary characters, and other irrelevant elements. Following this, we visualize the data to gain insights into its structure.

We train a model to classify whether the news is fake or true. For this purpose, the dataset is divided into training and test sets.

X_train, X_test, y_train, y_test = train_test_split(X_combined, y, test_size=0.2, random_state=42)

Next, we create and train classifiers

models = { "Logistic Regression": LogisticRegression(max_iter=1000), ...}

The proposed method involves the automated processing of news content to estimate the probability of it being fake. This is achieved using a pre-trained artificial intelligence model that analyzes a combination of linguistic, structural, and meta-informational features.

Existing methods for fake news detection typically rely on manual content moderation, basic keyword filtering, or URL blocking. These approaches suffer from significant limitations, including low accuracy, slow processing time, and poor adaptability to evolving disinformation tactics.

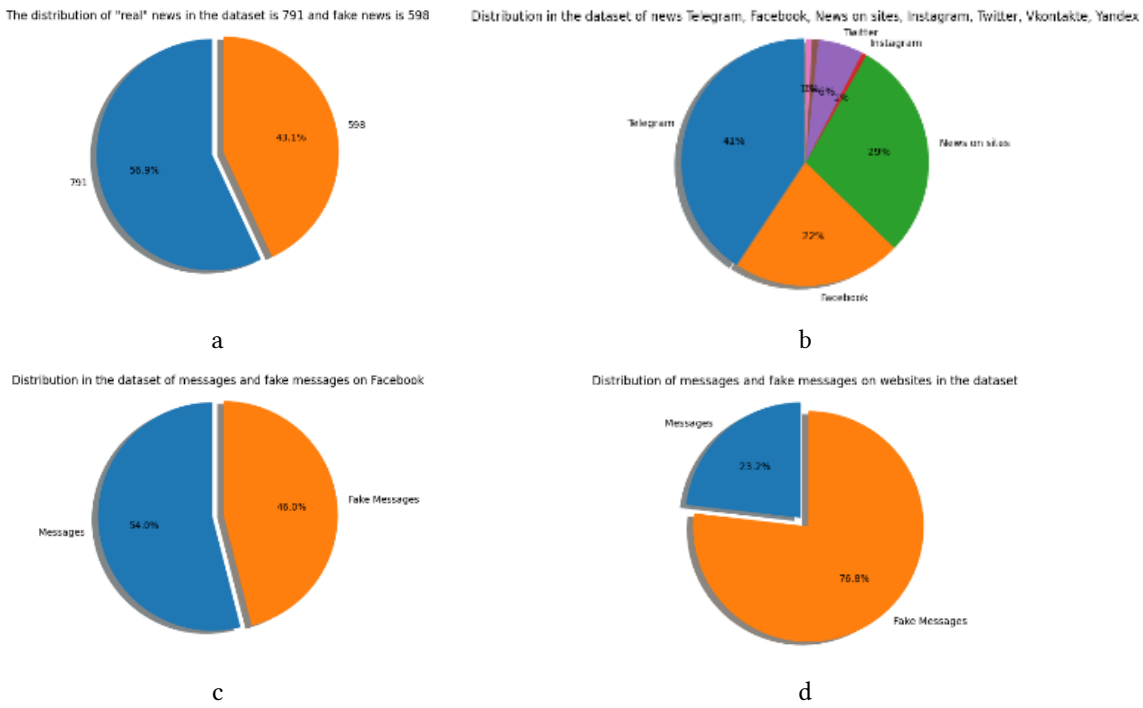

Figure 3: Dataset visualization showing: (a) fake vs. non-fake news; (b) distribution across social media platforms (Telegram, Facebook, Instagram, Twitter, Vkontakte, Yandex); (c) distribution on Facebook; (d) distribution on websites.

The most similar known method uses machine learning for fake news detection based on a limited set of input features. However, it lacks a comprehensive evaluation of the news structure, the credibility of the source, and the presence of external fact confirmations.

Low Accuracy of Keyword-Based Filtering: Many existing solutions rely on analyzing the frequency of specific keywords or phrases (e.g., “shock!”, “sensation!”, “never seen before”). However, such filters are easily bypassed through changes in wording or stylistic obfuscation, resulting in low effectiveness in identifying deliberately manipulative content.

Lack of Contextual and Structural Analysis: These methods often ignore the deeper structure of the text, such as sentence logic, coherence, stylistic consistency, and genre appropriateness. As a result, sophisticated fake news articles that mimic the style of legitimate journalism frequently go undetected.

No Verification of the Information Source: Most systems do not assess the credibility of the source, such as whether the website is verified, blacklisted, or exhibits suspicious domain characteristics. This allows the creation of fake websites with convincing names that can mislead both human readers and automated detection tools.

Current approaches rarely verify news by cross-referencing with other authoritative sources such as reputable news agencies, scientific portals, or fact-checking organizations. Consequently, even blatant fake news can sometimes be mistakenly accepted as reliable.

Many solutions lack self-learning or adaptive capabilities. They are vulnerable to evolving styles of fake news and new deception techniques, quickly becoming obsolete without continuous manual updates.

Manual moderation or systems relying on non-automated analysis are time-consuming, preventing prompt responses—especially critical during information attacks or crisis situations.

Some solutions operate only with English-language content and do not consider local context specifics. Additionally, they often support only a limited range of platforms.

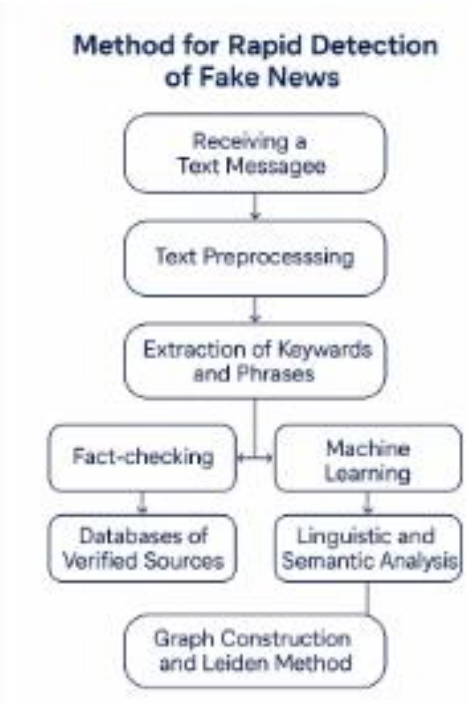

Figure 4: Method for Rapid Detection of Fake News

Two modern algorithms for community detection in networks have been developed with additional constraints such as spatial connectivity and boundary size. These enhanced methods, called ScLouvain and ScLeiden, are extensions of the traditional Louvain and Leiden algorithms, respectively. Both optimize the network structure by maximizing intra-community flows while minimizing inter-community flows.

In many complex networks, nodes tend to cluster into relatively dense groups, often referred to as communities[^1,^2]. This modular structure is typically unknown beforehand, making community detection a fundamental problem in network analysis. One of the most widely used approaches for this task is modularity optimization, which aims to maximize the difference between the actual number of edges within communities and the expected number of such edges in a random network.

5. Research experimental

As a result of the experiments, the following results were obtained by the classifiers. On the collected dataset, fake news was investigated using the k-nearest Neighbors methods (show Fig.5, Fig.6), support Vector Machines methods (show Fig.7, Fig. 8), decision tree classifier methods (show Fig.9, Fig. 10), random forests methods (show Fig. 11, Fig. 12), naive Bayes method (show Fig. 13, Fig. 14), Logistic Regression (show Fig. 15, Fig. 16).

5.1. Method k-nearest Neighbors

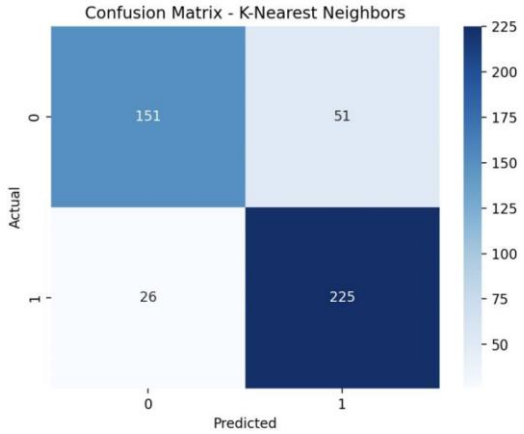

Figure 5: Method k-nearest Neighbors confusion matrix

K-Nearest Neighbors
Accuracy: 0.8300

	precision	recall	f1-score	support
0.0	0.85	0.75	0.80	202
1.0	0.82	0.90	0.85	251
accuracy			0.83	453
macro avg	0.83	0.82	0.83	453
weighted avg	0.83	0.83	0.83	453

Figure 6: Method k-nearest Neighbors

5.2. Methods Support Vector Machines

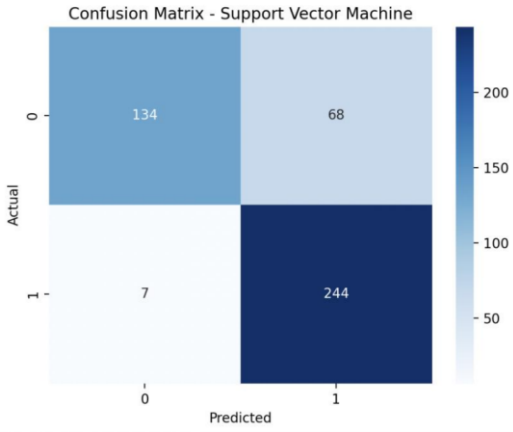

Figure 7: Method Support Vector Machines confusion matrix

Support Vector Machine
Accuracy: 0.8344

	precision	recall	f1-score	support
0.0	0.95	0.66	0.78	202
1.0	0.78	0.97	0.87	251
accuracy			0.83	453
macro avg	0.87	0.82	0.82	453
weighted avg	0.86	0.83	0.83	453

Figure 8: Methods Support Vector Machines

5.3. Decision Tree Classifier

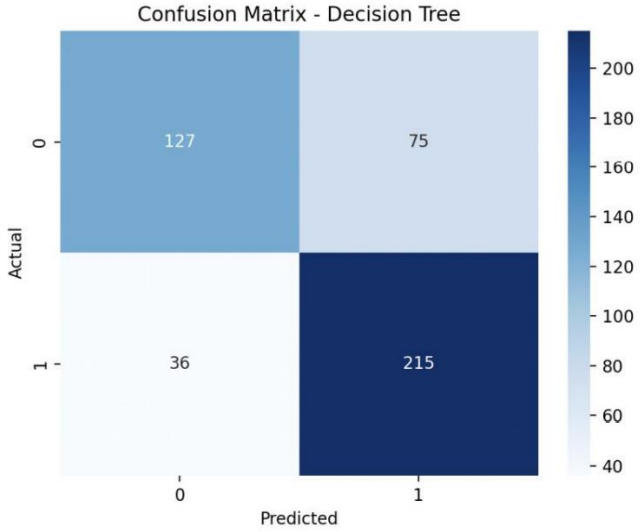

Figure 9: Methods Decision Tree classifier Confusion matrix

Decision Tree
Accuracy: 0.7550

	precision	recall	f1-score	support
0.0	0.78	0.63	0.70	202
1.0	0.74	0.86	0.79	251
accuracy			0.75	453
macro avg	0.76	0.74	0.75	453
weighted avg	0.76	0.75	0.75	453

Figure 10: Methods Decision Tree Classifier

5.4. Random Forests

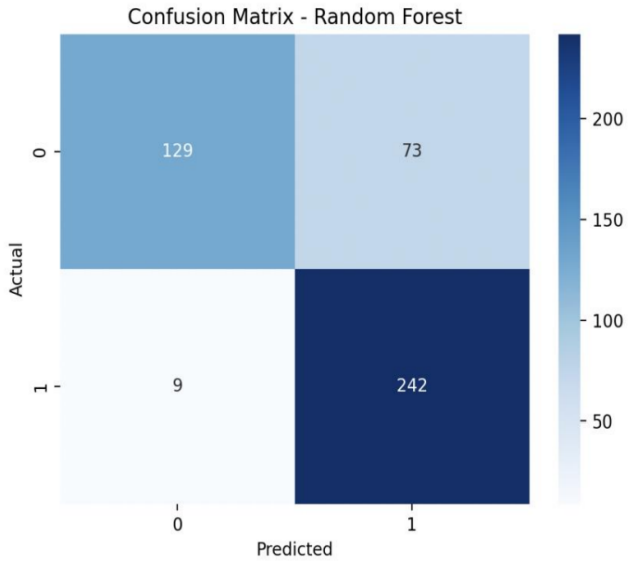

Figure 11: Methods Random Forests confusion matrix

Random Forest
Accuracy: 0.8190

	precision	recall	f1-score	support
0.0	0.93	0.64	0.76	202
1.0	0.77	0.96	0.86	251
accuracy			0.82	453
macro avg	0.85	0.80	0.81	453
weighted avg	0.84	0.82	0.81	453

Figure 12: Methods Random Forests

5.5. Naive Bayes method

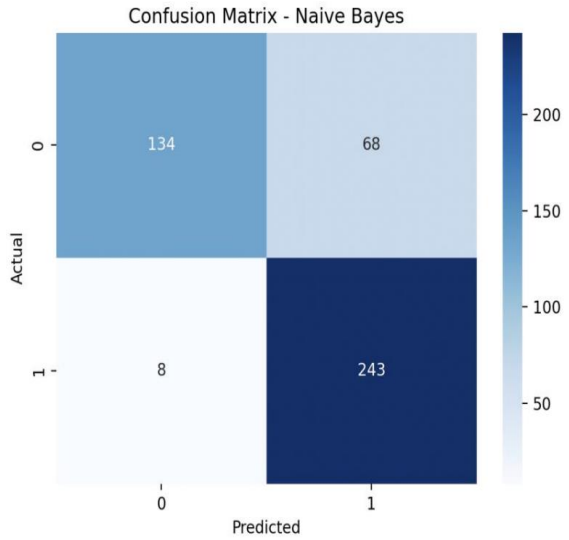

Figure 13: Methods Naive Bayes confusion matrix

Naive Bayes
Accuracy: 0.8322

	precision	recall	f1-score	support
0.0	0.94	0.66	0.78	202
1.0	0.78	0.97	0.86	251
accuracy			0.83	453
macro avg	0.86	0.82	0.82	453
weighted avg	0.85	0.83	0.83	453

Figure 14: Methods Naive Bayes

5.6. Logistic Regression

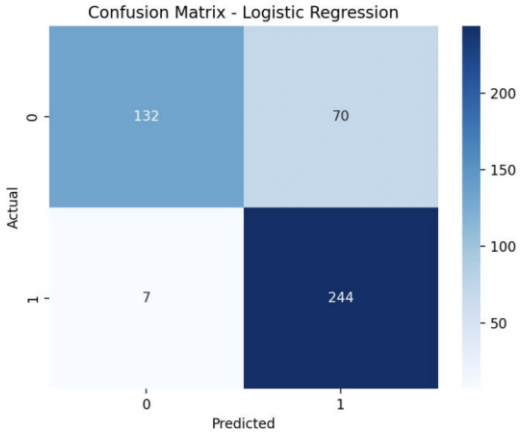

Figure 15: Methods Logistic Regression confusion matrix

The developed information system for detecting fake news in chatbots uses approaches to building information systems with information visualization, which are described in [20]. When constructing linear regression, functional studies on constructing curves in [22] were taken. When developing the information system for detecting fake news, system protection was used, which is based on the approaches described in [23]. Also, the ideology for building the system itself was taken from sources [24].

Logistic Regression
Accuracy: 0.8300

	precision	recall	f1-score	support
0.0	0.95	0.65	0.77	202
1.0	0.78	0.97	0.86	251
accuracy			0.83	453
macro avg	0.86	0.81	0.82	453
weighted avg	0.85	0.83	0.82	453

Figure 16: Methods Logistic Regression

A comparison of all proposed methods is shown in Fig. 17.

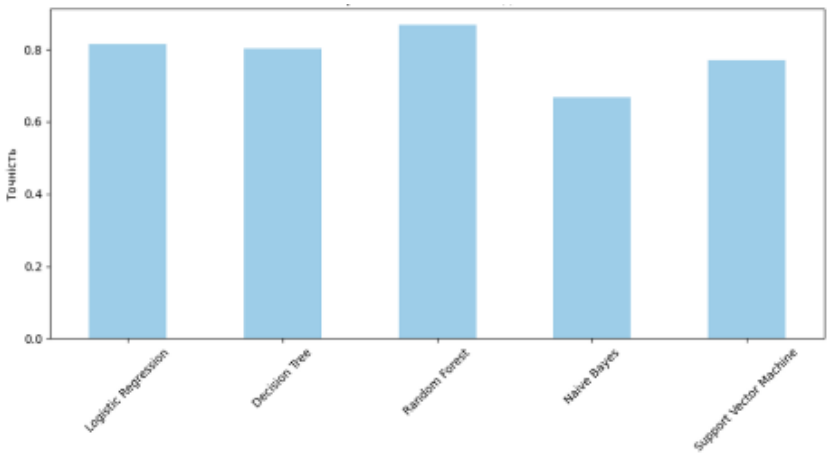

Figure 17: Comparison of accuracy of classifier estimates.

The best results in fake news detection were achieved by the Random Forest, Logistic Regression, and Support Vector Machine classifiers, with accuracies ranging from 93% to 95%.

6. Conclusion

In the digital age, information security is one of the key challenges for many societies, especially for countries undergoing political change or conflict. Ukraine, as a country significantly affected by information operations, faces the need to combat disinformation, fake News and propaganda. Accordingly, the development of tools for identifying and analysing such information threats is an urgent task that is of great importance for ensuring the country's information security. The relevance of this project cannot be overestimated in the conditions of the modern information space, where the fight for the truth has become almost synonymous with preserving national security. Information wars, in which the truth becomes the first victim, mercilessly bombard the public consciousness of millions of people, distorting reality and forming an artificial reality that serves the interests of external and internal antagonists. In Ukraine, on the front lines of the fight against hybrid threats, the lack of reliable tools for identifying disinformation can lead to systemic failures in public trust, the erosion of fundamental democratic values, and the stability of state institutions. It is not just a matter of media literacy; it is a matter of strategic defence of national security. The flywheel of disinformation can have a devastating effect not only on domestic political stability but also on Ukraine's international reputation, affecting the investment climate and bilateral relations with other states. A qualitatively new level of aggression in the information sphere requires an adequate response in the form of the development and implementation of advanced technological solutions. The project, which aims to create comprehensive tools for identifying fakes and disinformation, not only meets the critical need of Ukrainian society for reliable means of information verification but also improves the general culture of information consumption, strengthening the information resilience of the nation. This project will become a buffer that will protect Ukrainian society from false narratives and hostile information interference, ensuring the stable development of democratic institutions and values in the country. In this study, a text analysis system is developed using a Naive Bayesian classifier. Main prospects are using the developed system made it possible to increase the number of potential categories for classification, adding other languages and increasing the model accuracy. Currently, the accuracy of the model is 83%, which is a good indicator, but it needs to be improved in the future. The low accuracy of the results of text analysis is due to the complexity of processing Ukrainian-language texts. It is necessary to analyse the endings of the words, plural/singular, gender and case to process only nouns and reduce them to the nominative case. In the Ukrainian language, there are 7 cases with different endings for different words of different genders (feminine, neuter and masculine). It is necessary to have dictionaries of all endings and regular rules for reducing nouns to the nominative case (≈1000 rules), adjectives (≈100 rules) and verbs (several hundred rules). Future research will be aimed at increasing the functionality of the system, including adding other types of analysis and creating user interfaces.

News classification into fake and true categories was performed using various algorithms, including k-Nearest Neighbors, Support Vector Machines, Decision Trees, Random Forests, Naive Bayes, Linear Discriminant Analysis, and Logistic Regression. The effectiveness of these models was evaluated and their results compared. Support Vector Machines and Logistic Regression demonstrated the highest accuracy, making them particularly effective tools for fake news detection.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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