Method for Determining the Sentiment of Foreign News about Ukraine*

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Abstract

In the context of hybrid warfare, where information attacks serve as a strategic tool of influence, determining the sentiment of foreign-language news about Ukraine becomes particularly relevant. This paper proposes a method for automated sentiment analysis of texts, integrating natural language processing technologies, machine learning, and thematic classification algorithms. The proposed approach includes automated translation of foreign-language texts, preprocessing, content analysis, and sentiment index calculation, expressed as a percentage ranging from -100% to +100%. The method is implemented as a web application, enabling real-time assessment of information flows and detection of manipulative messages. Experimental results demonstrated an analysis accuracy of approximately 77%, confirming the effectiveness of the proposed approach for information security monitoring and combating disinformation.

Keywords

Sentiment analysis, natural language processing, machine learning, information security, automated translation

1. Introduction

In the modern information environment, where information technologies and social networks serve as key tools for shaping public opinion, the issue of hybrid warfare has become particularly relevant. Russia, employing a combination of methods—from military aggression to information operations—conducts a hybrid war against Ukraine aimed at destabilizing domestic politics, undermining trust in state institutions, and influencing the international political landscape.

The role of information technologies in this war is especially significant, as the dissemination of disinformation and manipulation of facts have become effective tools for influencing public consciousness both domestically and on the international stage. These actions give rise to multilingual information flows, where certain texts contain elements of both direct aggression and carefully crafted propaganda messages. In this context, there is an increasing demand for the development of automated text analysis systems that can quickly and accurately determine the sentiment and thematic orientation of informational messages.

The study presented in this paper aims to develop an integrated approach to text analysis using natural language processing (NLP) technologies, machine learning, and linguistic analysis. This approach enables not only the classification of texts into thematic categories but also the calculation of their emotional tone as a percentage. Special attention is given to the process of automated translation, which is crucial when dealing with an information space that includes

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texts written in different languages—a characteristic feature of the global scale of modern information attacks.

As hybrid threats intensify and information operations acquire strategic significance, the development of effective tools for analyzing textual information becomes increasingly relevant. The proposed method is designed to detect and analyze the emotional tone of messages, allowing for the timely identification of manipulative information flows and contributing to an objective understanding of events in the context of information warfare. This, in turn, is of great importance not only for Ukraine's national security but also for the international community striving to maintain stability in the global political environment.

The remainder of this paper is structured as follows. Section 2 provides an overview of recent research in this field, while Section 3 describes the proposed method. Section 4 focuses on implementation and case studies, and the "Conclusion" section summarizes the findings.

2. Review of Existing Solutions

In the modern information space, disinformation and public opinion manipulation have become an integral part of hybrid warfare, significantly affecting political, social, and military processes. Natural language processing (NLP), machine learning [1-2, 30, 31], and sentiment analysis technologies play a crucial role in such information conflicts, enabling the automated identification and classification of disinformation flows.

Padalko et al. (2024) [3] analyze the use of deep learning and NLP models, particularly XLNet, for classifying disinformation messages in hybrid warfare. Their study demonstrates the application of Kullback-Leibler Divergence to assess the content differences between news articles and their potential disinformation nature. The proposed approaches aim to enhance the automated analysis of information attacks in the context of Russia's war against Ukraine.

Virtosu & Goian (2023) [4] examine how artificial intelligence is used to create and spread disinformation as part of Russia's information attacks against Ukraine. The authors explore specific NLP and generative AI methods employed to manipulate public opinion via social media and news platforms.

Rodrigues (2023) [5] analyzes emotional polarization on Twitter regarding Russia's war against Ukraine, utilizing sentiment analysis techniques. The study covers the period from August 2022 to February 2023, revealing significant differences in the sentiment of posts between pro-Russian and pro-Ukrainian users.

Darwish et al. (2023) [6] apply machine learning methods to detect fake news related to the Russia-Ukraine conflict. The researchers examine stylistic and content-specific features of disinformation messages and propose algorithmic approaches for their detection.

Moy & Gradon (2023) [7] investigate the impact of artificial intelligence on information warfare, including the use of NLP techniques to analyze hybrid information attacks. They highlight the dual nature of AI in information warfare, emphasizing that it can be used both to combat disinformation and to spread it.

Alieva, Kloo & Carley (2024) [8] combine network analysis and NLP to study Russian propaganda on Twitter during Russia's invasion of Ukraine. Their analysis reveals how pro-Russian accounts coordinate information campaigns and influence online discourse.

Weigand (2024) [9] examines Russian disinformation campaigns in 2022 using text analysis and NLP techniques. The study identifies key themes promoted through disinformation channels and their impact on public perception.

Strubytskyi & Shakhovska (2023) [10] propose sentiment analysis methods for detecting hidden propaganda in news articles. They employ a hybrid approach, integrating classical sentiment analysis techniques with modern deep learning models.

Padalko, Chomko & Chumachenko (2024) [11] investigate how stop-word removal affects the accuracy of disinformation detection in the Ukrainian language. They demonstrate that meticulous text preprocessing can significantly enhance the effectiveness of NLP models in combating disinformation.

Suman et al. (2024) [12] use a hybrid deep learning approach to classify and analyze Twitter (X) posts related to Russia's war against Ukraine. Their model tracks sentiment shifts over time and identifies key trends in public attitudes.

Given the scale and intensity of disinformation attacks, there is a growing need for effective tools for the automatic analysis of textual content. This study aims to develop an integrated approach to sentiment analysis that combines automated translation, preprocessing, thematic classification, and lexicon-based analysis. This approach is designed to provide real-time and accurate detection of the emotional tone of informational messages, expressed as a percentage from -100% to +100%, which is highly relevant for countering disinformation attacks in the context of Russia's hybrid warfare on the international stage.

3. Method

This section presents a developed method for text sentiment analysis, which integrates automated translation, preprocessing, thematic classification, and lexical analysis. The method is designed to unify multilingual textual data and its subsequent analysis, allowing for an accurate evaluation of the emotional tone of messages expressed as a percentage from -100% to +100%. This approach is especially crucial in the context of hybrid warfare, where the information space is saturated with disinformation, and texts encompass multiple languages. The further structure of the method is outlined step-by-step and illustrated in Figure 1, helping to understand the logic of data processing from initial language detection to final result visualization.

Step 1. Automated Translation of the Text into Ukrainian

1.1. Determining the Language of the Original Text: Let T be the input text. Using the function f (implemented, for example, by the langdetect library), the language of the text is determined:

$$L = f(T), \tag{1}$$

where L is the language code (e.g., "en" for English, "uk" for Ukrainian). If $L = L_U$ (where L_U is the Ukrainian language), the translation step can be skipped.

1.2. Splitting the Text into Fragments: If $L \neq L_U$ or if the text is too large, T is split into n fragments:

$$T = \{ T1, T2, \dots, Tn \} \tag{2}$$

For each T_i, the following must be satisfied:

$$length(T_i) \leq L_{limit}, \tag{3}$$

where L_{limit} is the maximum allowable fragment length (e.g., 5000 characters). The splitting is done by paragraphs or sentences to preserve context.

1.3. Translation of Each Fragment: For each fragment T_i the translation function g is applied, which transforms the text from language L to the target language L_U:

$$T_i^U = g(T_i, L, L_U), \tag{4}$$

where: T_i— the original text fragment, g — the function that uses translation service APIs (e.g., DeepL, Google Translate, or Microsoft Translator), T_i^U — the translated fragment.

1.4. Merging Translated Fragments: After translating all n fragments, the resulting parts are combined into a single text:

$$T^U = \bigcup_{i=1}^{n} T_i^U \tag{5}$$

The result is a unified text in Ukrainian, ready for further processing and analysis.

Step 2. Preprocessing, Thematic Classification, and Lexical Analysis: This step is described in detail in the research [13].

2.1. Preprocessing [14-15]:

- Normalization and cleaning of the obtained text T^U from unnecessary characters
- Tokenization of the text with stop-word removal

2.2. Thematic Classification and Lexical Analysis:

- The text is classified into thematic categories using ML models that output probability distributions for each category.

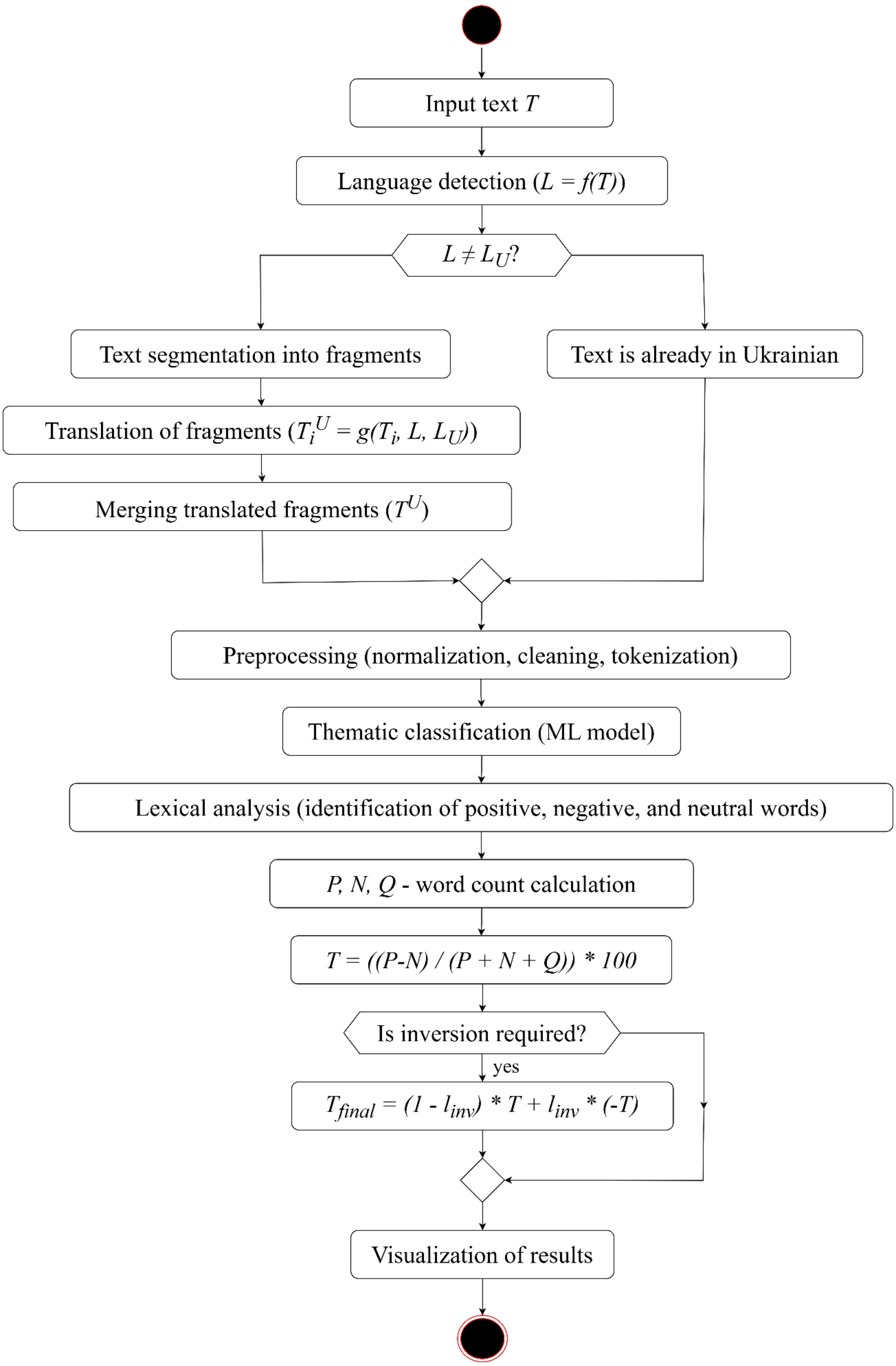

Figure 1: Sentiment Analysis Scheme with Integration of Automated Translation and Thematic Classification

- A dictionary is formed for the determined category, consisting of positive (D_{pos}), negative (D_{neg}) and neutral (D_{neut}) words
- For each token w, the emotional value function is defined as:

$$\delta(w) = \begin{cases} +1, & \text{якщо } \mathrm{w} \in \mathrm{D_{pos}}; \\ -1, & \text{якщо } w \in D_{neg}; \\ 0, & \text{якщо } w \in D_{neut} \text{ або інше.} \end{cases} \quad (6)$$

Step 3. Calculating the Sentiment Index and Visualizing Results: This step is described in detail in the research [13].

3.1. Calculating the Sentiment Index: Let P, N i Q represent the number of positive, negative, and neutral words, respectively. The sentiment index T is calculated using the formula:

$$T = \left(\frac{P - N}{P + N + Q}\right) \times 100 \quad (7)$$

The value of T ranges from -100% to +100%.

3.2. Sentiment Inversion and Visualization: If the text originates from an enemy source (without references to Ukraine), inversion is applied:

$$T_{final} = (1 - I_{inv}) * T + I_{inv} * (-T), \quad (8)$$

where $I_{inv} = 1$ if inversion is necessary, and 0 otherwise. The final result T_{final} along with the thematic classification, is displayed through a web interface.

The next section will present the implementation of the proposed approach, including practical application and analysis of the obtained results.

4. Case Study

For the practical implementation of the sentiment analysis method, a web application [16] was developed using the Streamlit framework. The development of the web application aimed to integrate several core functional modules that provide automated text translation, preprocessing, thematic classification, sentiment analysis, and result visualization.

The web application allows users to input a news article URL into a designated field (Figure 2), after which the system automatically extracts text from the specified web source. If the retrieved text is not in Ukrainian, automated translation is applied using APIs such as DeepL or Google Translate. The text is segmented into fragments based on length constraints, each fragment is translated separately, and then all translated parts are merged into a unified text. The translated text undergoes preprocessing, including normalization, tokenization, and stop-word removal. Subsequently, machine learning models perform thematic classification and compute a sentiment index expressed as a percentage ranging from –100% to +100% (Figure 3).

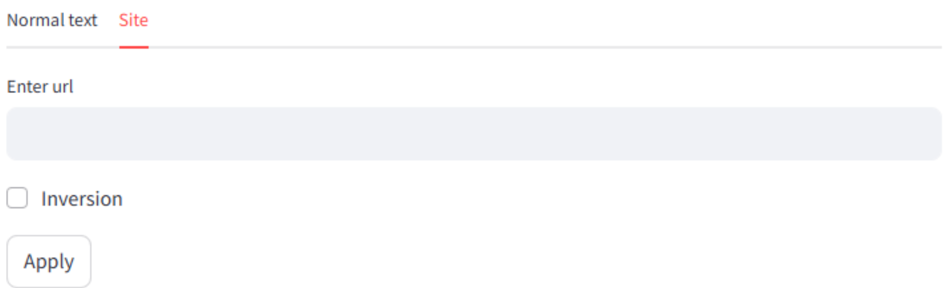

Figure 2: Main interface of the web application with a URL input field and an «Apply» button

The web application's user interface is presented as an interactive window, where, in addition to the URL input field, an "Apply" button initiates the analysis. Users can also apply sentiment inversion. After processing the text, the system displays the assigned thematic category and the calculated sentiment index, as illustrated in the corresponding screenshots (see Figure 3).

Additionally, analysis results can be summarized in a table format, showing multiple news articles with their thematic classifications and sentiment scores.

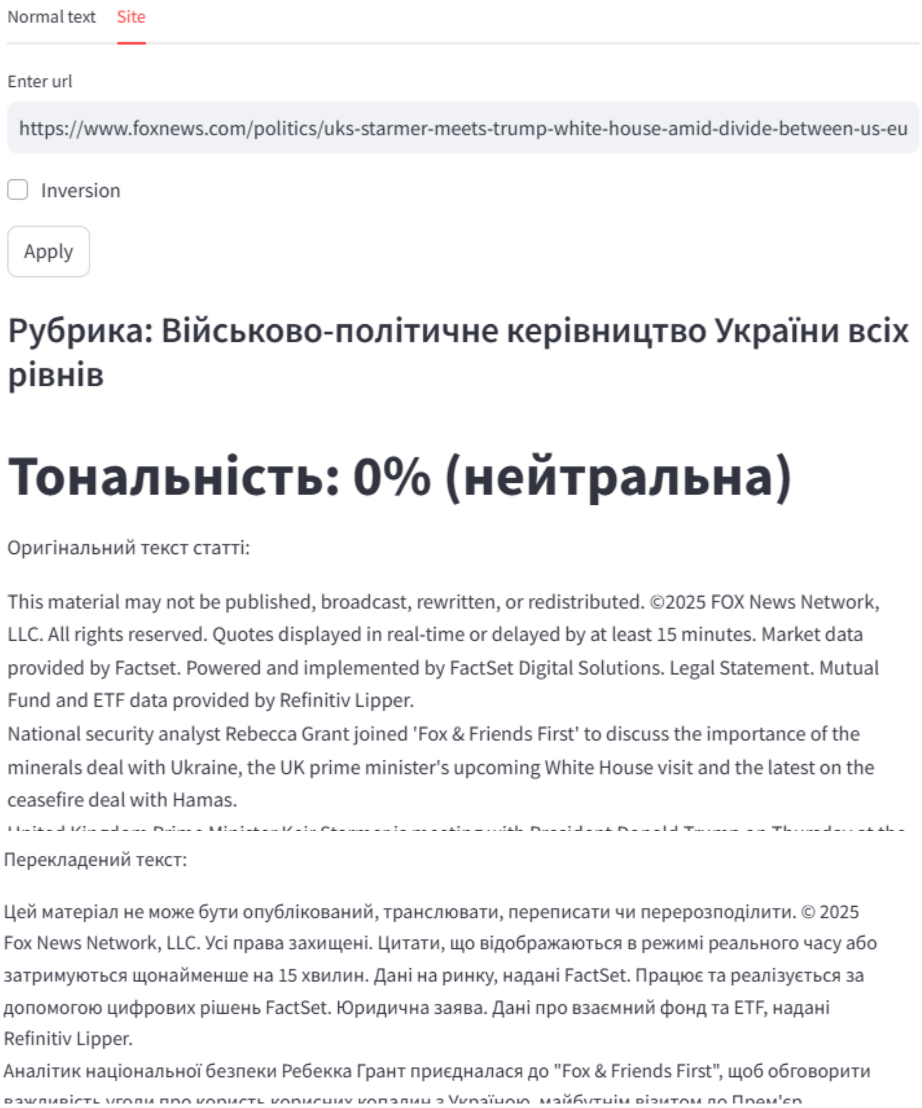

Figure 3: Example of sentiment analysis results, displaying the assigned thematic category and calculated sentiment index

Thus, the proposed web application provides an efficient, interactive, and visually intuitive mechanism for analyzing textual data, which is particularly crucial for the rapid detection of disinformation attacks in modern information warfare.

To demonstrate the effectiveness of the proposed approach, an experimental evaluation of the web application's performance was conducted. Table 1 presents examples of sentiment analysis results for various news articles, displaying their sentiment index and thematic classification.

The analysis of the performance of the sentiment classification system for news articles showed that, in most cases, the algorithm correctly classified the sentiment of the texts. Out of 13 news articles examined, the system correctly identified the sentiment in 10 cases, resulting in an accuracy of approximately 77%.

In particular, 100% of neutral articles (e.g., a review of the mineral resources agreement between the US and Ukraine) and clearly negative articles, such as CNN and Sky News reports on the conflict-laden meeting between Zelensky and Trump, were correctly classified.

However, in some cases, the algorithm could have made errors due to misleading headlines or mixed-tone texts that contained both positive and negative elements simultaneously.

Table 1
Sentiment Analysis of News Articles Processed by the Web Application

News Source	Thematic Category	Sentiment Index
Fox News. (2025, February 27). *UK's Starmer meets Trump at White House amid divide between U.S. and Europe over Ukraine peace deal*. [17]	Military-political leadership of Ukraine	0% (neutral)
Fox News. (2025, February 27). *6 times judges blocked Trump executive orders* [18]	Military-political leadership of Ukraine at all levels	-10%
Fox News. (2025, February 27). *U.S., Russian officials propose peace plan, lay groundwork for cooperation in Riyadh*. [19]	Military-political leadership of Ukraine at all levels	+10%
BBC News (2025 February 28) Trump commends Zelensky ahead of White House talks [20]	International image of Ukraine in the U.S., Canada, and the UK (English media)	+30%
CNN News (2025 February 28) What we do and don't know about Trump's 'very big deal' on Ukraine's mineral resources [21]	International image of Ukraine in the U.S., Canada, and the UK (English media)	+20%
CNN News (2025 February 28) Trump, Vance castigate Zelensky in tense Oval Office meeting [22]	International image of Ukraine in the U.S., Canada, and the UK (English media)	-20%
Fox News (2025 February 28) Trump, Zelenskyy to meet for key deal as NATO allies, Russia wait, watch [23]	International image of Ukraine in the U.S., Canada, and the UK (English media)	+20%
Fox News (2025 February 28) Why Zelenskyy keeps pushing for Ukraine NATO membership even though Trump says it's not happening [24]	International image of Ukraine in the U.S., Canada, and the UK (English media)	0% (neutral)
Sky News (2025 February 28) Donald Trump tells Volodymyr Zelenskyy 'you're gambling with World War Three' in fiery Oval Office meeting [25]	International image of Ukraine in the U.S., Canada, and the UK (English media)	-10%
BBC News (2025 February 28) What we know about US-Ukraine minerals deal [26]	International image of Ukraine in the U.S., Canada, and the UK (English media)	0% (neutral)
BBC News (2025 February 26) Zelensky to meet Trump in Washington to sign minerals deal [27]	International image of Ukraine in the U.S., Canada, and the UK (English media)	-10%
Fox News (2025 February 28) Trump says 'I can't believe I said that' when asked if he still thinks Zelenskyy is a dictator [28]	International image of Ukraine in the U.S., Canada, and the UK (English media)	+30%
Ukrayinska Pravda (2025 February 28) Cabinet of Ministers allows civilians who were captured to receive a deferral from mobilisation [29].	Armed Forces of Ukraine	+20%

Significant deviations from the expected results were observed in 3 articles (23%), where the system might have incorrectly identified the sentiment due to incomplete context analysis. For example, in the Fox News article about the meeting between Starmer and Trump at the White House, the tone was actually neutral-positive, but the use of the word "divide" in the headline might have led the system to classify the sentiment as negative. A similar situation occurred with an article about negotiations in Riyadh, where the use of the terms "peace plan" and "cooperation" could have led to a false positive interpretation, although the actual content of the article was tense and involved ultimatums from Russia. Additionally, in the Fox News article about Trump "not believing he called Zelensky a dictator," the system might have mistakenly classified the sentiment as negative due to the word "dictator," while the material was more neutral.

Therefore, despite the high accuracy in most cases, the system needs improvement when dealing with mixed or contextually complex texts, especially if the headline is misleading or contains strongly biased words. Adding deeper context analysis algorithms and identifying sentiment not only through keywords but also through the structure of the argumentation could reduce errors and improve classification accuracy from approximately 77% to ≥90% [32, 33].

Conclusions

The results of this study confirmed the effectiveness of the proposed integrated approach to automated sentiment analysis in news articles. The developed system, which combines automated translation, preprocessing, thematic classification, and lexicon-based analysis, achieved an overall accuracy of approximately 77%, a relatively high performance for automated NLP systems. The sentiment classification was entirely correct in 10 out of 13 analyzed cases (~77%), demonstrating a significant alignment with the actual emotional tone of the texts. The highest accuracy was observed in classifying neutral materials (100%) and explicitly negative news (CNN, Sky News – 100% accuracy).

Minor deviations from expected results were recorded in three cases (~23%), where the system misclassified sentiment due to ambiguous headlines or mixed emotional tones. For instance, in a Fox News article about a meeting between Starmer and Trump, the word "divide" may have led to a negative classification, despite the actual context being moderately positive. Similarly, a report on negotiations in Riyadh was misclassified as positive due to the phrase "peace plan," whereas the overall sentiment was tense. Additionally, an article discussing Trump’s remarks calling Zelenskyy a "dictator" was classified as negative due to the use of the word "dictator," despite the neutral tone of the material.

Thus, while the proposed system already demonstrates high accuracy in sentiment analysis, it can be further refined to correct context-dependent cases. Future research should focus on improving headline context interpretation and expanding semantic sentence analysis [34] to minimize classification errors. The integration of more advanced contextual analysis models (e.g., GPT-4, BERT with contextual expansion) is expected to increase overall classification accuracy to ≥90%, significantly enhancing the system’s effectiveness for real-world applications in information security. The works [35-38] suggest approaches to combining the use of artificial intelligence and web platforms.

Declaration on Generative AI

The authors used GPT-4 and DeepL to prepare this paper: Grammar and Spelling Checker. After using these tools, the authors reviewed and edited the content as necessary and are solely responsible for the content of the publication.

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