A hybrid neural network architecture for semantic-contextual analysis of emotions in social media

Vita Kashtan[†], Volodymyr Hnatushenko[*,†], Maksym Ovcharenko[†], Artem Ivanko[†]

Dnipro University of Technology, Dmytra Yavornytskoho Ave 19, Dnipro, 49005, Ukraine

Abstract

The paper proposes a hybrid neural network architecture for multi-class classification of the emotional state of social media texts, which combines contextual vector representations generated by the BERT model with extended structured features related to the user and message metadata. The proposed approach uses a multilayer perceptron network that combines linguistic and contextual information in a single representation. The results of the experimental study confirm the superiority of the proposed approach over traditional LSTM and CNN architectures, as well as over the separate use of BERT embeddings. The achieved classification accuracy is 90%, and the F1-measure is 0.91, which indicates the high efficiency of the model in conditions of high variability of language structures and stylistic features of social content.

Keywords

emotion state, contextual analysis, semantic analysis, deep learning, neural network architecture

1. Introduction

The current development period in the digital society is characterized by the rapid growth of data volumes resulting from user activity on social media platforms such as Twitter, Facebook, and other microblogging services [1]. These platforms have become key channels for the spontaneous expression of opinions, emotions, and real-time reactions to events. Despite their brevity and informal style, messages posted on social networks often reflect deep aspects of users' psycho-emotional states, making them a valuable source for public opinion analysis, consumer behavior prediction, and studying social processes [2].

However, such messages' short, non-standard, and often context-rich nature poses significant challenges for traditional natural language processing methods. Conventional linguistic models, which primarily focus on syntactic and semantic analysis, usually fail to adequately interpret the emotional nuances of expressions, especially without considering the interaction context, user social activity, and platform-specific characteristics. In the business environment, similar difficulties arise when analyzing large volumes of voice and textual data received by contact centers, where service quality increasingly depends on a deep understanding of the emotional dynamics of communication.

Sentiment analysis, or emotional text classification, is one of the key tasks in Natural Language Processing, aimed at automatically identifying the emotional tone of an utterance that reflects the author's attitude toward an object, event, or phenomenon [3]. In this context, the central concept is

MoDaST 2025: Modern Data Science Technologies Doctoral Consortium, June, 15, 2025, Lviv, Ukraine

[*] Corresponding author.
[†] These authors contributed equally.
vitalionkaa@gmail.com (V. Kashtan); vvgnat@ukr.net (V. Hnatushenko); ovcharenko.m.a@nmu.one (M. Ovcharenko); ivanko.a.m@nmu.one (A. Ivanko)
0000-0002-0395-5895 (V. Kashtan); 0000-0003-3140-3788 (V. Hnatushenko); 0009-0006-0730-0913 (M. Ovcharenko); 0009-0002-0491-5374 (A. Ivanko)

the opinion holder, the subject expressing a viewpoint. It may be an individual, a group, an organization, or a collective entity. A distinction is made between direct emotional expression, which explicitly relates to the object, and indirect emotion, which stems from the evaluation of events or consequences associated with it [4].

Most existing sentiment analysis models applied to social media content focus exclusively on the linguistic content of messages, overlooking user metadata, the topic of discussion, or the specific nature of the platform. This limits their ability to accurately detect emotions, especially under conditions of high linguistic variability, the use of slang, emojis, and multimodal elements.

Thus, the study aims to overcome the limitations of existing emotion analysis methods and develop a comprehensive approach that ensures higher accuracy and adaptability under real-world conditions in social media and business communication. The architecture proposed in this work opens up new prospects for the automation of emotional content evaluation and for enhancing the effectiveness of interaction in the digital environment.

2. Related works

Over the past decades, numerous methods for automated emotion analysis have been proposed, among which three main approaches dominate: rule- and lexicon-based methods, machine learning techniques, and deep learning models. The most common classifiers are the Naive Bayes classifier and the Support Vector Machine (SVM) [5]. These models demonstrate effectiveness on well-structured textual datasets where the emotional tone of expressions is clear and easily recognizable (e.g., distinctly positive or negative); however, they perform poorly when adapting to new thematic domains or stylistically different content. As noted by Paltoglou and Giachanou [6], the primary limitation of these approaches is their high sensitivity to the subject domain, which leads to a loss of generalization capability when the context changes. This issue arises from the difficulty of creating sufficiently comprehensive and representative training datasets for specific tasks.

Lexicon-based methods rely on affective lexicons containing words assigned with positive or negative values. Well-known examples of such lexicons include General Inquirer [7], SentiWordNet [8], and WordNet-Affect [9]. Some studies [10] demonstrate the effectiveness of lexicon-based analysis in social media contexts, especially when enhanced with syntactic rules [11]. However, the success of these methods heavily depends on the lexicon's completeness, the vocabulary's domain specificity, and their inability to adequately reflect contextual changes in meaning [12]. Furthermore, lexicons do not cover the dynamic vocabulary of social media, including slang, emojis, and abbreviations.

Over the past decade, deep learning (DL), implemented through multilayer neural networks, has become a key direction in the evolution of emotion analysis methods. Due to its ability to automatically extract high-level abstract features from unstructured data, DL has demonstrated high effectiveness in complex tasks, particularly in computer vision, satellite image processing, object recognition, speech processing, and text analysis [13, 14, 15, 16]. One example of the successful application of deep learning in sentiment analysis on Twitter is the Sentiment-Specific Word Embedding approach proposed in [17]. In this approach, distance learning based on pre-labeled tweets was used to train vector representations of words. Further research indicates that traditional embedding methods do not accurately reflect the sentiment information of rarely used words. To this end, the Bayesian Estimation-based Sentiment Word Embedding model was proposed, which provides more accurate extraction of emotional information from such words using Bayesian estimation and a special loss function. It has significantly improved the quality of embedding and the overall accuracy of sentiment analysis [18]. The fusion of unstructured data from various sources is a significant area of contemporary research in data processing and artificial intelligence [19]. By combining information from textual, visual, audio, and other types of unstructured data, deep learning-based systems can generate more comprehensive and context-rich representations, thereby enhancing recognition and classification accuracy in complex tasks [20].

Further development in this field is associated with the use of convolutional neural networks (CNN) for phrase and document analysis [21], as well as recurrent architectures, notably Long Short-Term Memory (LSTM) networks [22]. In [22], a hierarchical LSTM model was proposed that considers context at the individual tweet and message stream levels. Additionally, several types of context (social, topical, conversational) were adapted and represented as binary features. Results obtained on a corpus of 15,000 tweets annotated with three classes (positive, negative, neutral) demonstrated a significant improvement in accuracy compared to baseline models (SVM, LSTM-RNN, CNN). The study proposes using hybrid deep learning models with textual representations generated by BERT to analyze reviews from Indonesian e-commerce platforms. Comparison of the results showed that models with BERT representation outperform models with classical embeddings [23, 24].

To overcome the limitations of the approaches above, hybrid methods [25] have been proposed that combine lexical analysis with machine learning. The linguistic analysis stage typically generates input features for subsequent classification, and the results are used for iterative dictionary expansion and model improvement [26]. Despite this, hybrid approaches remain limited in their ability to model the' complex semantic and pragmatic structure of utterances.

Despite the active development of approaches for the automated analysis of emotional states in texts, particularly in social media, modern methods still exhibit several significant limitations. Traditional approaches display semantic rigidity, which hinders the accurate recognition of emotions in messages containing a high degree of informal, contextually variable vocabulary characteristic of digital communication. Moreover, such models typically have limited adaptability: algorithms trained in one domain tend to perform poorly when transferred to other subject areas or topics. One of the key challenges remains the neglect of social context and metadata: most approaches focus exclusively on textual content, overlooking critical characteristics such as writing style, temporal dynamics of messages, user activity, follower count, or the author's influence within the network. Integrating multidimensional features within a unified model also poses a challenge; the growing volume of available structured information necessitates architectures capable of effectively combining linguistic, behavioral, and contextual attributes.

3. Problem statement

Although transformer-based models, particularly BERT, demonstrate high effectiveness in text classification due to their ability to capture sentence-level contextual information, they are not inherently designed to process additional structured features such as social context or user profile characteristics without specialized architectural modifications. Therefore, developing a hybrid architecture integrating high-level context-aware language representations generated by BERT with multidimensional information about the user or the publication environment remains relevant. Such an approach can significantly improve the accuracy of emotional state classification of messages in dynamic information environments.

This study aims to design and experimentally evaluate a hybrid neural network architecture that combines contextual vector representations of text obtained via the BERT model with extended user-related features. It is achieved by integrating them into a multi-level architecture based on a multilayer perceptron (MLP) to enhance the accuracy of semantic and contextual sentiment analysis in social media content.

4. Proposed approach

The proposed architecture of hybrid semantic-contextual analysis of emotions in social content, shown in Figure 1, consists of four key steps: data collection and preprocessing, extraction of extended features, construction of a hybrid model, and evaluation of its effectiveness.

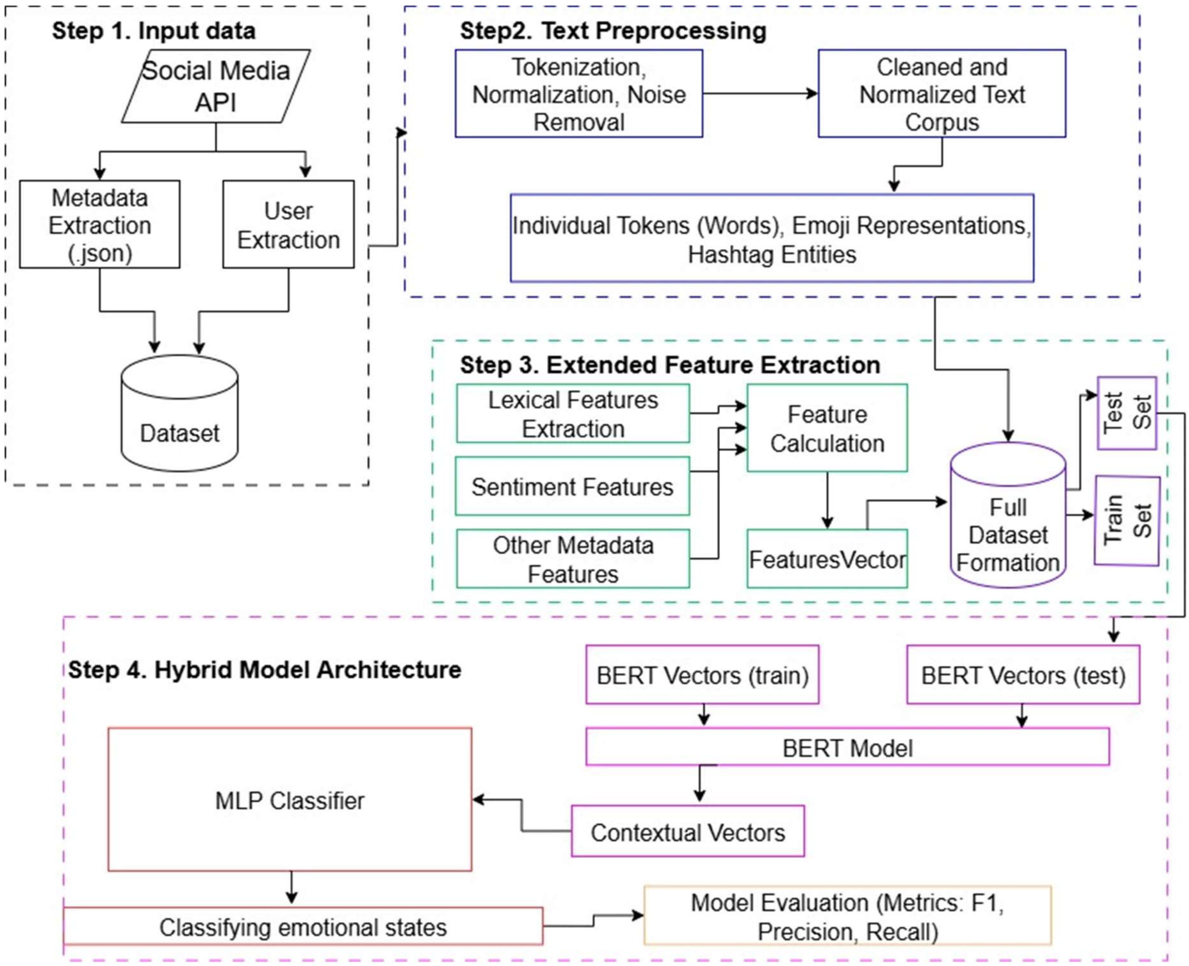

Figure 1: Diagram of the proposed approach.

At the first step, data collection and initial preprocessing are performed, primarily using APIs of social media platforms such as Twitter. Let the set of messages be denoted as $M = \{m_1, m_2, \dots, m_N\}$ obtained via social media APIs. For each message m_i the textual content T_i, a set of metadata in JSON format JSON $\mathbf{d}_i \in \mathbb{R}^p$ (e.g., timestamp, number of retweets and likes), and user-related information $\mathbf{u}_i \in \mathbb{R}^q$ (e.g., number of followers, posting history, etc.) are extracted. All collected components form an extended input dataset:

$$D = \{(T_i, \mathbf{d}_i, \mathbf{u}_i) | i = 1, \dots N\}. \tag{1}$$

The second step involves text pre-processing to convert raw content into a format suitable for analysis. The process includes tokenization, breaking the text into linguistic units, normalizing (lowercase translation, error correction), and removing noise elements: stop words, URLs, hashtags, and user mentions. At the same time, emojis and hashtags are not entirely removed, but transformed into special representations, as they carry significant emotional and contextual meaning in social media. This results in a cleaned and normalized text corpus.

$$T_i \to \{w_{i1}, w_{i2}, \dots w_{iLi}\}, \tag{2}$$

where T_i is the text;; w_{ij} is the j-th token in message i, L_i is the length of the tokenized text $\tilde{T}_i$.

The third step focuses on extracting advanced features that reflect various aspects of the messages and their authors. Lexical features include word frequency, n-gram sequences, number of words and punctuation marks, and the presence of slang or foul language.

$$f_{lex}: \tilde{T}_i \to \mathbf{f}_{lex,i} \in \mathbb{R}^{d1}, \tag{3}$$

where d_l is the dimensionality of lexical features.

Sentiment features are based on external affective dictionaries and pre-trained models that assess the polarity and subjectivity of the text, as well as take into account emotion enhancers or weakeners. User metadata (number of followers, publication history, verification status) and message characteristics (time of publication, activity in the form of retweets and likes, geolocation) are also used to generate contextual features. After extraction, all features are calculated and combined into a feature vector for each message, forming a complete dataset further divided into training and test sets.

$$\mathbf{f}_{meta,i} = [\mathbf{d}_i, \mathbf{u}_i] \in \mathbb{R}^{d2}. \quad (4)$$

The main component of the proposed architecture is a hybrid model that combines powerful contextual representations generated by the transformational BERT [23, 24] model with traditional and user-generated features. The cleaned and normalized text is fed to the pre-trained BERT model, which produces contextual vector embeddings for each message that consider both the semantic and syntactic context of the text. The resulting BERT vectors are concatenated with the extended feature vector generated in the previous step. The combined vector serves as input to a multilayer perceptron network that learns to classify the emotional state of a message into predefined categories (positive, negative, neutral, and more detailed emotions such as joy, sadness, anger, etc.) MLP can model complex nonlinear relationships between input features and target classes.

The final stage involves evaluating the model's performance using classical classification metrics: F1-score, Precision, and Recall on a test dataset. This hybrid approach, which integrates deep contextual representations of text with multidimensional features, is expected to provide a more accurate and comprehensive semantic and contextual analysis of emotions in social content compared to methods based solely on text or individual feature sets.

5. Experiment

A textual dataset collected from the Twitter social media platform experimentally validated the proposed hybrid neural network architecture. The choice of Twitter is motivated by its popularity as a medium for expressing spontaneous opinions and emotions, as well as the fact that tweets, though limited to 280 characters, often contain sufficiently meaningful information for public opinion analysis.

The primary test dataset consists of approximately 80,000 textual messages related to the global COVID-19 pandemic. These data were collected over three months, from March 2020 to May 2020 [27], covering the phase of active virus spread and public discourse around related events. Hashtags, an integral part of Twitter content, were used not only as markers for sentiment classification but also as an effective means for filtering and selecting relevant data, ensuring the thematic consistency of the dataset.

Analysis of this dataset reveals key statistical patterns in the characteristics of textual messages that may significantly influence their emotional tone. In particular, based on the histograms of key linguistic and structural features (Figure 2), the following characteristics are observed:

1. The number of words and text length indicate that most tweets are short, condensing information within a limited character space.

2. The number of unique words reflects the lexical diversity used in the messages.

3. The number of stop words captures the frequency of commonly used words, which are traditionally removed during text preprocessing but may carry indicative value in specific models.

4. Average word length provides insight into the level of formality or informality of the language.

5. The number of punctuation marks, especially exclamation marks, may indicate emotional intensity.

6. The number of URL links points to the use of external information sources, which may form part of the message context.

7. The number of hashtags reflects the authors' intent to categorize messages, highlight topics, or associate with specific communities.

8. The number of users mentioned indicates the level of social interaction, an essential context component.

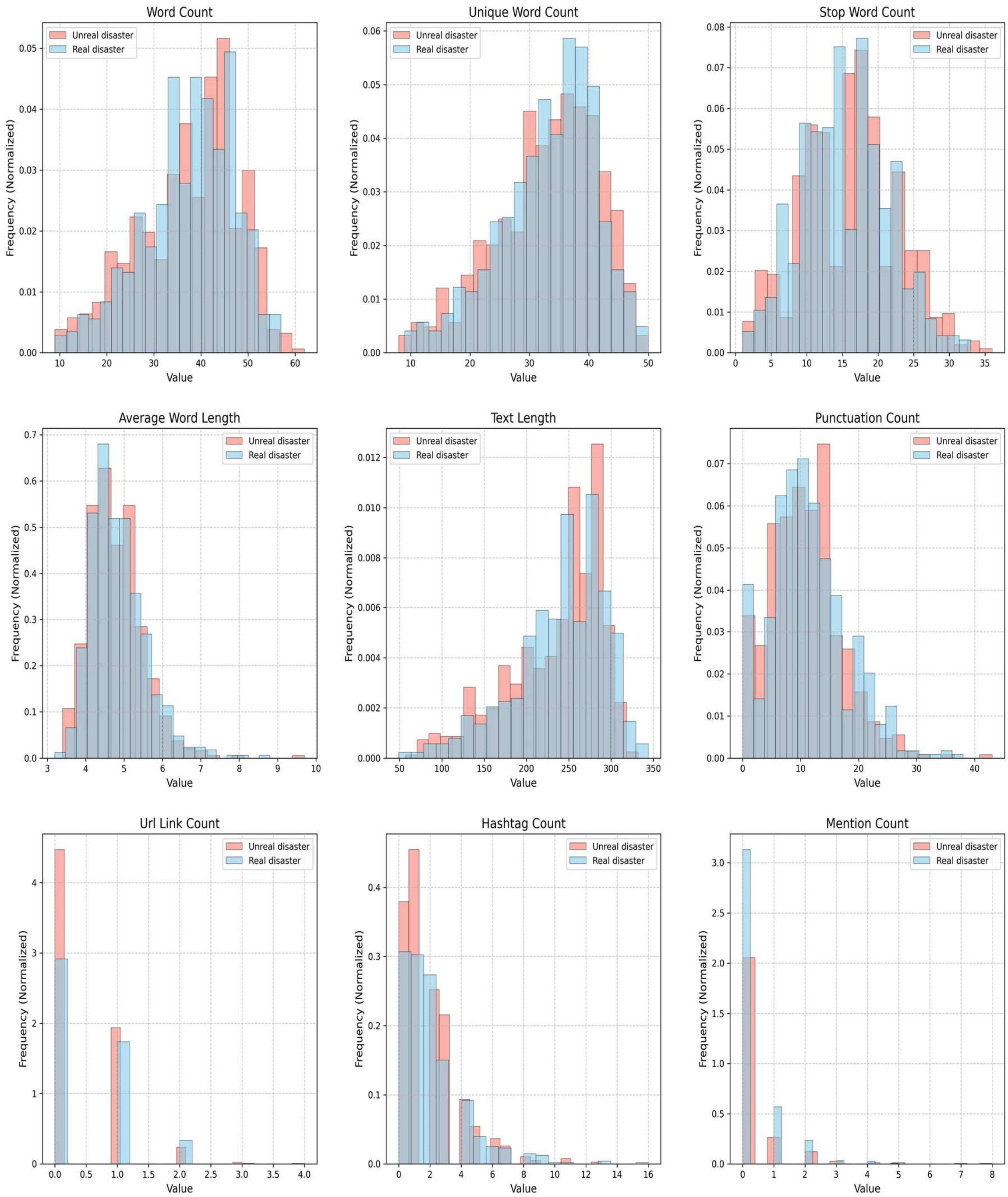

Figure 2: Histogram of the distribution of key linguistic and structural features.

The obtained distributions confirm the need for a multidimensional approach to analysis, since the emotional content of messages depends not only on their lexical content but also on their structural and social characteristics.

In addition to linguistic features, we analyzed the geographical distribution of tweets. As shown in Figure 3, the highest concentration of messages is observed in the United States, London, Washington, New York, Los Angeles, Canada, and Toronto. The availability of geographical data allows us to consider regional peculiarities of emotional coloring, which can be important for a deeper contextual analysis and interpretation of sentiments related to local events or social trends.

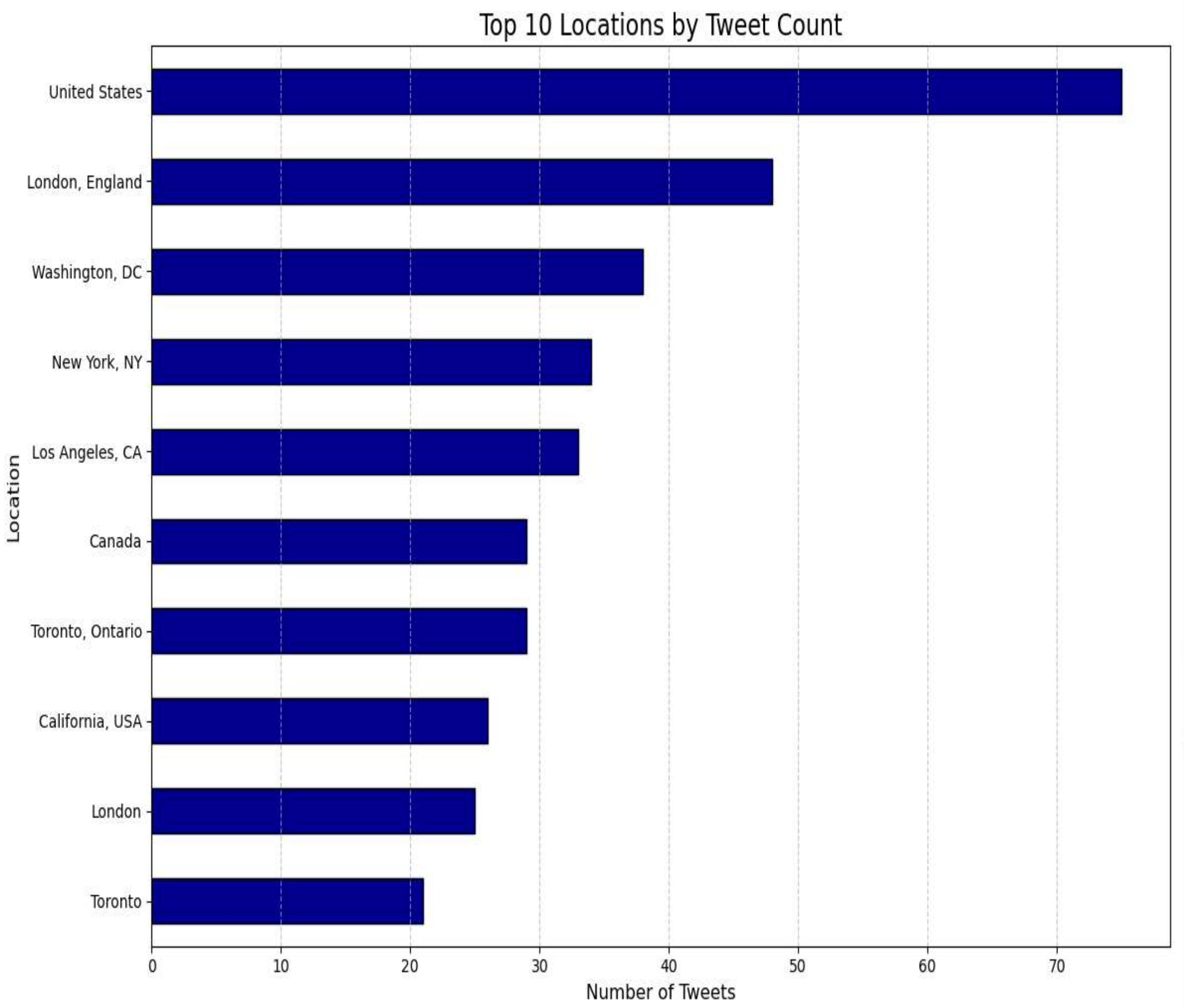

Figure 3: The geographical distribution of tweets.

6. Results and Discussion

Experimental results were conducted to evaluate the effectiveness of the proposed hybrid neural network architecture by comparing it with several baseline models. The results are presented in tables with summarized comparative metrics, including Accuracy, F1-score, Precision, and Recall (in Macro Average format) [28], and a detailed classification report for the model that demonstrated the highest efficiency.

The results of the comparative analysis of neural networks presented in Table 1 demonstrate a significant improvement in the performance of the proposed hybrid architecture compared to the baseline models. Traditional LSTM and CNN models with classical tokenization showed average Precision and F1-score values in the range of 0.72-0.75, indicating a moderate classification accuracy level. The BERT model in the standalone version significantly exceeded these results, reaching a Precision of 0.83 and an F1-score of 0.80, due to its ability to take into account the contextual representation of the text.

Integration of BERT embeddings into traditional LSTM and CNN also improved the results. Still, the proposed approach, which combines BERT contextual representations with multidimensional user features in a hybrid architecture, achieved the highest values of all metrics: Precision - 0.94, F1-score - 0.91, Precision (Macro Avg) - 0.90, and Recall (Macro Avg) - 0.91. It indicates a significant increase in the accuracy, balance, and completeness of the classification of the emotional state of messages compared to other models, confirming the proposed methodology's effectiveness.

Table 1
Comparative analysis of neural network models

Model	Precision	F1-score (Macro Avg)	Precision (Macro Avg)	Recall (Macro Avg)
LSTM (Traditional)	0.72	0.72	0.76	0.72
CNN (Traditional)	0.74	0.75	0.76	0.75
BERT (Standalone)	0.83	0.80	0.89	0.85
LSTM (with BERT Embeddings)	0.78	0.79	0.711	0.78
CNN (with BERT Embeddings)	0.75	0.75	0.78	0.74
Proposed approach	0.94	0.91	0.90	0.91

A detailed classification report for the BERT+MLP model with five-class categorization is shown in Table 2.

Table 2
Quantitative metrics of the proposed approach (BERT+MLP)

Class	Precision	Recall	F1-score
Extremely Negative	0.96	0.90	0.93
Negative	0.72	0.89	0.89
Neutral	0.91	0.92	0.91
Positive	0.73	0.70	0.71
Extremely Positive	0.90	0.87	0.70
accuracy			0.90
macro avg	0.94	0.90	0.91
weighted avg	0.92	0.90	0.90

The Precision, Recall, and F1-score metrics for most classes demonstrate values above 0.70, which indicates that the model is balanced and stable. In particular, the “Extremely Negative” and “Neutral” classes are characterized by the highest scores, with a Precision of 0.96 and 0.91, respectively, indicating accurate recognition of strongly negative and neutral messages. Although the “Negative”, ‘Positive’ and “Extremely Positive” classes show slightly lower accuracy or completeness, the overall classification accuracy rate is 90%, and the average macro F1-score reaches 0.91. It demonstrates that the model can effectively balance between all classes, given their unevenness in the training set. The weighted average also confirms the stability and reliability of the model when working with real data, which is essential for practical applications in analyzing emotional states of social content.

Confusion matrix analysis is a key step in evaluating the performance of multiclass emotion classification models, as it allows for a detailed examination of classification accuracy for each class and helps identify specific types of errors, including false positives and false negatives (Fig. 4).

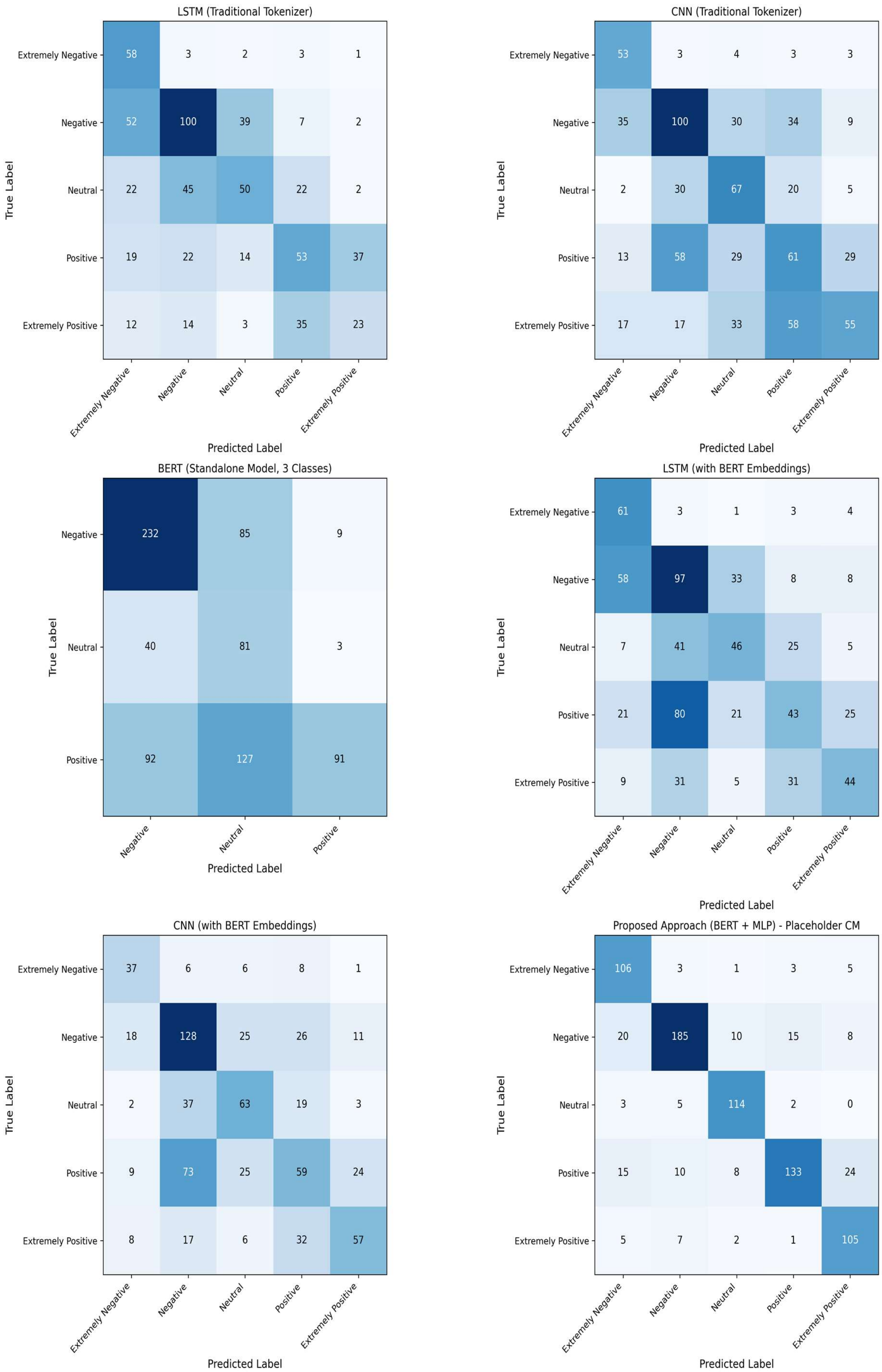

Figure 4: Confusion matrix analysis.

The traditional LSTM model using standard tokenization shows a limited ability to recognize emotional classes accurately. The highest classification accuracy is observed for the classes "Negative" (100 instances), "Extremely Negative" (58 instances), and "Positive" (53 instances), while the "Neutral" (50 instances) and especially "Extremely Positive" (23 instances) classes show significantly lower accuracy. A considerable amount of confusion is observed between neighboring categories. For example, "Negative" is often misclassified as either "Extremely Negative" or "Neutral." Similarly, the "Extremely Positive" class is frequently confused with both "Positive" and "Negative," indicating the model's insufficient ability to distinguish between levels of emotional intensity. The CNN model with traditional tokenization demonstrates performance similar to LSTM, with slight improvements in the classification of extreme classes ("Extremely Negative" – 53 instances, "Extremely Positive" – 55 cases). However, classification errors are still concentrated around confusion between "Negative" and both "Extremely Negative" and "Positive," as well as difficulties in accurately identifying "Neutral" and "Positive," which limits the model's ability to delineate the emotional spectrum.

The BERT model, operating with three aggregated classes ("Negative," "Neutral," and "Positive"), demonstrates a significant performance improvement compared to traditional approaches, particularly for the "Negative" class (232 correct predictions). However, even under these conditions, classification errors, especially the confusion between "Neutral" and either "Negative" or "Positive," as well as misclassifications between "Positive" and "Negative," indicate the model's difficulty in clearly distinguishing between closely related emotional categories. Integrating BERT embeddings as input features for the LSTM model results in a moderate improvement over the traditional LSTM. There is an increase in the number of correct predictions for the "Negative" (97 instances) and "Extremely Negative" (61 cases) classes. However, the "Neutral," "Positive," and "Extremely Positive" classes still exhibit significant confusion, suggesting that simple input of embeddings without more sophisticated integration mechanisms is insufficient. Similar trends are observed with CNN using BERT embeddings. Moderate improvements are achieved for "Negative" (128 instances), "Neutral" (63 instances), and "Extremely Positive" (57 instances). However, "Positive" and "Neutral" continue to be confused with each other, and with "Negative," the overall number of classification errors remains noticeable. Finally, the confusion matrix of the proposed hybrid architecture (BERT + MLP) demonstrates substantially higher accuracy and a markedly reduced number of misclassifications across all five emotional categories. It is characterized by a high number of correct predictions in each class, including "Extremely Negative" (106 instances), "Negative" (185), "Neutral" (114), "Positive" (133), and "Extremely Positive" (105), along with a minimal level of confusion. It indicates the high effectiveness of integrating contextual BERT embeddings with enriched features via a multilayer perceptron, enabling more accurate and nuanced differentiation of emotional states.

Thus, the confusion matrix analysis confirms that traditional LSTM and CNN architectures, especially without contextual representations, have significant limitations in multiclass emotion classification from textual data. While the standalone BERT model enhances overall performance, achieving high precision in distinguishing emotional intensity and spectrum requires the combination of contextual embeddings with additional features in a hybrid neural network architecture.

A correlation analysis was conducted using Pearson's coefficient to better understand the relationships between the extracted features and the target mood variable. The results are displayed as a correlation matrix (Figure 5), demonstrating the degree of linear dependence between pairs of variables. The values of Pearson's coefficient range from -1 to +1, where +1 indicates a strong positive correlation, -1 indicates a strong negative correlation, and 0 indicates no linear dependence. The visualization uses a color scale, where red shades correspond to positive and blue to negative correlations. The analysis of the correlation matrix showed a high interconnectedness of the features characterizing the length of the text: there is a strong positive correlation between the number of words (word_count), the number of unique words (unique_word_count), the number of stop words (stop_word_count) and the length of the text

(text_length), with coefficients ranging from 0.65 to 0.98. It indicates that these features, on the one hand, reflect a common aspect - the amount of textual content. The average word length (average_word_length) showed a moderate negative correlation with the features related to the number of words and text length (from -0.41 to -0.60), which can be interpreted as a tendency to use shorter words in longer messages, a phenomenon typical of the informal style of communication in social networks.

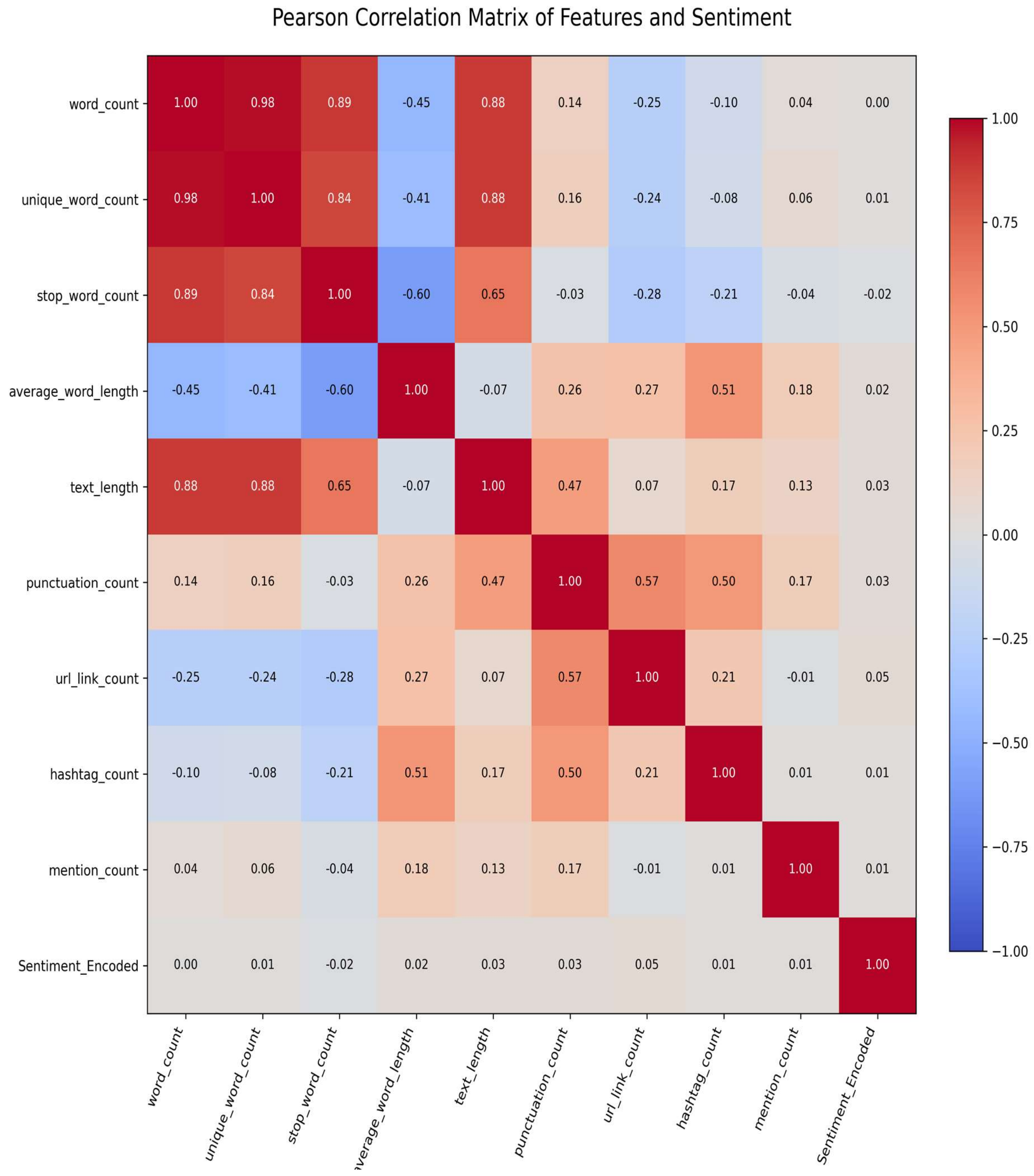

Figure 5: Analysis of the correlation between features and mood.

Regarding the features related to format and metadata, it was found that the number of punctuation marks (punctuation_count) positively correlates with text length (0.47), which is logical since longer texts tend to include more punctuation. In contrast, the number of URL links (url_link_count) shows a weak negative correlation with text length and word count (approximately -0.25), suggesting that messages containing external links are typically more concise. The number of hashtags (hashtag_count) exhibits a weak negative correlation with text length (-0.21) and a moderate positive correlation with punctuation count (0.50), possibly indicating stylistic patterns in tweets with a high number of hashtags. The number of mentions (mention_count) shows almost no correlation with other features (coefficients between 0.04 and 0.18), highlighting its relative independence from linguistic characteristics.

The most important finding concerns the correlation between all the aforementioned features and the target variable, sentiment (Sentiment_Encoded). The analysis showed that none of the surface-level linguistic or structural features exhibit a significant linear relationship with sentiment: the correlation coefficients range from -0.02 to 0.03, effectively zero. These results demonstrate the insufficiency of relying solely on traditional surface-level features for accurate and semantically rich emotional tone analysis in social content. They further underscore the necessity of employing more complex models capable of capturing nonlinear dependencies and leveraging deep contextual text representations, such as those generated by the BERT model. The integration of such representations with extended features, as proposed in our hybrid neural network architecture, is reasonable and well-justified. Thus, the correlation analysis highlights the importance of a comprehensive, multidimensional approach to overcoming the limitations of traditional sentiment analysis methods.

7. Conclusions

This study developed and experimentally validated a hybrid neural network architecture for semantic-contextual analysis of emotions in social content. The proposed model combines contextual vector representations of text generated by the BERT transformer model with multidimensional extended user features and message metadata. To integrate these different types of input data, a multilayer perceptron network is used to match linguistic and structured information effectively. The results of the experimental comparison with traditional LSTM and CNN architectures and the separate use of BERT or BERT embedding demonstrated the superiority of the proposed approach in all key metrics. The hybrid BERT + MLP model achieved the highest results: F1-measure (macro average) was 0.91, precision was 0.94, recall was 0.90, and overall classification accuracy was 0.90. High performance was also recorded for individual emotional classes: F1-measure for "Extremely Negative" was 0.93, for 'Neutral' 0.91, and for "Negative" 0.89.

Additional correlation analysis revealed that superficial linguistic and structural features, such as the number of punctuation marks, hashtags, mentions, or URL links, do not have a significant linear relationship with the message's sentiment. However, including these features in the model allowed us to identify complex non-linear relationships, increasing classification accuracy.

Thus, the study's results confirm the feasibility and effectiveness of the proposed hybrid architecture for emotional analysis of social content. Combining contextual language representations based on BERT with extended structural characteristics allows for high accuracy in information heterogeneity and stylistic variability of texts in social networks.

Acknowledgements

The study was conducted as part of the international educational project "Safe Artificial Intelligence: The European Legal Dimension" [101176092, a joint project of Dnipro University of Technology, Erasmus+ Jean Monnet Foundation, and the European Education and Culture Executive Agency (EACEA)]. Support from the European Commission for the publication of this work does not imply endorsement of its content, which solely reflects the views and opinions of the authors, and the Commission cannot be held responsible for any use that may be made of the information contained therein. Co-funded by the European Union

Declaration on Generative AI

The authors used Grammarly to check the grammar.

References

[1] S. A. Salloum, M. Al-Emran, A. A. Monem, K. Shaalan, Using Text Mining Techniques for Extracting Information from Research Articles, in: Intelligent Natural Language Processing: Trends and Applications, Springer International Publishing, Cham, 2017, pp. 373–397. doi:10.1007/978-3-319-67056-0_18.

[2] Z. Drus, H. Khalid, Sentiment Analysis in Social Media and Its Application: Systematic Literature Review, Procedia Comput. Sci. 161 (2019) 707–714. doi:10.1016/j.procs.2019.11.174.

[3] S. Voloshyn, V. Vysotska, O. Markiv, I. Dyyak, I. Budz, V. Schuchmann. “Sentiment Analysis Technology of English Newspapers Quotes Based on Neural Network as Public Opinion Influences Identification Tool”. 2022 IEEE 17th International Conference on Computer Sciences and Information Technologies (CSIT), IEEE, 2022. doi:10.1109/csit56902.2022.10000627.

[4] K. Sunil, S. Beniwal, Sentiment Analysis: A Tool for Mining Opinions and Emotions, SSRN Electron. J. (2020). doi:10.2139/ssrn.3746951.

[5] A. Alqahtani, S. B. Khan, J. Alqahtani, S. AlYami, F. Alfayez, Sentiment Analysis of Semantically Interoperable Social Media Platforms Using Computational Intelligence Techniques, Appl. Sci. 13.13 (2023) 7599. doi:10.3390/app13137599.

[6] G. Paltoglou, A. Giachanou, Opinion Retrieval: Searching for Opinions in Social Media, in: Professional Search in the Modern World, Springer International Publishing, Cham, 2014, pp. 193–214. doi:10.1007/978-3-319-12511-4_10.

[7] J. Park, H. J. Lee, S. Cho, Automatic construction of direction-aware sentiment lexicon using direction-dependent words, Lang. Resour. Eval. (2024). doi:10.1007/s10579-024-09737-9.

[8] S. Wu, F. Wu, Y. Chang, C. Wu, Y. Huang, Automatic construction of target-specific sentiment lexicon, Expert Syst. With Appl. 116 (2019) 285–298. doi:10.1016/j.eswa.2018.09.024.

[9] G. Badaro, H. Jundi, H. Hajj, W. El-Hajj. “EmoWordNet: Automatic Expansion of Emotion Lexicon Using English WordNet”. Proceedings of the Seventh Joint Conference on Lexical and Computational Semantics, Association for Computational Linguistics, Stroudsburg, PA, USA, 2018. doi:10.18653/v1/s18-2009.

[10] R. Menaha, K. Ananthi, Reviewing the effectiveness of lexicon-based techniques for sentiment analysis in massive open online courses, Int. J. Data Sci. Anal. (2024). doi:10.1007/s41060-024-00585-y.

[11] J. Chen, S. Becken, B. Stantic, Lexicon based Chinese language sentiment analysis method, Comput. Sci. Inf. Syst. 16.2 (2019) 639–655. doi:10.2298/csis181015013c.

[12] E.-U. Rahman, R. Sarma, R. Sinha, P. Sinha, A. Pradhan, A Survey on Twitter Sentiment Analysis, Int. J. Comput. Sci. Eng. 6.11 (2018) 644–648. doi:10.26438/ijcse/v6i11.644648.

[13] V.J. Kashtan, V.V. Hnatushenko, Y.I. Shedlovska. “Processing technology of multispectral remote sensing images”. 2017 IEEE International Young Scientists Forum on Applied Physics and Engineering (YSF), Lviv, Ukraine, 2017, pp. 355–358. doi: 10.1109/YSF.2017.8126647.

[14] D. Holubinka, V. Vysotska, S. Vladov, Y. Ushenko, M. Talakh, Y. Tomka, Intelligent System for Recognizing Tone and Categorizing Text in Media News at an Electronic Business Based on Sentiment and Sarcasm Analysis, Int. J. Inf. Eng. Electron. Bus. 17.1 (2025) 90–139. doi:10.5815/ijieeb.2025.01.06.

[15] V. Kashtan, V. Hnatushenko, Deep Learning Technology for Automatic Burned Area Extraction Using Satellite High Spatial Resolution Images, in: Lecture Notes in Data Engineering, Computational Intelligence, and Decision Making, Springer International Publishing, Cham, 2022, pp. 664–685. doi:10.1007/978-3-031-16203-9_37.

[16] V. Y. Kashtan, V. V. Hnatushenko, Automated building damage detection on digital imagery using machine learning, Nauk. Visnyk Natsionalnoho Hirnychoho Universytetu No. 6 (2023) 134–140. doi:10.33271/nvngu/2023-6/134.

[17] J. Tang, Y. Xue, Z. Wang, S. Hu, T. Gong, Y. Chen, H. Zhao, L. Xiao, Bayesian estimation-based sentiment word embedding model for sentiment analysis, CAAI Trans. Intell. Technol. (2021). doi:10.1049/cit2.12037.
[18] K. Bhuvaneshwari, D. S. A. J. Rani, D. V. V. Haragopal, Sentiment Analysis of Tweets on Telangana State Government Flagship Schemes, Int. J. Eng. Adv. Technol. 12.1 (2022) 23–27. doi:10.35940/ijeat.a3794.1012122.
[19] V. Hnatushenko, Vik. Hnatushenko, O. Kavats, V. Kashtan. (2015). Pansharpening technology of high resolution multispectral and panchromatic satellite images, Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu, 91-98.
[20] T T. Jiao, C. Guo, X. Feng, Y. Chen, J. Song, A Comprehensive Survey on Deep Learning Multi-Modal Fusion: Methods, Technologies and Applications, Comput., Mater. & Contin. 80.1 (2024) 1–35. doi:10.32604/cmc.2024.053204.
[21] A. Severyn, A. Moschitti, Twitter Sentiment Analysis with Deep Convolutional Neural Networks, in: SIGIR '15: The 38th International ACM SIGIR conference on research and development in Information Retrieval, ACM, New York, NY, USA, 2015. doi:10.1145/2766462.2767830.
[22] Y. Zhang, J. Zheng, Y. Jiang, G. Huang, R. Chen, A Text Sentiment Classification Modeling Method Based on Coordinated CNN-LSTM-Attention Model, Chin. J. Electron. 28.1 (2019) 120–126. doi:10.1049/cje.2018.11.004.
[23] H. Murfi, S. Theresia Gowandi, G. Ardaneswari, S. Nurrohmah, BERT-based combination of convolutional and recurrent neural network for Indonesian sentiment analysis, Appl. Soft Comput. 151 (2024) 111112. doi:10.1016/j.asoc.2023.111112.
[24] R. Catelli, S. Pelosi, M. Esposito, Lexicon-Based vs. Bert-Based Sentiment Analysis: A Comparative Study in Italian, Electronics 11.3 (2022) 374. doi:10.3390/electronics11030374.
[25] L. Barbaglia, S. Consoli, S. Manzan, L. Tiozzo Pezzoli, E. Tosetti, Sentiment analysis of economic text: A lexicon-based approach, Econ. Inq. (2024). doi:10.1111/ecin.13264.
[26] O. Tverdokhlib, V. Vysotska, P. Pukach, M. Vovk, Information Technology for Identifying Hate Speech in Online Communication Based on Machine Learning, у: Data-Centric Business and Applications, Springer Nature Switzerland, Cham, 2024, с. 339–369. doi:10.1007/978-3-031-54012-7_15.
[27] Coronavirus tweets NLP. URL: https://www.kaggle.com/datasets/datatattle/covid-19-nlp-text-classification
[28] V. Hnatushenko, D. Mozgovoy, V. Vasyliev. "Accuracy evaluation of automated object recognition using multispectral aerial images and neural network", Proc. SPIE 10806, Tenth International Conference on Digital Image Processing (ICDIP 2018), 108060H (9 August 2018); https://doi.org/10.1117/12.2502905.