Analysis of the emotional coloring of text using machine and deep learning methods

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ABSTRACT

The presented scientific article is a comprehensive study of machine learning and deep learning methods in the context of emotion recognition in text data. The main goal of the study is to conduct a comprehensive analysis and comparison of various machine learning and deep learning methods to classify emotions in text. During the work, special attention was paid to the analysis of traditional machine learning algorithms, such as multinomial naive Bayes (MNB), multilayer perceptron (MLP), and support vector machine (SVM), as well as the use of deep learning methods based on long short-term memory (LSTM). The experimental part of the study involves the analysis of different data sets covering a variety of text styles and contexts. The experimental results are analyzed in detail, identifying the advantages and limitations of each method. The article provides practical recommendations for choosing the optimal method depending on the specific tasks and context of the application. The data obtained is important for the development of intelligent systems that can effectively adapt to the emotional aspects of interaction with users. Overall, this work makes a significant contribution to the field of emotion recognition in text and provides a basis for further research in this area.

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1. INTRODUCTION

This study examined the effects of different methods for recognizing emotions in text. Although there has been previous research examining the impact of traditional machine learning methods such as multinomial naive Bayes (MNB) [1]–[3], multilayer perceptron (MLP) [4]–[6], and support vector machine

(SVM) [7]–[9], they have not sufficiently identified key aspects of their impact on text emotion. This study focuses on analyzing the effects of using advanced deep learning methods based on long short-term memory (LSTM) [10], [11]. Although previous research has focused on the impact of traditional methods, this study addresses their impact in the context of contemporary challenges and opportunities, which can have important implications for the results of text emotional analysis [12], [13].

The purpose of our study is to conduct a comparative analysis of the effectiveness of the above methods for recognizing emotions in text. We aim to identify the advantages and limitations of each method and provide practical guidance on selecting the most appropriate method depending on the specific application and application context. In this article, we'll look at the main trends in emotion recognition before going into detail about each method. This will provide a general context for understanding the importance of the emotional aspect in a text and the role that different methods play in this context. Following this, we will present a detailed overview of each method, ranging from classical machine learning methods [14], [15] to modern deep learning approaches [16]. Additionally, the study examined the effects of using different methods on the analysis of emotional nuances in the text. Although previous studies have focused on the impact of traditional methods, this study addressed their impact in the context of different styles and text contexts, making it comprehensive and more applicable to various fields. In conclusion, the results not only provide a detailed analysis of the advantages and limitations of each method but also provide practical recommendations for selecting the optimal approach depending on the specific tasks and application context.

The study [17] aims to predict emotions based on the colors present in images and videos using machine learning approaches. The purpose of the paper is threefold: i) developing a machine learning algorithm that classifies emotions based on colors in an image; ii) selecting the best algorithm from the first phase and applying it to color-based emotion analysis in movie sequences; and iii) developing an online survey to test the accuracy of annotations collected on emotion data in films. The study [18] discusses a speech emotion recognition (SER) system that uses spectral and prosodic features, such as Mel-frequency cepstral coefficients (MFCC) and pitch, to more accurately identify the speaker's emotional state. Support vector machines (SVM), radial basis functions (RBF), and back propagation networks are used to classify speaker gender and recognize emotions. The study presents a new system that outperforms existing ones in the field in terms of accuracy (average 78%) and reduction in false positives. The article discusses the importance of emotions in human communication and introduces the concept of recognizing emotions in speech through audio signal analysis.

Kumar and Martin [19] reviews the impact of artificial intelligence on global practice, with an emphasis on emotion recognition. The paper describes significant contributions to the field of emotion recognition using both traditional and deep machine learning methodologies, detailing the limitations and challenges of the approach. The authors intend to conduct a comparative study of machine and deep learning algorithms and determine the best accuracy rates for emotion recognition. This review includes various feature extraction methods, classification models, and datasets covering emotion recognition in facial images, speech, and nonverbal communication. The authors also present the results of using hybrid classification techniques in recognizing emotions in speech. The work highlights the applicability of these technologies to automated decision-making in a variety of industries, from customer service to healthcare to manufacturing. The study [20] addresses the challenges associated with sentiment analysis in social media, such as insufficient attention to semantic relationships of emotional characteristics over long distances, ineffective capture of emotional words, and over-reliance on manual annotation. The study presents a user emotion recognition model to analyze the emotional aspects of microblog events. Using data collection and preprocessing methods, three types of inspiring texts were obtained: “joy”, “anger” and “sadness”. Created an algorithm that uses a linear discriminant analysis (LDA) model, an emotional dictionary, and manual annotation to extract emotional words.

Płaza *et al.* [21] examines the relevance of using virtual assistants in contact center systems and their growing popularity. The main task of a virtual assistant is to recognize the client's intentions, and it is important to note that these intentions often directly depend on the emotional state during communication. However, scientific literature has not identified specific types of emotions in contact centers that correspond to the tasks they perform. The main goal of the work is to develop an emotion classification for machine detection of affectively charged content in conversations, specifically focused on the contact center industry.

We found that using deep learning, especially LSTM-based models, significantly improves the accuracy of emotion classification in text. This validates the benefits of deep learning in natural language processing and sentiment analysis, demonstrating its potential for creating more powerful and adaptive sentiment analysis systems. Our study confirms that deep learning models, especially LSTMs, achieve high performance in emotion classification tasks, which is consistent with current trends in emotional text analysis research. This suggests that LSTM-based approaches may become preferred in the development of sentiment analysis tools and automated support systems.

2. METHOD

The methodology of this study plays a key role in providing a qualitative analysis of emotions in the text. In the process of data preprocessing, text normalization [22] is used, including converting it to lowercase for unification, and removing unnecessary characters and stop words. Word-level tokenization [23] is also used to divide text into individual tokens. An important step is the use of pre-trained word embeddings [24] to improve text representation and take into account semantic relationships between words [25]. Model selection includes MNB, MLP, SVM, and LSTM. Each model requires tuning optimal parameters such as MNB parameters, MLP and SVM hyperparameters, and LSTM parameters including a number of layers and input data sizes. Training is carried out on a training data set, followed by validation on a separate validation set to evaluate performance and tune parameters. To assess the quality of models, metrics are used, including accuracy, F1-measure, ROC-AUC, and others, depending on the specific goals of the task. The comparison is made based on the models' accuracy, learning speed, and ability to process complex emotional expressions in text. Detailed analysis and comparison of the performance of various machine learning and deep learning models allow us to conclude the best models for the task of classifying emotions in text. Particular attention is paid to deep learning, in particular LSTM models as shown in Figure 1, and their potential in analyzing sentiment in text.

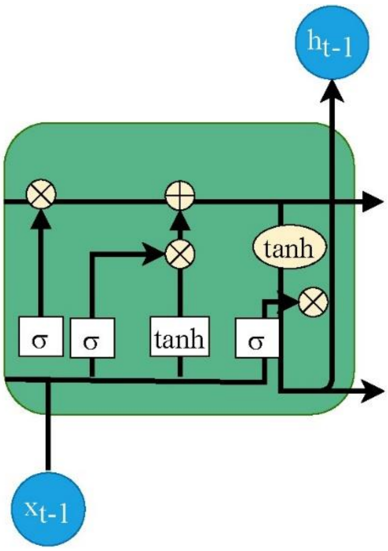


Figure 1. LSTM model architecture

A detailed discussion of the LSTM model includes a description of its structure and operating principles. LSTM, as a type of recurrent neural network, is superior to other models due to its ability to process sequences of data while preserving contextual information. This provides a more accurate interpretation of the emotional tone of the text, making LSTM the preferred choice for sentiment analysis in natural language. Its inclusion in the study significantly improves the accuracy and adaptability of models to the complexity of natural language, providing a powerful tool for the development of more advanced sentiment analysis systems and chatbots. The study highlights the importance of further improving methodology and developing new models to more accurately recognize and analyze complex emotional states in text. Possible directions include optimizing model parameters, using more complex architectures, and integrating additional features to improve the generalization ability of models.

3. RESULTS AND DISCUSSION

The beginning of analysis of emotions in the text begins with the selection of a specific sentence for analysis. Example: “This book left an incredible impression on me and touched my soul deeply”. The first step is text normalization. Normalization involves converting text to lowercase and removing extraneous characters and punctuation. This allows you to unify the text and avoid differences associated with letter case and punctuation. As a result, the original sentence after normalization: “This book left an incredible impression on me and touched my soul deeply”. Next, the text is broken down into individual words or tokens. This process is called tokenization and allows you to represent text as a sequence of individual words.

The tokenization process results in the creation of a list of tokens: [“this”, “book”, “left”, “in”, “me”, “incredible”, “impression”, “and”, “deeply”, “touched”, “my”, “soul”].

To analyze emotions in text, you need to represent the words in a numerical format that a machine-learning model can understand. For this purpose, pre-trained word embeddings are used. Word embeddings are numeric vectors that map words into a multidimensional space, taking into account the semantic relationships between them. Selection of pre-trained word embeddings trained on large text data corpora (e.g. Word2Vec, GloVe). Convert each word (token) from the token list into a corresponding numeric vector using selected embeddings. Machine learning or deep learning models are selected to analyze emotions in text. This may include choosing models such as multinomial naive Bayes, multilayer perceptron, support vector machine, or deep neural networks such as LSTM. The parameters of the selected model are tuned, such as hyperparameters (e.g. SVM parameters) or network parameters (e.g. number of layers and input data sizes for LSTM). The selected model is trained on training data that includes pre-vectorized sentences and their associated emotion labels. The model is evaluated on validation data and its performance is measured using metrics such as accuracy, F1-score, and others to analyze the results of a given proposal as shown in Figure 2.

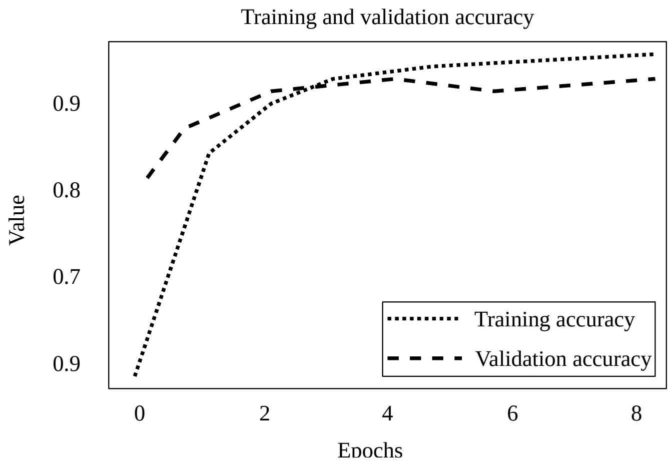


Figure 2. LSTM model accuracy plot

This graph shows the change in the accuracy of the LSTM model during training and validation. The x-axis shows the number of training epochs, and the y-axis shows the accuracy of the model, which is measured in the range from 0 to 1. The graph shows two curves: one reflects the accuracy of the training data set, and the other on the validation data set. This representation allows us to evaluate not only the model’s ability to learn from the existing data set but also its generalization ability on data that did not participate in training. The loss graph as shown in Figure 3 shows the dynamics of changes in the loss function of the LSTM model during training. The x-axis shows the number of epochs, and the y-axis shows the value of the loss function. The graph includes two lines: for the training and validation data sets, respectively.

The study relies on text data divided into training, validation, and test sets. The training set contains 16,000 examples, while the validation and test sets contain 2,000 examples each annotated with emotion labels, providing a basis for training and evaluating the models. The data preprocessing process included text normalization, tokenization, vectorization, and the use of pre-trained embeddings, thereby improving the text representation before training the models. The MNB method showed an accuracy of 0.84, MLP-0.89, and SVM-0.87. The LSTM-based model achieved an accuracy of 0.9299 on the validation set and 0.9245 on the test set, outperforming traditional algorithms. MNB showed an accuracy of 0.84, making it a strong candidate for text classification, although with limitations in handling complex dependencies in data. MLP, with settings of 100,100, alpha=0.01, achieved an accuracy of 0.89, demonstrating its ability to learn from complex text data and adapt to various emotional expressions. The SVM achieved an accuracy of 0.87, proving its effectiveness in separating text data based on its sentiment. In addition to analyzing machine learning models, an LSTM-based deep neural network was developed, including embedding layers and three bidirectional LSTM layers. This model achieved an outstanding accuracy of 0.9299 on the validation set and 0.9245 on the test dataset, which significantly exceeds the results of traditional machine learning models as shown in Figure 4.

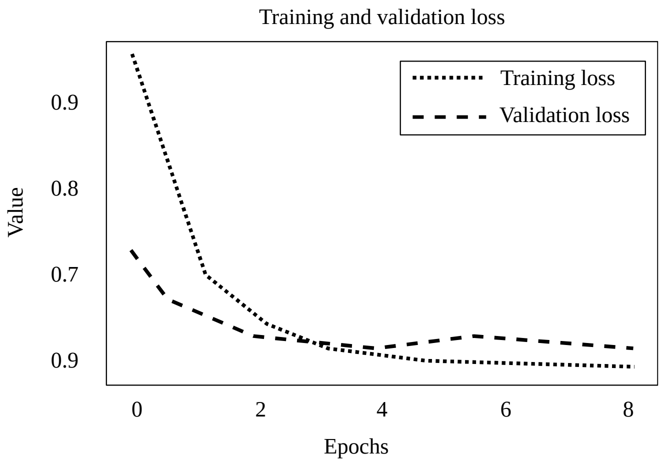
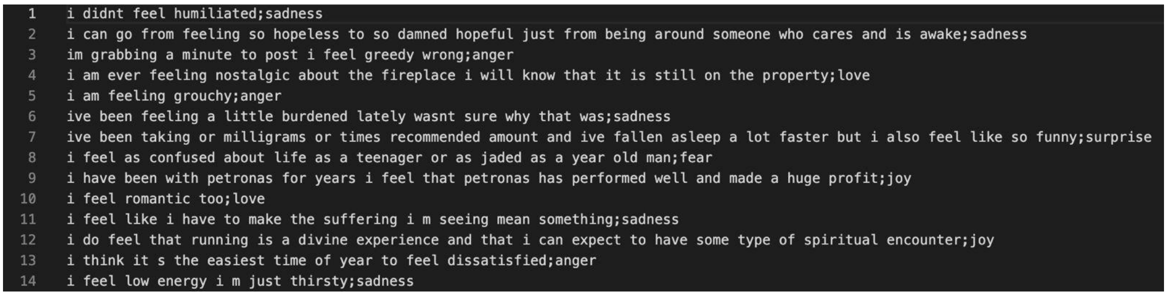


Figure 3. Loss graph for LSTM model



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i didnt feel humiliated;sadness
i can go from feeling so hopeless to so damned hopeful just from being around someone who cares and is awake;sadness
im grabbing a minute to post i feel greedy wrong;anger
i am ever feeling nostalgic about the fireplace i will know that it is still on the property;love
i am feeling grouchy;anger
ive been feeling a little burdened lately wasnt sure why that was;sadness
ive been taking or milligrams or times recommended amount and ive fallen asleep a lot faster but i also feel like so funny;surprise
i feel as confused about life as a teenager or as jaded as a year old man;fear
i have been with petronas for years i feel that petronas has performed well and made a huge profit;joy
i feel romantic too;love
i feel like i have to make the suffering i m seeing mean something;sadness
i do feel that running is a divine experience and that i can expect to have some type of spiritual encounter;joy
i think it s the easiest time of year to feel dissatisfied;anger
i feel low energy i m just thirsty;sadness
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Figure 4. Original text

The comparison showed that deep neural networks, especially those based on LSTM, significantly outperform traditional machine learning models in emotion classification accuracy. This validates the benefits of deep learning in natural language processing and emotion analysis of text, demonstrating its potential for creating more powerful and adaptive sentiment analysis systems. The comparison confirms that deep learning, especially LSTM-based models, outperforms traditional machine learning methods on the task of emotion classification. This study highlights the relevance of deep learning for natural language analysis as shown in Figure 5 and provides directions for future developments in this area.

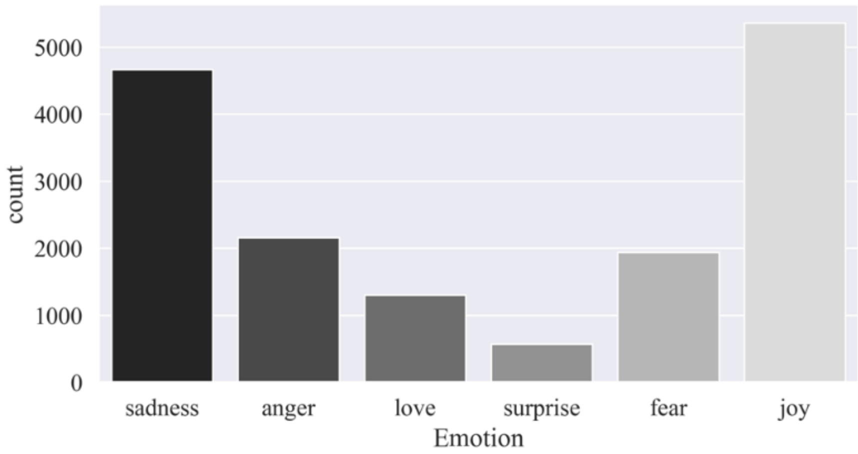

Figure 5. The result of the amount of emotion in the text

The results of the text analysis provide the opportunity for a deeper understanding of the expressed emotions in a given sentence, based on the work of the selected model and its assessments. Based on the data obtained, the conclusion highlights the key characteristic of the model in terms of its ability to effectively analyze the emotional content of the text. A systematic summary of the analysis results in the conclusion highlights the strengths of the proposed methodology, providing a structured and evidence-based approach to classifying emotions in text. The uniqueness of this methodology lies in its ability to take into account the semantic context of words, which provides the basis for high accuracy in solving the problem of emotion classification. Additionally, the proposed methodology provides an important tool for studying the emotional aspects of textual information. It not only ensures accuracy in determining emotions but also allows for an in-depth analysis of semantic connections between words, which is especially important for a correct understanding of the context as shown in Figure 6. This approach promotes a more nuanced perception of emotions in text and increases the model's sensitivity to complex expressions of emotions.

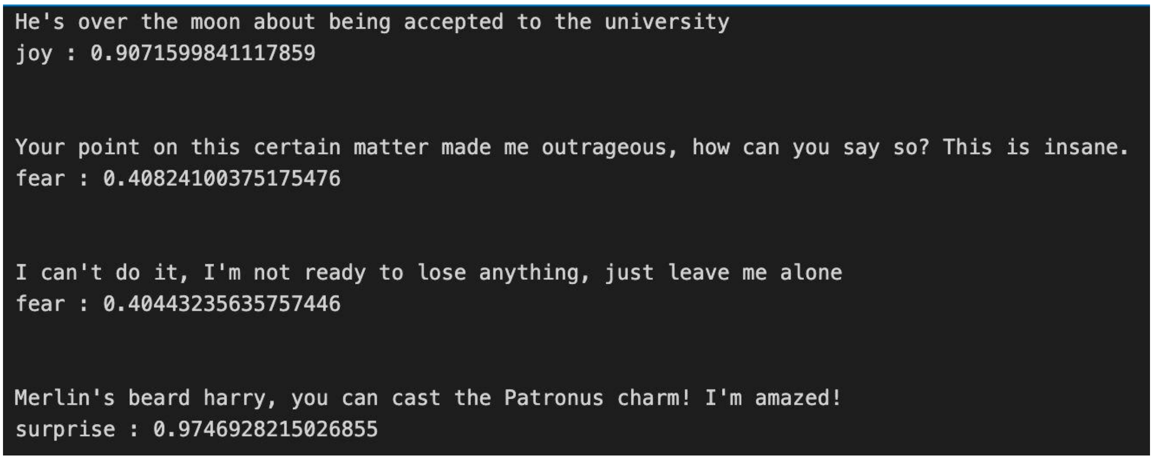

Figure 6. Accuracy of emotion in text

Our results open new horizons for natural language research and allow for a deeper understanding and perception of the emotional aspects of textual information. Future research could focus on developing sentiment analysis tools, automated support systems, and chatbots that can effectively interact and respond to the emotional context of communication. Also, the results of this study can serve as the basis for further improvements in methodology and the development of new models capable of more accurately recognizing and analyzing complex emotional states in text. This may include optimizing model parameters, using more complex architectures, and integrating additional features to improve the generalization ability of models. Thus, the presented methodology, based on the analysis of emotions in text, opens up new horizons for research in the field of natural language and allows us to more deeply understand and perceive the emotional aspects of textual information.

4. CONCLUSION

In conclusion, our research focuses on analyzing the emotional content of text using various machine learning and deep learning techniques. We strictly separate text data into training, validation, and test sets, thereby providing a robust basis for training and evaluating models. The data preprocessing process, which includes text normalization, tokenization, and vectorization using pre-trained embeddings, is a key step that improves text representation before training models. During the experiments, we compared the performance of different machine-learning models. MNB achieved an accuracy of 0.84, demonstrating its potential for text classification despite its limitations in handling complex data dependencies. The MLP model with parameters 100 and 100, alpha=0.01 achieved an accuracy of 0.89, highlighting its ability to learn from complex text data and adapt to different emotional expressions. The SVM achieved an accuracy of 0.87, indicating its effectiveness in separating text data based on sentiment.

An important result was the superiority of the LSTM-based deep neural network, including embedding layers and three bidirectional LSTM layers. This model achieved an outstanding accuracy of 0.9299 on the validation dataset and 0.9245 on the test dataset, outperforming traditional machine learning models. This highlights the potential of deep learning to analyze emotions in text. In general, the results of our study confirm the effectiveness of using various methods for analyzing emotions in text. The proposed research methodology represents an important contribution to the field of natural language analysis and machine learning, opening new possibilities for creating more accurate and adaptive sentiment analysis systems in different contexts. The conclusion of this study highlights the relevance of applying deep learning, in particular LSTM-based models, to emotion classification tasks in text, providing valuable directions for future developments in this area.

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