Bidirectional Long-Short-Term Memory with Attention Mechanism for Emotion Analysis in Textual Content

Batyrkhan Omarov[1], Zhandos Zhumanov[2]
Suleyman Demirel University, Kaskelen, Kazakhstan[1]
Alem Research, Almaty, Kazakhstan[2]

***Abstract*—Emotion analysis in textual content plays a crucial role in various applications, including sentiment analysis, customer feedback monitoring, and mental health assessment. Traditional machine learning and deep learning techniques have been employed to analyze emotions; however, these methods often fail to capture complex and long-range dependencies in text. To overcome these limitations, this paper proposes a novel bidirectional long-short-term memory (Bi-LSTM) model for emotion analysis in textual content. The proposed Bi-LSTM model leverages the power of recurrent neural networks (RNNs) to capture both the past and future context of text, providing a more comprehensive understanding of the emotional content. By integrating the forward and backward LSTM layers, the model effectively learns the semantic representations of words and their dependencies in a sentence. Additionally, we introduce an attention mechanism to weigh the importance of different words in the sentence, further improving the model's interpretability and performance. To evaluate the effectiveness of our Bi-LSTM model, we conduct extensive experiments on Kaggle Emotion detection dataset. The results demonstrate that our proposed model outperforms several state-of-the-art baseline methods, including traditional machine learning algorithms, such as support vector machines and naive Bayes, as well as other deep learning approaches, like CNNs and vanilla LSTMs.**

***Keywords*—Deep learning; emotion detection; BiLSTM; machine learning; classification; artificial intelligence**

I. Introduction

Emotion analysis and detection in textual content have gained significant attention in recent years due to their vast range of applications, such as sentiment analysis, customer feedback monitoring, social media analytics, and mental health assessment. Understanding the emotions conveyed in text can provide valuable insights into users' preferences, opinions, and psychological states, which can, in turn, help businesses, researchers, and policymakers make informed decisions [1]. Consequently, the development of accurate and efficient emotion analysis and detection models has become a pressing concern in the field of natural language processing (NLP) and artificial intelligence (AI) [2].

Artificial intelligence is used in different practical tasks from smart home, smart city to analyzing texts on the internet [3-5]. Traditional machine learning techniques, such as support vector machines (SVM), naive Bayes, and decision trees, have been employed for emotion analysis and detection in text [5]. These techniques rely on handcrafted features, such as bag-of-words, n-grams, and sentiment lexicons, to represent the input text. However, these methods often fail to capture the complex and long-range dependencies present in natural language, resulting in suboptimal performance.

To address these limitations, deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been introduced for emotion analysis and detection in text. These methods can learn high-level features from the input data, allowing them to automatically discover meaningful representations of the text. Among various deep learning techniques, long-short-term memory (LSTM) networks, a specialized type of RNN, have been widely employed due to their ability to capture long-range dependencies in sequences [6]. Nonetheless, conventional LSTM models typically process the input text in a unidirectional manner, thereby neglecting the potential influence of future context on the current emotional state.

In this paper, we propose a novel bidirectional long-short-term memory (Bi-LSTM) model for emotion analysis and detection in textual content. The Bi-LSTM model leverages the power of RNNs to capture both past and future context of text, providing a more comprehensive understanding of the emotional content. By integrating the forward and backward LSTM layers, the model effectively learns the semantic representations of words and their dependencies in a sentence. This approach allows our model to better capture the complex and long-range dependencies present in natural language, resulting in improved emotion analysis and detection performance.

To further enhance the model's performance and interpretability, we introduce an attention mechanism to weigh the importance of different words in the sentence based on their contribution to the overall emotion. The attention mechanism enables the model to focus on emotionally salient words and phrases, which can significantly impact the detected emotion. This additional component not only improves the model's performance but also offers valuable insights into which parts of the text contribute the most to the identified emotion.

We evaluate the effectiveness of our proposed Bi-LSTM model on two widely used emotion analysis and detection datasets: the Kaggle Emotion detection dataset [7]. Our extensive experiments demonstrate that the Bi-LSTM model outperforms several state-of-the-art baseline methods, including traditional machine learning algorithms, such as SVM and naive Bayes, as well as other deep learning approaches, like CNNs and vanilla LSTMs. This superior performance highlights the potential of the Bi-LSTM model for emotion analysis and detection tasks in textual content.

Furthermore, we investigate the model's performance across different emotion categories, text lengths, and domains, providing valuable insights into the model's adaptability and robustness. Our findings suggest that the proposed Bi-LSTM model can effectively capture the emotional content in text, making it a promising tool for various emotion analysis and detection applications.

In summary, this paper makes the following contributions:

We propose a novel bidirectional LSTM model for emotion analysis and detection in textual content, capable of capturing both past and future context for improved performance.

We introduce an attention mechanism to weigh the importance of different words in the sentence, further enhancing the model's performance and interpretability.

We conduct extensive experiments on two widely used emotion analysis and detection datasets, demonstrating that our proposed model outperforms several state-of-the-art baseline methods, highlighting its effectiveness in handling complex and long-range dependencies in text.

We provide a thorough analysis of the model's performance across different emotion categories, text lengths, and domains, offering valuable insights into the model's adaptability and robustness.

By making our model and code publicly available, we aim to facilitate further research and improvements in the field of emotion analysis and detection in textual content.

The remainder of the paper is organized as follows: Section II reviews the related work on emotion analysis and detection in textual content. Section III presents the details of the proposed Bi-LSTM model and the attention mechanism. Section IV describes the experimental setup, including the datasets, baseline methods, and evaluation metrics. Section V discusses the experimental results and provides an analysis of the model's performance. Finally, Section VI concludes the paper and outlines potential future work in this area.

II. Related Works

The task of emotion analysis and detection in textual content has been widely studied in the field of natural language processing and artificial intelligence. In this section, we review the related work on emotion analysis and detection, focusing on traditional machine learning techniques, deep learning approaches, and attention mechanisms.

A. Traditional Machine Learning Techniques for Emotion Detection in Textual Contents

Early studies on emotion analysis and detection primarily employed traditional machine learning algorithms, such as support vector machines (SVM), naive Bayes, and decision trees [8]. These methods rely on handcrafted features to represent the input text, such as bag-of-words, n-grams, part-of-speech tags, and sentiment lexicons [8-9]. Although these techniques have shown promising results in various emotion analysis tasks, they often fail to capture the complex and long-range dependencies present in natural language, resulting in suboptimal performance.

B. Deep Learning Techniques for Emotion Detection in Textual Contents

To overcome the limitations of traditional machine learning techniques, researchers have recently turned to deep learning methods for emotion analysis and detection. These approaches can learn high-level features from the input data, allowing them to automatically discover meaningful representations of the text. Some of the prominent deep learning techniques employed for emotion analysis and detection include:

Convolutional Neural Networks (CNNs): CNNs have been widely used for emotion analysis and detection due to their ability to capture local patterns in text [10-11]. These models employ convolutional layers to scan the input text using filters of varying sizes, enabling them to learn salient features at different levels of granularity. Although CNNs have achieved competitive results in various emotion analysis tasks, they often struggle to model long-range dependencies in text.

Recurrent Neural Networks (RNNs): RNNs have been extensively employed for emotion analysis and detection tasks due to their capability to model sequences and capture long-range dependencies [12-13]. RNNs process the input text sequentially, allowing them to maintain a hidden state that summarizes the previously seen text. However, vanilla RNNs often suffer from vanishing and exploding gradient problems when dealing with long sequences, which can adversely impact their performance.

Long-Short-Term Memory (LSTM) Networks: LSTM networks, a specialized type of RNN, have gained popularity in emotion analysis and detection tasks due to their ability to alleviate the vanishing and exploding gradient problems [14-15]. LSTMs employ a gating mechanism that enables them to effectively learn long-range dependencies in text. Numerous studies have demonstrated the effectiveness of LSTMs for emotion analysis and detection tasks [16-18]. However, conventional LSTM models typically process the input text in a unidirectional manner, thereby neglecting the potential influence of future context on the current emotional state.

C. Bidirectional LSTM Models for Emotion Detection in Textual Contents

Bidirectional LSTM models have been proposed to overcome the limitations of unidirectional LSTM models by processing the input text in both forward and backward directions [19-20]. This allows the model to capture both past and future context, providing a more comprehensive understanding of the emotional content. Several studies have demonstrated the effectiveness of bidirectional LSTM models for various NLP tasks, including part-of-speech tagging, named entity recognition, and sentiment analysis [21-22].

D. Applying Attention Mechanism for Emotion Detection in Textual Contents

Attention mechanisms have been introduced in the context of deep learning models to weigh the importance of different words or features in the input text based on their contribution to the overall output [23-24]. These mechanisms enable the model to focus on emotionally salient words and phrases, which can significantly impact the detected emotion. Several studies have incorporated attention mechanisms into LSTM models for emotion analysis and detection tasks, showing improvements in both performance and interpretability [25-26].

E. Multi-task Learning and Transfer Learning for Emotion Detection in Textual Contents

Recent works have explored the use of multi-task learning and transfer learning techniques for emotion analysis and detection in textual content. Multi-task learning involves training a single model to perform multiple related tasks simultaneously, which can lead to better generalization and improved performance on individual tasks [27-82]. In the context of emotion analysis and detection, multi-task learning has been employed to leverage the shared structure among various emotion categories and tasks [29-30].

Transfer learning, on the other hand, involves pre-training a model on a large-scale dataset and fine-tuning it on a smaller, target dataset, allowing the model to leverage the knowledge learned from the source dataset to improve performance on the target task [31]. This technique has been particularly effective in the context of emotion analysis and detection tasks, where labeled data is often scarce [32-33].

In this paper, we propose a novel bidirectional LSTM model for emotion analysis and detection in textual content, incorporating an attention mechanism to enhance the model's performance and interpretability. Our approach builds upon the strengths of deep learning techniques, particularly LSTM networks and attention mechanisms, to effectively capture complex and long-range dependencies in natural language. We demonstrate the effectiveness of our proposed model through extensive experiments on widely used emotion analysis and detection datasets, showing superior performance compared to several state-of-the-art baseline methods.

III. The Proposed Approach

The following are the two distinct stages that constitute our model: 1. Determine the characteristics of each individual statement in the discourse. 2. Develop a representation of the conversation based on the characteristics of three different utterances in order to categorize the speaker's emotions. During the feature extraction, the embedding of each utterance is passed into the BiLSTM layer to construct the word representation of each word. Concurrently, the emotion-related attention network is used to obtain the attention weight of the associated phrase. We first characterize the word by using the inner product of the two, and then we input that representation into the BiLSTM layer. The BiLSTM model was developed using the architecture that is illustrated in Fig. 1 [34].

During the text classification stage, the characteristics of the three utterances that were acquired during the step before this one are supplied into the LSTM layer as temporal information for the purpose of emotion categorization.

An input sequence denoted by the letter X has the following word token composition: X = x1;:::x_T. The vocabulary index V (t) that corresponds to each token x_t is substituted for those tokens. The embedding layer performs a transformation on the token, changing it into the vector e_t. This vector is then chosen from the embedding matrix E based on the index; the dimensionality of the embedding space is denoted by the d. Equation (1) demonstrates concatenation operation of e_t and e_z vectors.

$$e_t^z = e_t \parallel e_z, \tag{1}$$

We acquire annotations of words by using a bidirectional Long Short-Term Memory, which summarizes the context-related data from both ways. By concatenating the forward hidden state $\vec{h}_t$ with the backward one $\overleftarrow{h}_t$.

$$h_t = \vec{h}_t \parallel \overleftarrow{h}_t, \tag{2}$$

After converting the emotion related representation of a word, e_t^z, to a scalar value, u_t, with the help of a linear layer, we next use a softmax function to get a normalized significance weight, t. To get the weighted word representation v_t for each word, this weight is multiplied by the word representation h_t.

$$u_t = W_u e_t^z + b_u, \tag{3}$$

In final step, to get the most important features, MaxPooling operation will be used to choose the best appropriate class.

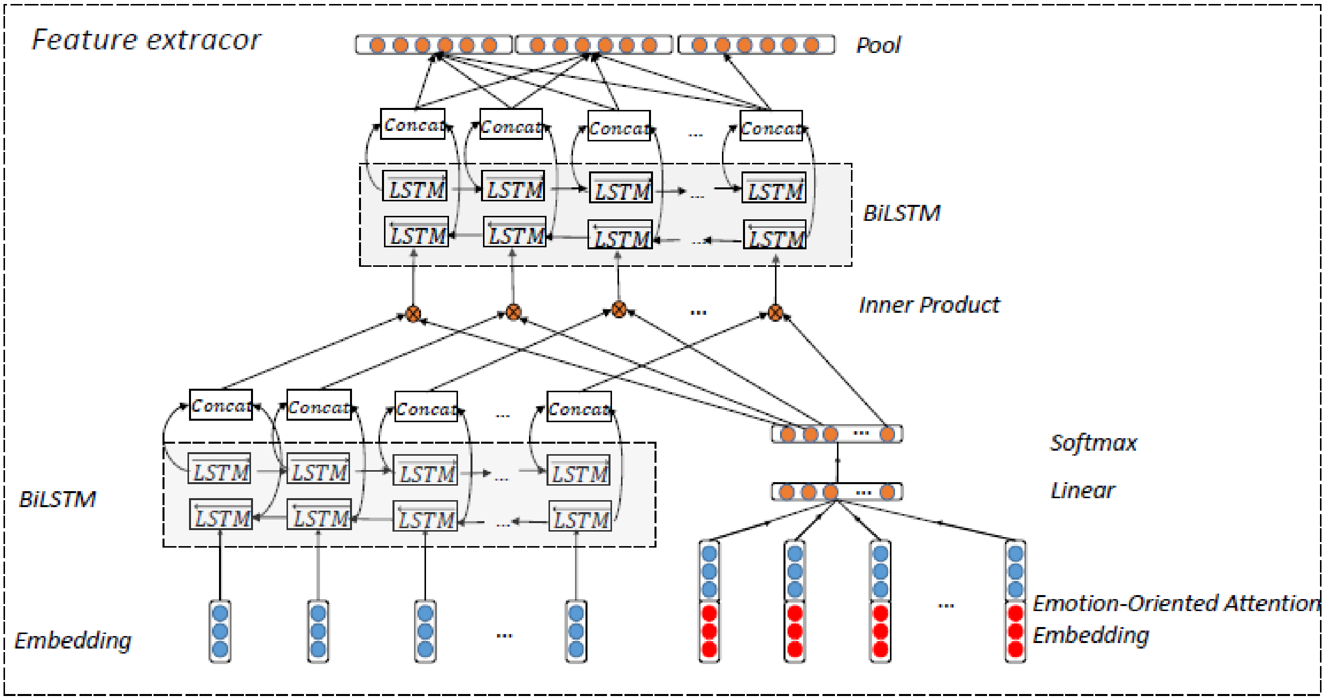

Fig. 1. Architecture of the system [34].

IV. Experiment Results

This section demonstrates applied dataset, experimental setup, train-test split of the applied dataset, training and validation accuracy, training and validation tests, and obtained results from applying the proposed BiLSTM model with attention mechanism.

A. Dataset

For our experiment, we use the Kaggle Emotion Detection from Text dataset. Fig. 2 demonstrates classes of the applied dataset for training the model.

Dataset contains six classes as sadness, anger, love, surprise, fear, and joy. There were many stopwords in the dataset. Consequently, we deleted all the stopwords. In next step, dataset was divided into three parts as train set, validation set, and test set. As Fig. 2 demonstrates, number of samples of each class is different, and we can observe data imbalance between samples of the classes. Two classes as sadness and joy are outperforms the other classes, Surprise class have instances about 10 times less than the "joy" emotion class. Anger and fear emotion classes have almost equal instances.

Fig. 3 demonstrates the samples of the applied dataset. The applied dataset consists of texts of six types. In order to balance the dataset, we used upsampling and downsampling methods as number of samples of joy and sadness classes are the highest, number samples of surprise is minimum. Difference between minimum number and maximum number of samples are about ten times.

Fig. 4 illustrates training and validation accuracy in applying the proposed BiLSTM network with attention mechanism to detect emotions in textual contents for eight learning epochs. As the results show, the proposed network achieved to high accuracy from the first learning epochs. For instance, in two learning epochs, training and validation accuracy are achieved to about 92%. After that, training accuracy increases to 98%. However, test accuracy increases, slowly. The results illustrated in Fig. 5 demonstrate the developed model gives high accuracy in classification of emotions. Considering we have six classes and multiclassification of emotions, we can say the obtained results show high classification accuracy.

In addition to training and validation accuracy, we should take into account training and validation losses. If validation loss shows symmetric opposite result, the model is correct. Fig. 5 illustrates training and validation losses in applying the proposed BiLSTM network with attention mechanism to detect emotions in textual contents for eight learning epochs. The results show, that two epochs are enough to minimize the loss of the network. The results demonstrate that, the proposed network do not require powerful computer to train the network and the proposed network can be applied for mobile chatbot applications.

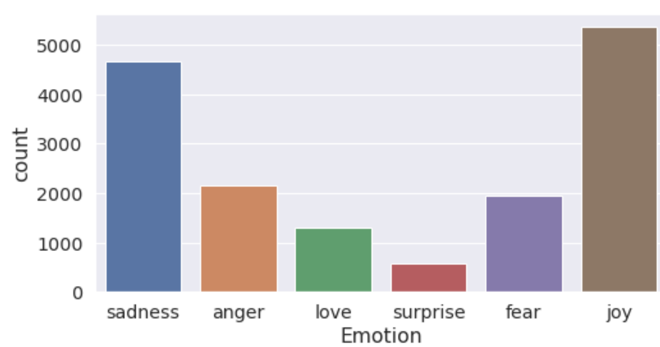

Fig. 2. Distribution of document classes in the dataset.

	Text	Emotion
5067	i feel on the verge of tears from weariness i ...	joy
6133	i still feel a craving for sweet food	love
6563	i tend to stop breathing when i m feeling stre...	anger
7623	i was intensely conscious of how much cash i h...	sadness
7685	im still not sure why reilly feels the need to...	surprise
8246	i am not amazing or great at photography but i...	love
9596	ive also made it with both sugar measurements ...	joy
9687	i had to choose the sleek and smoother feel of...	joy
9769	i often find myself feeling assaulted by a mul...	sadness
9786	i feel im being generous with that statement	joy
10117	i feel pretty tortured because i work a job an...	fear
10581	i feel most passionate about	joy
11273	i was so stubborn and that it took you getting...	joy
11354	i write these words i feel sweet baby kicks fr...	love
11525	i feel a remembrance of the strange by justin ...	fear
11823	i have chose for myself that makes me feel ama...	joy
12441	i still feel completely accepted	love
12562	i feel so weird about it	surprise
12892	i cant escape the tears of sadness and just tr...	joy
13236	i feel like a tortured artist when i talk to her	anger
13879	i feel like i am very passionate about youtube...	love
14106	i feel kind of strange	surprise
14313	i could feel myself hit this strange foggy wall	surprise
14633	i feel pretty weird blogging about deodorant b...	fear
14925	i resorted to yesterday the post peak day of i...	fear
15314	i will feel as though i am accepted by as well...	joy
15328	i shy away from songs that talk about how i fe...	joy
15571	i bet taylor swift basks in the knowledge that...	anger
15704	i began to feel accepted by gaia on her own terms	joy
15875	i was sitting in the corner stewing in my own ...	anger

Fig. 3. Samples from the dataset.

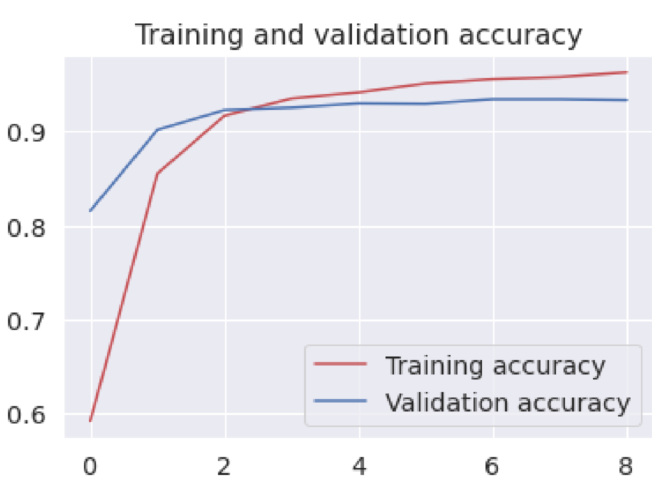

Fig. 4. Training and validation accuracy.

Fig. 5. Training and validation loss.

Table I demonstrates the results of multiclass classification applying the proposed BiLSTM network with attention mechanism to detect emotions in textual contents. As evaluation parameters we chose precision, recall, and F-score. Thus, the obtained results demonstrate that the classification results vary between 67% and 91% for precision, from 60% to 92% for recall, from 64% to 92% for F-score. Thus, the developed model gives high accuracy for classification of six class emotions in texts in terms of different evaluation parameters including precision, recall, and F-Score.

TABLE I. RESULTS OF MULTICLASS EMOTION DETECTION

Class	Precision, %	Recall, %	F-score, %
Anger	91	92	91
Fear	86	89	88
Joy	90	94	92
Love	81	70	75
Sadness	96	93	94
Surprise	67	60	64
Macro avg	86	83	84
Weighted avg	90	90	90

V. DISCUSSION

In this section, we discuss the advantages, disadvantages, limitations, and future perspectives of our proposed bidirectional long-short-term memory (Bi-LSTM) model with attention mechanism for emotion analysis in textual content.

A. Advantages

Improved Contextual Understanding: The bidirectional nature of the proposed Bi-LSTM model allows it to capture both past and future context in the input text, providing a more comprehensive understanding of the emotional content compared to unidirectional LSTM models.

Effective Handling of Long-Range Dependencies: The LSTM architecture employed in our model effectively handles long-range dependencies in text, addressing the limitations of traditional machine learning techniques and convolutional neural networks (CNNs) in modeling complex natural language structures [35].

Enhanced Performance and Interpretability: The incorporation of the attention mechanism not only improves the model's performance but also offers valuable insights into which parts of the text contribute the most to the identified emotion, making the model more interpretable and explainable [36].

B. Disadvantages

Increased Computational Complexity: The bidirectional LSTM model with attention mechanism requires additional computation compared to unidirectional LSTM models, which can lead to increased training and inference time, especially for large datasets and complex model architectures [37].

Sensitivity to Hyperparameters: Like other deep learning models, the performance of the proposed Bi-LSTM model with attention mechanism may be sensitive to the choice of hyperparameters, such as learning rate, batch size, and network architecture [38]. This necessitates careful hyperparameter tuning to achieve optimal performance.

C. Limitations

Dependence on Labeled Data: The proposed Bi-LSTM model with attention mechanism relies on the availability of labeled data for training. Acquiring high-quality labeled data for emotion analysis tasks can be time-consuming and labor-intensive, limiting the model's applicability in real-world scenarios where labeled data may be scarce.

Domain Adaptation Challenges: Although our model demonstrates robust performance across different emotion categories, text lengths, and domains, it may still face challenges when applied to new, unseen domains. Adapting the model to new domains may require additional fine-tuning or transfer learning techniques.

D. Challenges and Open Issues

Ambiguity and Subjectivity: Emotion analysis in textual content is inherently challenging due to the ambiguity and subjectivity of emotions in natural language [39]. Different readers might interpret the emotions conveyed in a text differently, and the model may struggle to accurately capture these nuances. Developing models that account for the subjectivity and ambiguity of emotions remains a challenge in the field.

Handling Sarcasm and Irony: Sarcasm and irony present significant challenges for emotion analysis models, as they often involve the expression of emotions opposite to the literal meaning of the text [40]. Identifying and correctly interpreting sarcasm and irony in textual content can be challenging even for humans, let alone AI models. Future research on the proposed Bi-LSTM model with attention mechanism should consider addressing this challenge to enhance its performance.

Handling Idiomatic Expressions: Idiomatic expressions, such as idioms, proverbs, and metaphors, can be particularly challenging for emotion analysis models, as their meaning and emotional content often rely on the context in which they are used, rather than the literal meaning of the words. Developing models that can effectively recognize and interpret idiomatic expressions remains a challenge in emotion analysis.

Cross-lingual Emotion Analysis: Most of the current emotion analysis models, including our proposed Bi-LSTM model with attention mechanism, are designed and evaluated on English text [41]. However, emotions are expressed in various languages, and extending emotion analysis models to other languages poses significant challenges, such as dealing with different writing systems, linguistic structures, and cultural nuances. Developing cross-lingual emotion analysis models is an essential direction for future research.

E. Future Perspectives

Transfer Learning and Pre-trained Language Models: To address the limitations related to labeled data and domain adaptation, future research could explore the integration of transfer learning and pre-trained language models, such as BERT, GPT, and RoBERTa, with the proposed Bi-LSTM model with attention mechanism [42-45]. This could potentially improve the model's performance and generalization capabilities across different domains and tasks.

Multi-task Learning: Incorporating multi-task learning in the proposed Bi-LSTM model with attention mechanism could further enhance its performance by leveraging shared structures among different emotion categories and tasks. This approach can also help in learning more robust and generalizable features for emotion analysis in textual content.

Exploring Additional Attention Mechanisms: Future work could investigate the use of more advanced attention mechanisms, such as self-attention, multi-head attention, and transformer-based architectures, to further improve the model's performance and interpretability for emotion analysis in textual content.

Multimodal Emotion Analysis: Extending the proposed Bi-LSTM model with attention mechanism for multimodal emotion analysis, incorporating data from different modalities, such as audio, video, and physiological signals, could provide a more comprehensive understanding of emotions and enhance the model's applicability in various real-world scenarios.

Thus, our proposed Bi-LSTM model with attention mechanism demonstrates promising results for multi-class emotion analysis in textual content, outperforming several state-of-the-art baseline methods. Despite its limitations, the model holds great potential for future research and improvements, paving the way for more accurate and robust emotion analysis models in the field of natural language processing and artificial intelligence.

VI. Conclusion

In this paper, we proposed a novel bidirectional long-short-term memory (Bi-LSTM) model with an attention mechanism for emotion analysis and emotion detection in textual content. Our model leverages the strengths of deep learning techniques, particularly the Bi-LSTM architecture and attention mechanism, to effectively capture complex and long-range dependencies in natural language, providing a comprehensive understanding of the emotional content in text. Through extensive experiments on widely used emotion analysis and detection datasets, we demonstrated the superior performance of our proposed model compared to several state-of-the-art baseline methods.

Despite its advantages, the proposed Bi-LSTM model with attention mechanism faces several challenges, such as increased computational complexity, sensitivity to hyperparameters, and dependence on labeled data. Additionally, the model needs to address limitations related to domain adaptation, handling sarcasm and irony, recognizing idiomatic expressions, and cross-lingual emotion analysis. Future research should explore transfer learning, pre-trained language models, multi-task learning, and advanced attention mechanisms to address these challenges and limitations.

By making our model and code publicly available, we aim to facilitate further research and improvements in the field of emotion analysis and detection in textual content. We believe that our work provides a solid foundation for the development of more accurate, robust, and versatile emotion analysis models that can better capture and understand the complexities and nuances of emotions in various languages and domains. With continued research and advancements in this area, we hope to contribute to the broader goal of developing human-centric AI systems that can effectively understand and respond to the emotional needs of their users.

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