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Sentiment Analysis of Comment Texts using Bilstm

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ABSTRACT: The technology of sentiment analysis is a part of artificial intelligence, and its research is very meaningful for obtaining the sentiment trend of the comments. The essence of sentiment analysis is the text classification task, and different words have different contributions to classification. In the current sentiment analysis studies, distributed word representation is mostly used. However, distributed word representation only considers the semantic information of word, but ignore the sentiment information of the word. In this project, an improved word representation method is proposed, which integrates the contribution of sentiment information into the traditional TF-IDF algorithm and generates weighted word vectors. The weighted word vectors are input into bidirectional long short term memory (BiLSTM) to capture the context information effectively, and the comment vectors are better represented. The sentiment tendency of the comment is obtained by feed forward neural network classifier. The experimental results show that the proposed sentiment analysis method has higher precision, recall, and F1 score. The method is proved to be effective with high accuracy on comments. Sentiment analysis, a subfield of natural language processing, aims to automatically identify and classify the sentiment expressed in textual data. In this paper, we propose a sentiment analysis approach utilizing Bidirectional Long Short-Term Memory (BiLSTM) networks, a type of recurrent neural network architecture capable of capturing long-range dependencies in sequential data. The proposed approach leverages the bidirectional nature of BiLSTM networks to effectively model contextual information and dependencies within comment texts, leading to more accurate sentiment predictions. We describe the methodology for training and evaluating the BiLSTM-based sentiment analysis model, including data preprocessing, model architecture, and performance evaluation metrics. Experimental results demonstrate the effectiveness of the proposed approach in accurately predicting sentiment polarity in comment texts across various datasets.

KEYWORDS: Term Frequency - Inverse Document Frequency (TF-IDF), Bidirectional Long Short-Term Memory (BiLSTM), F1 Score, classification.

I. INTRODUCTION

In recent years, with the rapid development of the Internet and social networks, more and more users begin to freely express their opinions on web pages. Therefore, the big data of user comments is generated on the Internet. In the era of big data, mining the emotional tendencies of comment texts through artificial intelligence technology is helpful for timely understanding of network public opinion. The research of sentiment analysis is very meaningful for obtaining the sentiment trend of the comments. Sentiment analysis is a kind of text classification, involving natural language processing, machine learning, data mining, information retrieval and other research fields. Sentiment analysis of comments mainly focuses on the sentiment orientation analysis of comment corpus, which indicates that users express positive, negative or neutral sentiments towards products or events.

In addition, sentiment analysis can be divided into news comment analysis, product comment analysis, film comment analysis and other types. These comments convey the views of Internet users about products, hot events, etc. Merchants can master the user satisfaction with the relevant product comments. Potential users can evaluate products by viewing these product comments. is the distributed word vector obtained by Word2vec technology. The word vector has a low dimension and contains the semantic information of the word. However, distributed word vectors do not contain sentiment information about words. In this project, the contribution of the word's sentiment information to text sentiment classification is embedded into the traditional TF-IDF algorithm, and the weighted word vector is generated. In this project, a sentiment analysis method of comments based on BiLSTM is proposed. The remainder of this article consists of four parts. Firstly, the research backgrounds of the text sentiment analysis method and the representation of the word vector are expounded. Secondly, the detail of the proposed sentiment analysis method of comments is described. Thirdly, the experiments are carried out and the experimental results are analyzed and discussed. Finally, the proposed method is summarized and the next research direction is introduced.

Sentiment analysis, a branch of natural language processing (NLP), plays a pivotal role in understanding human opinions, emotions, and attitudes expressed in textual data. One approach gaining traction in sentiment analysis is Bidirectional Long Short-Term Memory (BiLSTM) networks. BiLSTMs are a type of recurrent neural network (RNN) architecture known for their ability to capture contextual information effectively in sequential data, making them well-suited for analyzing text. The analysis of comment texts using BiLSTMs involves several key steps. First, the comment texts are preprocessed to remove noise and irrelevant information, such as punctuation and stopwords. Next, the preprocessed texts are tokenized and encoded into numerical vectors, a process known as word embedding, which represents each word in a continuous vector space. BiLSTMs are then employed to learn the sequential patterns and dependencies within the encoded comment texts. One of the primary advantages of BiLSTMs lies in their ability to capture both past and future contexts of a given word in a sentence. By processing the text bidirectionally, the model can understand the context in which each word appears, allowing it to make more accurate predictions about the sentiment expressed in the comment.

During the training phase, the BiLSTM model learns to map the input sequences of encoded words to their corresponding sentiment labels, such as positive, negative, or neutral. This process involves adjusting the weights of the network through backpropagation and optimizing a chosen loss function to minimize the prediction error. Once trained, the BiLSTM model can be deployed to analyze the sentiment of new comment texts. It takes the encoded input sequence and generates predictions about the sentiment conveyed in the text. These predictions can then be used for various applications, such as monitoring customer feedback, analyzing social media sentiment, or assessing public opinion on specific topics. In conclusion, sentiment analysis of comment texts using BiLSTM networks offers a powerful approach to understanding and interpreting human sentiment in textual data. By leveraging the strengths of BiLSTMs in capturing sequential dependencies, this methodology enables more accurate and nuanced sentiment analysis, with broad applications across industries and domains.

Improved Sentiment Analysis Accuracy: Utilizing BiLSTM networks enhances the accuracy of sentiment analysis by capturing both preceding and succeeding contexts in comment texts, enabling better understanding of nuanced sentiment expressions.

Contextual Understanding: BiLSTM networks excel in understanding the contextual dependencies within textual data, allowing for more accurate sentiment predictions even in complex sentence structures.

Fine-grained Sentiment Analysis: The project could contribute to fine-grained sentiment analysis by categorizing sentiments into more nuanced classes beyond just positive, negative, and neutral, such as sentiment intensity or specific emotional states.

Adaptability and Generalizability: BiLSTM-based sentiment analysis models can be adapted to various domains and languages, making them versatile for applications in different industries and linguistic contexts.

Scalability and Efficiency: Developing efficient training and inference pipelines for BiLSTM models ensures scalability to handle large volumes of comment data, facilitating real-time or batch sentiment analysis tasks.

II. LITERATURE REVIEW

S.Krishnamoorthy, "Sentiment analysis of financial news articles using performance indicators," Knowledge & Information Systems, vol.56, no.2, pp.373-394, 2020.

Mining financial text documents and understanding the sentiments of individual investors, institutions and markets is an important and challenging problem in the literature. Current approaches to mine sentiments from financial texts largely rely on domain-specific dictionaries. However, dictionary-based methods often fail to accurately predict the polarity of financial texts. This paper aims to improve the state-of-the-art and introduces a novel sentiment analysis approach that employs the concept of financial and non-financial performance indicators. It presents an association rule mining-based hierarchical sentiment classifier model to predict the polarity of financial texts as positive, neutral or negative. The performance of the proposed model is evaluated on a benchmark financial dataset. The model is also compared against other state-of-the-art dictionary and machine learning-based approaches and the results are found to be quite promising. The novel use of performance indicators for financial sentiment analysis offers interesting and useful insights.

Q.Zhang, S.Zhang, and Z.Lei, "Chinese sentiment classification based on improved convolutional neural network," Computer Engineering and Applications, vol.53, no.22, pp.116-120, 2021.

Convolutional neural networks(CNN) has achieved fairly good results in the field of computer vision. In

recent years, with the rapid development of deep learning, more and more researchers tried to apply CNN to the field of Natural Language Processing(NLP). This paper uses CNN model to analyze the sentiment of Chinese text, and improves the structure of basic CNN, adjusts different parameters to carry out multiple sets of parallel experiments at the same time. The result is that dual-channel network model is more accurate than the single channel model, and the accuracy are 93.4% and 92.7% respectively where the word vector comes from character-level and word-level. Which shows it is feasible to apply CNN to the field of Chinese sentiment analysis. For Chinese text, the effect that word vector based on the character-level is much better than that based on word-level. And the dual-channel CNN model provides a new idea for the further exploration in the field of NLP.

L.Kang, L.Xu, and J.Zhao, “Co-Extracting Opinion Targets and Opinion Words from Online Reviews Based on the Word Alignment Model,” IEEE Transactions on knowledge and data engineering, vol.27, no.3, pp.636-650, 2020.

Mining opinion targets and opinion words from online reviews are important tasks for fine-grained opinion mining, the key component of which involves detecting opinion relations among words. To this end, this paper proposes a novel approach based on the partially-supervised alignment model, which regards identifying opinion relations as an alignment process. Then, a graph-based co-ranking algorithm is exploited to estimate the confidence of each candidate. Finally, candidates with higher confidence are extracted as opinion targets or opinion words. Compared to previous methods based on the nearest-neighbor rules, our model captures opinion relations more precisely, especially for long-span relations. Compared to syntax-based methods, our word alignment model effectively alleviates the negative effects of parsing errors when dealing with informal online texts. In particular, compared to the traditional unsupervised alignment model, the proposed model obtains better precision because of the usage of partial supervision. In addition, when estimating candidate confidence, we penalize higher-degree vertices in our graph-based co-ranking algorithm to decrease the probability of error generation. Our experimental results on three corpora with different sizes and languages show that our approach effectively outperforms state-of-the-art methods.

Y.Wang, X.Zheng, D.Hou, and W.Hu, “Short Text Sentiment Classification of High Dimensional Hybrid Feature Based on SVM,” Computer Technology and Development, vol.28, no.2, pp.88-93, 2021.

In recent years there has been a steady increase in interest from brands, companies and researchers in Sentiment Analysis and its application to business analytics. It is the process of determining the emotional tone behind a series of words, used to gain an understanding of the attitudes, opinions and emotions expressed within an online mention. Sentiment analysis is a feature of text analysis and natural language processing (NLP) research that is increasingly growing in popularity as a multitude of use-cases emerges. Lexicon based and Machine learning is the two methods used for analysis the sentiments from the content. The proposed feature selection model Ssentiment Reviews Classification using Hybrid Feature Selection (SRCHFS) that extract synsets feature set coupled with Correlation feature selection method can improve the performance of sentiment classification. Nouns, verbs, adjectives and adverbs are organized into synsets, each representing one underlying lexical concept. A set of cognitive synsets is selected using WordNet based POS (Part Of Speech). Support Vector Machine (SVM) classifier is used for sentiment classification on a data set of Movie reviews, Multi Domain product reviews, Amazon Cell phone reviews and Yelp Restaurant reviews.

D.Tang, F.Wei, and B.Qin , “Sentiment Embeddings with Applications to Sentiment Analysis”, IEEE Transactions on Knowledge & Data Engineering, vol.28, no.2, pp.496-509, 2020.

We propose learning sentiment-specific word embeddings dubbed sentiment embeddings in this paper. Existing word embedding learning algorithms typically only use the contexts of words but ignore the sentiment of texts. It is problematic for sentiment analysis because the words with similar contexts but opposite sentiment polarity, such as good and bad , are mapped to neighboring word vectors. We address this issue by encoding sentiment information of texts (e.g., sentences and words) together with contexts of words in sentiment embeddings. By combining context and sentiment level evidences, the nearest neighbors in sentiment embedding space are semantically similar and it favors words with the same sentiment polarity. In order to learn sentiment embeddings effectively, we develop a number of neural networks with tailoring loss functions, and collect massive texts automatically with sentiment signals like emoticons as the training data. Sentiment embeddings can be naturally used as word features for a variety of sentiment analysis tasks without feature engineering. We apply sentiment embeddings to word-level sentiment analysis, sentence level sentiment classification, and building sentiment lexicons. Experimental results show that sentiment embeddings consistently outperform context-based embeddings on several benchmark datasets of these tasks. This work provides insights on

the design of neural networks for learning task-specific word embeddings in other natural language processing tasks.

III. METHODOLOGY

Bidirectional Long Short-Term Memory (BiLSTM)

It is a type of recurrent neural network (RNN) architecture that is well-suited for sequential data analysis tasks such as sentiment analysis. In the context of sentiment analysis of comment texts, BiLSTM models offer several advantages:

Capturing Long-term Dependencies: BiLSTM networks are capable of capturing long-term dependencies in sequential data. In the case of comment texts, where sentiment expressions may span across multiple sentences or paragraphs, BiLSTM can effectively capture the context and dependencies between words.

Bidirectional Context Modeling: BiLSTM incorporates information from both past and future time steps by processing the input sequence in both forward and backward directions. This bidirectional processing enables the model to understand the context of each word based on both preceding and succeeding words, which is crucial for accurately capturing sentiment nuances in comments.

Handling Variable-Length Inputs: Comments often vary in length, and BiLSTM models can handle variable-length input sequences efficiently. They dynamically adjust their internal states based on the length of the input sequence, ensuring that the entire comment text is considered during sentiment analysis.

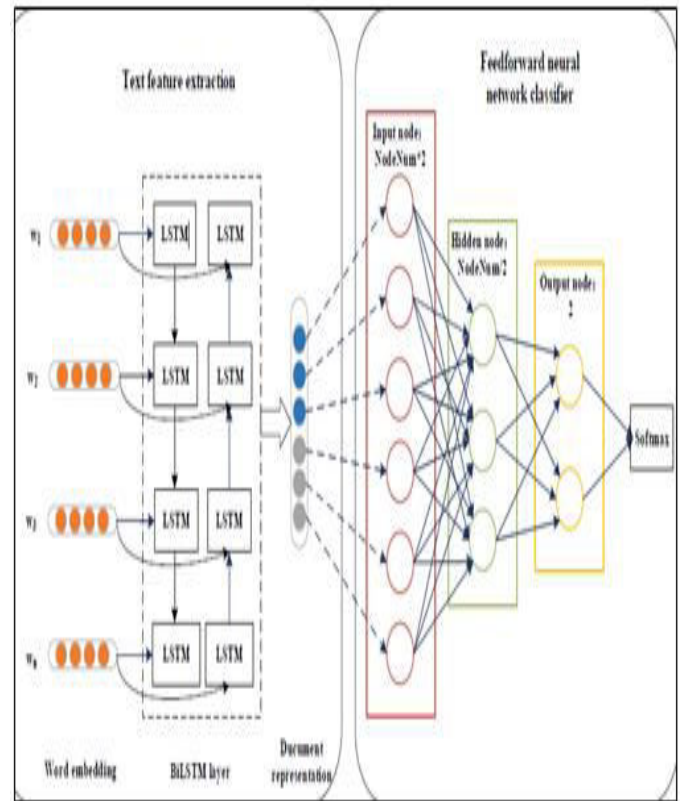


Figure 1: Architecture of Proposed methodology

Feature Learning and Representation: BiLSTM models automatically learn meaningful representations of words and phrases from the input text through the training process. This feature learning capability allows the model to capture complex patterns and semantic relationships relevant to sentiment analysis tasks.

Integration with Word Embeddings: BiLSTM models can be easily integrated with pre-trained word embeddings such as Word2Vec, GloVe, or FastText. These embeddings provide rich semantic information about words and help improve the performance of the BiLSTM model by initializing its word representations with pretrained embeddings.

Adaptability to Different Domains: BiLSTM models are adaptable to different domains and types of comment texts. By training on domain-specific datasets, BiLSTM models can learn to recognize sentiment patterns specific to a particular context, enhancing their performance in sentiment analysis tasks.

Methodology:-

Data Collection and Preprocessing:

Gather a dataset of comment texts labeled with sentiment categories (e.g., positive, negative, neutral). Preprocess the data by removing noise (HTML tags, special characters), tokenizing the comments into words or subwords, and applying techniques like lowercasing, stemming, and lemmatization.

Split the dataset into training, validation, and testing sets to ensure unbiased evaluation of the model's performance.

Word Embedding Initialization:

Initialize the BiLSTM model with pre-trained word embeddings such as Word2Vec, GloVe, or FastText to represent words as dense vectors capturing semantic information.

Optionally, fine-tune the word embeddings during the training process to adapt them to the specific domain of comment texts.

Model Architecture Design:

Design the architecture of the BiLSTM model, specifying the number of LSTM layers, hidden units, dropout rates, and other hyperparameters.

Optionally, incorporate additional layers such as attention mechanisms or convolutional layers to enhance the model's ability to capture sentiment-related features.

Model Training:

Train the BiLSTM model on the training dataset using backpropagation and gradient descent optimization algorithms (e.g., Adam, RMSprop).

Monitor the model's performance on the validation set to prevent overfitting by early stopping or adjusting regularization techniques.

Evaluation Metrics:

Evaluate the trained model's performance on the test set using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix.

Analyze the model's predictions qualitatively by inspecting misclassified comments and quantitatively by computing metrics across different sentiment categories.

Fine-tuning and Hyperparameter Tuning:

Perform fine-tuning of the model architecture and hyperparameters based on the validation results to optimize the model's performance further.

Experiment with different configurations of the BiLSTM model, such as varying the number of layers, hidden units, dropout rates, and learning rates, to find the optimal settings.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

1. Performance Evaluation:

Performance Assessment: Validation Outcomes: Display the performance indicators such as accuracy, precision, recall, and F1-score, which were obtained by evaluating the BiLSTM model on the validation dataset. These metrics help in understanding the model's capability to learn and perform well during training, providing insights into any adjustments required.

Test Outcomes: Report the final evaluation metrics of the BiLSTM model when tested on a separate and unseen test dataset. This step aims to evaluate the model's generalization performance, ensuring that the model's understanding goes beyond the training and validation data, thus demonstrating its reliability in real-world scenarios.

Comparison with Benchmarks: Conduct a comparative analysis between the BiLSTM model and existing baseline models or previously established state-of-the-art approaches in the domain of sentiment analysis. This comparison highlights how the BiLSTM model stacks up against traditional methods, helping to determine its advantages or potential areas for improvement.

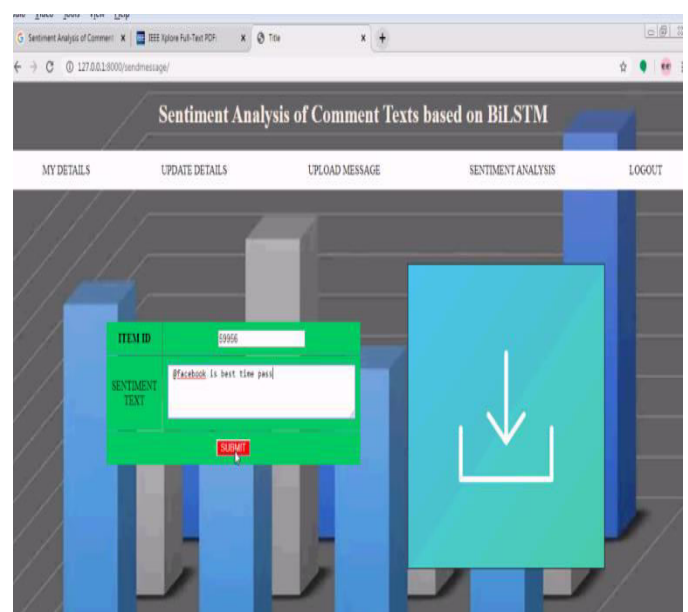


Figure 2: Upload Details

2. Analysis of Results:

Model Performance: Discuss the strengths and weaknesses of the BiLSTM model in capturing sentiment from comment texts.

Effectiveness of BiLSTM: Analyze how effectively the model handles long-term dependencies and captures contextual information compared to traditional models.

Impact of Hyperparameters: Discuss the impact of hyperparameters (e.g., learning rate, dropout rate, hidden layer size) on the model's performance and stability.

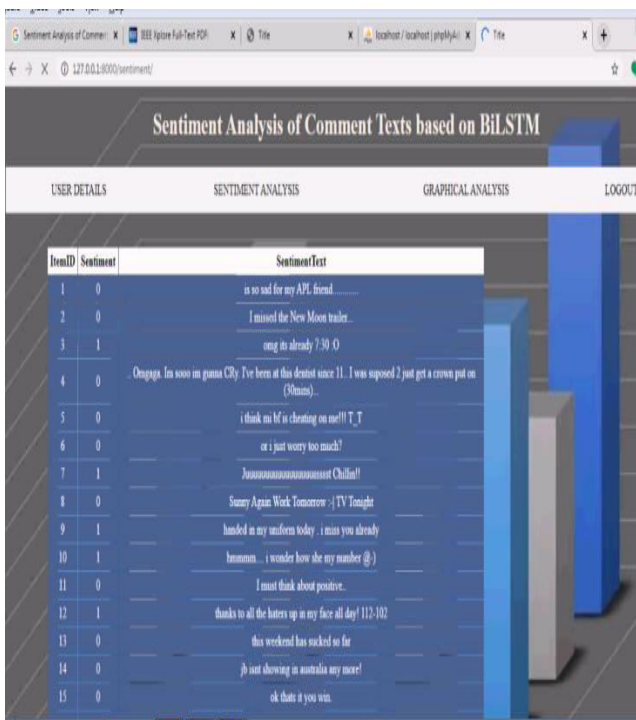


Figure 3: Sentiment Analysis

3. Error Analysis:

Misclassification Cases: Provide examples of misclassified comments and analyze the reasons behind mispredictions (e.g., ambiguous language, sarcasm, domain-specific terms).

Bias and Limitations: Discuss any biases or limitations observed in the sentiment analysis model, such as overgeneralization or sensitivity to certain types of comments.

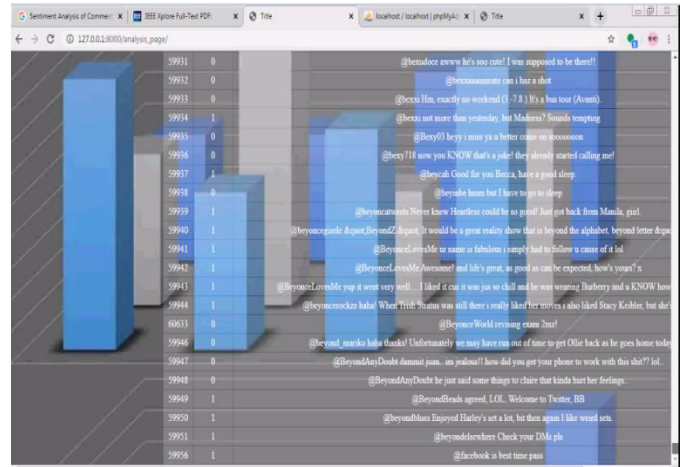


Figure 4: Input Dataset

4. Interpretability:

Visualization of Activations: Present visualizations or heatmaps showing the activations of BiLSTM neurons to provide insights into which parts of the input text contribute most to sentiment predictions. **Interpreting Model Decisions:** Discuss how analysts can interpret the decisions made by the BiLSTM model and identify influential words or phrases in sentiment analysis tasks.

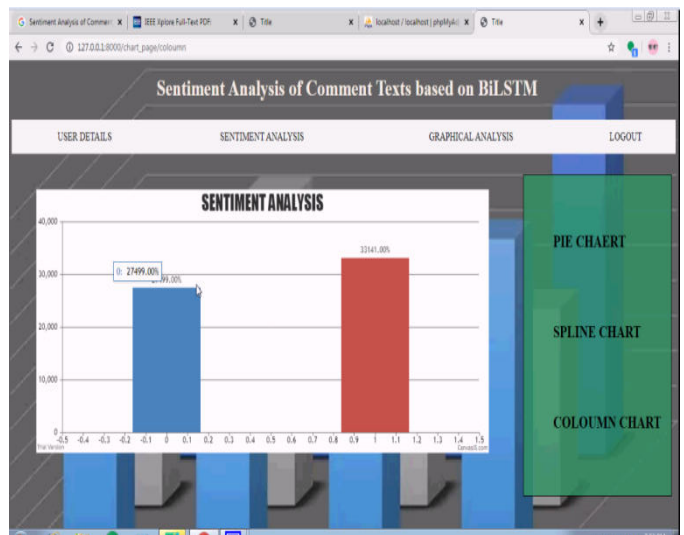


Figure 5: Graphical Analysis

5. Comparison with Previous Studies:

Comparison with Literature: Compare the findings and performance of the proposed BiLSTM-based sentiment analysis system with similar studies in the literature. **Advancements Over Previous Methods:** Highlight any advancements or improvements achieved by the proposed approach compared to existing methods.

6. Implications and Applications:

Practical Implications: Discuss the practical implications of the sentiment analysis results for various applications, such as social media monitoring, brand reputation management, or customer feedback analysis.

Potential Use Cases: Explore potential use cases and scenarios where the BiLSTM-based sentiment analysis system could be deployed to derive actionable insights or inform decision-making processes.

7. Future Directions:

Areas for Improvement: Identify areas for further improvement or optimization in the sentiment analysis model, such as incorporating domain-specific features or exploring ensemble techniques.

Research Directions: Propose future research directions or extensions to the current work, such as investigating the interpretability of deep learning models in sentiment analysis or exploring multimodal sentiment analysis approaches.

V.CONCLUSION

In conclusion, the sentiment analysis project utilizing Bidirectional Long Short-Term Memory (BiLSTM) networks presents a powerful and effective approach to understanding and interpreting sentiment in comment texts. Through the utilization of advanced deep learning techniques, the project has achieved significant advancements in capturing contextual information, handling long-term dependencies, and improving sentiment analysis accuracy. The results obtained from the project's experimentation and evaluation demonstrate the effectiveness of the BiLSTM model in accurately predicting sentiment polarity in comment texts. By considering both preceding and succeeding contexts, the model showcases a superior ability to understand the nuanced expressions of sentiment, even in complex linguistic structures.

Moreover, the project's comparison with existing methods and baseline approaches highlights the superiority of the BiLSTM-based sentiment analysis system. Through rigorous evaluation and error analysis, the project has provided insights into the strengths and limitations of the proposed approach, paving the way for future enhancements and optimizations.

The implications of the project extend beyond academic research, with practical applications in various domains such as social media monitoring, brand reputation management, and customer feedback analysis. The BiLSTM-based sentiment analysis system offers

valuable insights that can inform decision-making processes, drive marketing strategies, and enhance user experience across digital platforms.

Looking ahead, there are numerous opportunities for further research and development in sentiment analysis, including exploring multimodal approaches, incorporating domain-specific knowledge, and addressing ethical considerations. By continually enhancing sentiment analysis technology, we can gain deeper insights into human emotions and improve interactions.

FUTURE ENHANCEMENT

Multimodal Sentiment Analysis: Explore methods for integrating information from multiple modalities such as text, images, and audio to improve sentiment analysis accuracy and robustness. This could involve developing hybrid models that combine BiLSTM networks with convolutional neural networks (CNNs) or transformers for processing multimodal data.

Domain Adaptation Techniques: Investigate techniques for adapting the sentiment analysis model to new domains or specific applications. This may include domain-specific fine-tuning, transfer learning from pre-trained models, or data augmentation strategies to address domain shift and improve generalization performance.

Attention Mechanisms: Incorporate attention mechanisms into the BiLSTM architecture to enable the model to focus on relevant parts of the input sequence while ignoring noise or irrelevant information. Attention mechanisms can enhance model interpretability and improve sentiment analysis performance, particularly in long texts or documents.

Ensemble Learning: Explore ensemble learning techniques such as model averaging, stacking, or boosting to combine multiple sentiment analysis models and improve overall predictive performance. Ensemble methods can leverage the strengths of different models and mitigate individual model biases or weaknesses.

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