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Emotion Recognition from Formal Text (Poetry)

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Abstract:- The field of computational intelligence has mostly overlooked the classification of emotional states from poetry or formal text in recent times, unlike informal textual content such as SMS, email, chat and online reviews. To fill this gap, a new study proposes an emotional state classification system for poetry text that utilizes Deep Learning technology. Specifically, the study intends to use an attention-based C-LSTM model to categorize poetry text into various emotional states, including love, joy, hope, sadness, and anger.

I. INTRODUCTION

The detection and classification of emotional states, opinions, and sentiments have become a topic of interest for experts in natural language processing, computational linguistics, and computational intelligence.

There are two types of texts that can be analyzed by machines, formal and informal. Formal textual content includes poetry, novels, essays, plays, and legal documents, while informal textual content pertains to SMS, chat, and social media posts.

However, the complex nature of formal text, particular poetry, makes it challenging to detect and classify emotional states. Machine learning techniques have been successful in extracting and analyzing emotional states and themes from both formal and informal text. For example, multi-label emotion classification can be used to classify mixed data that is a combination of two or more languages.

Support Vector Machines (SVM) and BiLSTM classifiers can classify poetry into two emotional classes. However, a more accurate classification of emotional states can be achieved using an attention-based C-LSTM model, which combines the Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and attention mechanism of deep learning. This proposed approach can classify formal text (poetry) into up to 5 emotional classes, which is an extension from the baseline work.

II. RELATED WORK

This section presents a brief overview of relevant studies on emotion classification in poetry text.

In recent years, many researches have carried out works on emotion recognition using machine learning techniques. Sreeja and Mahalakshmi [1] developed an emotional state recognition system classifies poetry text based on different emotion categories using the Naïve Bayes machine learning classifier.

Other approaches have also been explored, such as comparing SVM and Naïve Bayes algorithm for emotion classification in poetry, However, all these models and approaches face a common challenge of limited dataset size.

To increase the versatility of the model, different contexts or domains can be included in the problem. For instance, adding phonemic features can enable the model to classify emotions from audio files, such as music. Similarly, the addition of a speech-to-text converter can make the model useful as an interpreter between two individuals.

III. LITERATURE SURVEY

We researched papers related to our topic and came across a few papers with similar objective that helped us gain some insight into the topic at hand.

We have discussed those papers here in brief:

A. Multi-Label Emotion Classification on Code-Mixed Text: Data and Methods:

Authors: Iqra Ameer, Geigori Sidorov. IEEE, 2021.

The multi-label emotion classification task aims to identify all possible emotions in a written text that best represent the author's mental state. Multi-label data means data that is written in more than one language i.e., Hindi+English, Hindi+Urdu, etc.

In this paper, the researchers have conducted their experimentation on textual data i.e., SMS in conversation where it is common to use multi-label data. The internet is the most prominent source in promoting global, linguistic code-mixed culture. Therefore, there was a need to develop standard evaluation resources and methods for code-mixed texts for various applications, such as author profiling, sentiment analysis, emotion analysis, etc.

Here, the authors have compared results obtained from classical machine learning (content-based methods – three word n-gram features and eight character n-gram features), deep learning (CNN, RNN, Bi-RNN, GRU, Bi-GRU, LSTM, and Bi-LSTM), and transfer learning-based methods (BERT and XLNet) on their proposed corpus.

Conclusion and Future Work: Code-mixed data was used to classify emotional states from the text and results from different machine learning, deep learning, and transfer-based learning algorithms were compared. The authors also plans to apply other transfer learning-based models such as RoBERTa, DistilBERT, etc. They think an ensamble of the model would be considered to increase classification performance.

B. Individual Emotion Recognition Approach Combine Gated Recurrent Unit with Emotion Distribution Model:

Authors: Chanf Liu, Taiao Liu, Shuojue Yang, and Yajun Du. IEEE, 2021.

Mining individual emotions from the data is extremely challenging work in many fields, such as opinion monitoring, business decisions, and information prediction. In this paper, the authors proposed an individual emotion-identifying model called semantic emoticon emotion recognition (SEER).

First, they divided the input short text into four categories by using the emotion dictionary and emoticons. Second, they combined a bidirectional gated recurrent unit (Bi-GRU) network with an attention mechanism to capture the emotion vectors of input text from the word aspect. Third, they constructed an emoticon distribution model to obtain the emotion vectors in a large quantity of social network data. Fourth, according to different types of input short texts. Finally, they classified the short text emotions into categories depending on the final emotion vector. The experimental results showed that the SEER is an effective method for improving the accuracy of emotion recognition.

Conclusion and Future Works: In this experiment, they used comparative experiments to determine the value of the parameters in the SEER model and decide whether the attention mechanism can achieve best performance. In future works, the authors will continue to construct datasets of various sizes in which each sentence contains one or more emoticons and test their SEER model. They plan to extend emotion representation of emoticons.

C. Improving Textual Emotion Recognition Based on Intra- and Inter-Class Variation:

Authors: Hassan Alhuzali and Sophia Ananiadou

Previous research has tackled the automatic classification of emotion expressions in text by maximising the probability of the correct emotion class using cross-entropy loss. However, this approach does not account for intra- and inter-class variations within and between emotion classes. To overcome this problem, the authors of this paper introduced a variant of triplet centre loss as an auxiliary task to emotion classification. This allows TER models to learn compact and discriminate features.

Furthermore, they introduce a method for evaluating the impact of intra- and inter-class variations on each emotion class. Experiments performed on three data sets demonstrate the effectiveness of their method when applied to each emotion class in comparison to previous approaches. Finally, they present analysis that illustrate the benefits of the method in terms of improving the prediction scores as well as producing discriminative features.

Conclusion: They showed the effectiveness of incorporating both intra- and inter-class variations into TER, demonstrating their ability to increase model performance as well as to introduce discriminative features. The experiment also demonstrated the advantages and utility of VTCL as an auxiliary loss for emotion classification.

D. Semantic Emotion Neural Network for Emotion Recognition from Text:

Authors: Erdenebileg Batbaatar, Meijing Li, and Keun Ho Ryu. IEEE, 2019.

The previously presented models cannot capture the emotional relationship between words. Recently, some emotional word embeddings are proposed but it requires semantic and syntactic information vice versa. To address this issue, the authors of this paper proposed a novel neural network architecture, called SENN (Semantic-Emotion Neural Network) which can utilize both semantic/syntactic and emotional information by adopting pre-trained word representations.

SENN model has mainly two sub-networks, the first network uses bidirectional Long-Short Term Memory (BiLSTM) to capture contextual information and focusese on semantic relationship, the second network uses the convolutional neural network (CNN) to extract emotional features and focuses on the emotional relationship between words from the text.

They conducted a comprehensive performance evaluation for the proposed model using standard real-world datasets. The experimental results show that the proposed model achieves a significantly superior quality of emotion recognition with various state of the art approaches and further can be improved by other emotional word embeddings.

Conclusion and Future Works: The results from the conducted experiment shows that their model achieve better performance compared with the state-of-the-art baseline methods. Their proposed framework is general enough to be applied to more scenarios. In the future works, they will extend proposed CNN based emotion encoding and BiLSTM based semantic encoding to other tasks such as affective computing and sentiment analysis. It is possible to improve the performance of SENN model by using the larger emotion word embeddings.

IV. CONCLUSION

We have completed the stage 1 of our project for the final year engineering. Till now we have researched various similar work that has been done in the similar field to gain some insight on the problem at hand.

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