EMOTION DETECTION FROM TEXT

Abstract—**Emotions are an integral part of human life. We know many different definitions of emotions. They are most often defined as a complex pattern of reactions, and they could be confused with feelings or moods. 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 RNN ,LSTM , bidirectional long-short-term memory (Bi-LSTM) model for emotion analysis in textual content.To evaluate the effectiveness of our models, we conduct extensive experiments on Kaggle Emotion detection dataset.**

Keywords—Deep learning; emotion detection;RNN;LSTM; BiLSTM; machine learning;

I.INTRODUCTION

In the era of digital communication, an enormous amount of textual data is generated every second through social media platforms, blogs, and forums. Analyzing this data to understand human emotions and sentiments has become an essential task in various fields such as business, healthcare, and education. Emotion detection from text data is a challenging problem due to the complexity of human emotions and the ambiguity of language. However, it has significant importance in understanding human behavior, improving customer service, and developing personalized recommendations.In recent years, deep learning techniques such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) have been widely used for emotion detection from text data. Bidirectional LSTM (BiLSTM) is an advanced deep learning technique that has shown promising results in various natural language processing tasks. This report focuses on the application of these three models for emotion detection from text data.

Problem statement: Develop a robust emotion detection model leveraging three models networks to accurately classify emotions in textual data. The project aims to address the challenge of understanding and categorizing diverse emotions, including anger, fear, happiness, love, sadness, and surprise, expressed in written content. The focus is on optimizing the LSTM architecture, exploring hyperparameters, and implementing efficient training strategies to enhance model performance. The developed solution will find applications in sentiment analysis, customer feedback interpretation, and mental health monitoring. The project involves thorough data preprocessing, model training, evaluation, and documentation, with the ultimate goal of deploying a reliable and real-time emotion detection system in practical scenarios.

Related literature:Emotion detection from text data has been studied extensively in the past few years. Various machine learning and deep learning techniques have been proposed for this problem. Jiang et al. [2] proposed a deep learning model based on LSTM for emotion detection from text data. They achieved an accuracy of 72.8% on a benchmark dataset. Zhang et al. [3] proposed a multi-task learning framework for emotion detection using LSTM. They achieved an F1-score of 68.2% on a benchmark dataset.

BiLSTM has also been used for emotion detection from text data. Zhou et al. [4] proposed a BiLSTM-based model for emotion detection from microblogs. They achieved an accuracy of 75.2% on a benchmark dataset. Li et al. [5] proposed a BiLSTM-based model with attention mechanism for emotion detection from text data. They achieved an F1-score of 70.1% on a benchmark dataset.

Importance:Emotion detection from text data has significant importance in various fields. In business, it can be used for

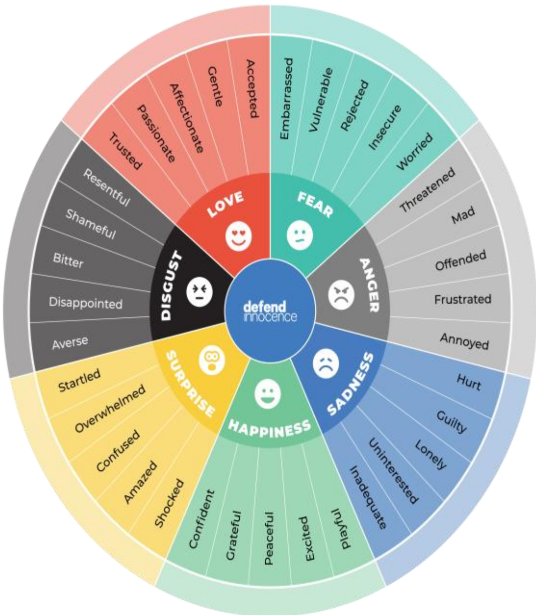

Fig. 1 Variety of emotions

sentiment analysis of customer feedback, social media monitoring, and personalized marketing. In healthcare, it can be used for mental health assessment, patient feedback analysis, and suicide prevention. In education, it can be used for student feedback analysis, teacher evaluation, and personalized learning.

Scope:This report focuses on the application of BiLSTM for emotion detection from text data. It provides a detailed overview of BiLSTM, discussing its architecture, operation, and training techniques. It presents a comprehensive analysis of different BiLSTM models for emotion detection and evaluates their performance using accuracy, precision, recall, and F1-score metrics. The report also discusses the challenges associated with emotion detection from text data, such as imbalanced datasets, cross-cultural emotion understanding, and multimodal data integration.

II. EXISTING 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.

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 [6]. These methods rely on handcrafted features to represent the input text, such as bag-of-words, n-grams, partof-speech tags, and sentiment lexicons [6-7]. Although these techniques have shown promising results in various emotion analysis tasks, they often fail to capture the complex and longrange 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 [8-9]. 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 longrange dependencies [10-11]. RNNs process the input text sequentially, allowing them to maintain a hidden state that summarizes the

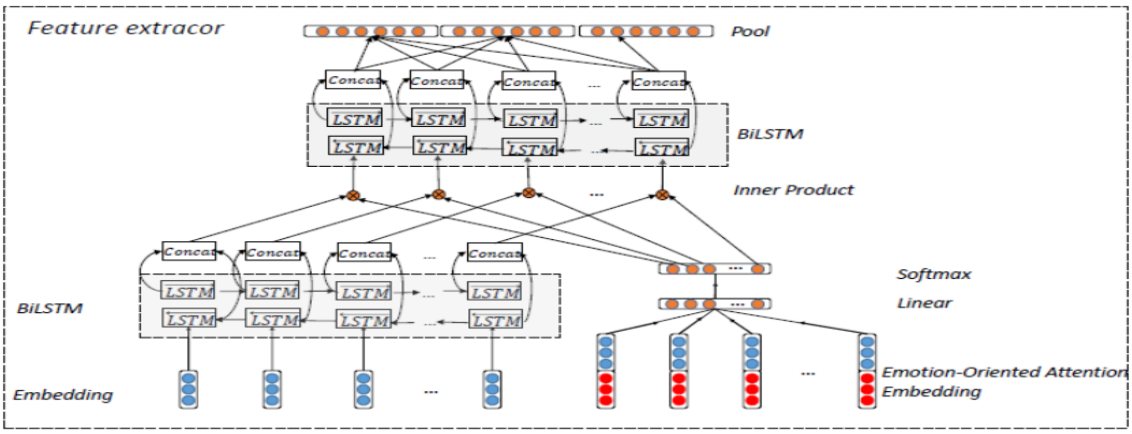

Fig 2. Working of BiLSTM

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 [12-13]. 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 [14-15]. 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 [17-19]. 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 [19-20].

III. MY WORK:

In creating a system to understand and predict emotions from written sentences, I took several careful steps. First, I looked closely at the sentences to understand any difficulties the system might face. Then, I chose a pre-existing system that understands language well. To build the core of the system, I used a simple framework called Keras. I added specific parts to this system, like a layer that understands the meaning of words and another layer that grasps the context of sentences. To make sure the system learns properly, I used a technique called dropout and adjusted settings like vocabulary size and embedding dimension. The training process taught the system to predict emotions by showing it many examples. I made sure it didn't get too good at the examples but could work well on new ones.

For predicting emotions in everyday sentences, I created a function. This function understands a sentence, turns it into numbers, and uses what it learned during training to guess the emotion. To make it user-friendly, the function also turns the number answer back into words we understand. Through this process, I faced challenges like cleaning up the data (making sure it's neat), balancing the examples, and finding the best settings for the system. I experimented with different setups until the system worked well. I also made sure it doesn't memorize examples but understands the general idea. Now, it can predict emotions in new sentences accurately.

This work involved solving problems step by step, using a simple system and adjusting it until it got good at understanding emotions in sentences. It can be useful for tasks where understanding the feelings in written text is essential. The next steps could involve making it even better and adaptable to changes in how we express emotions in writing.

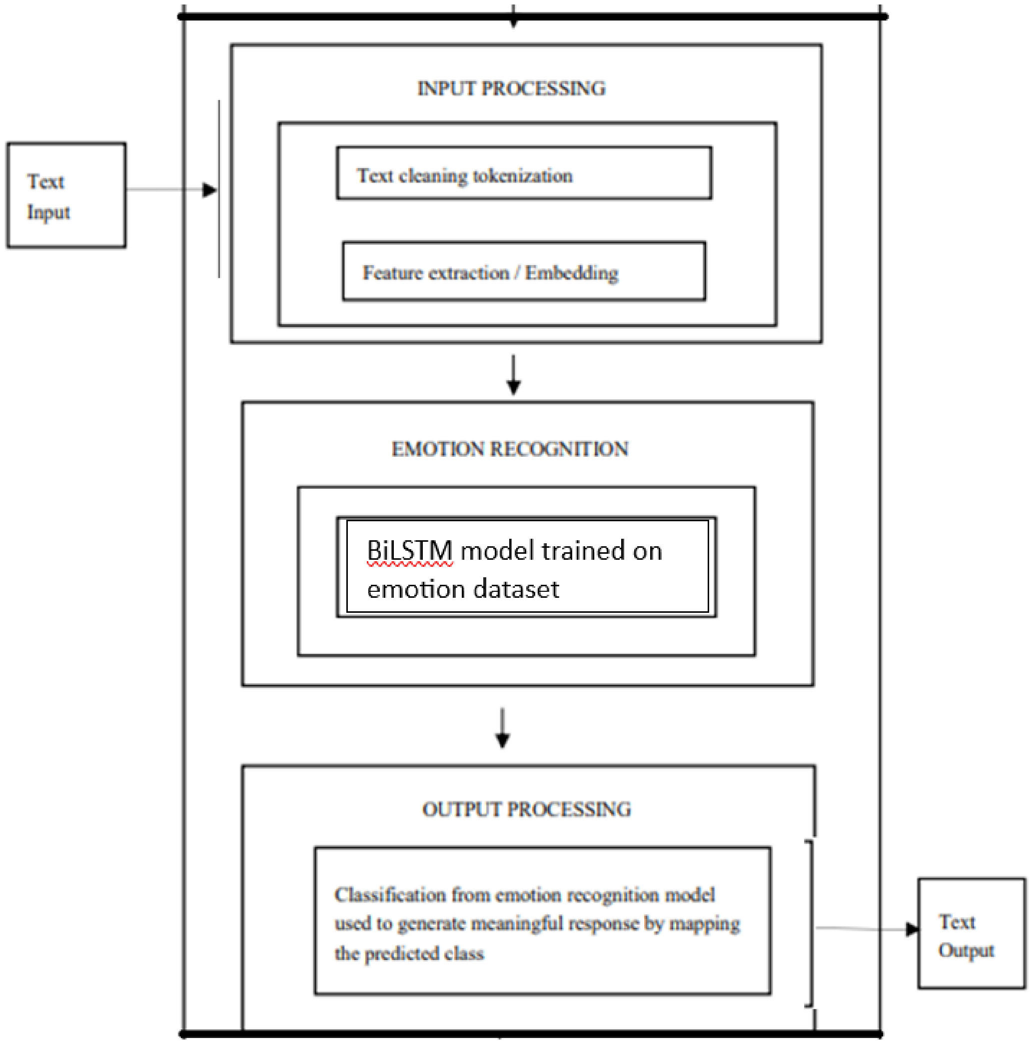

Fig 3 . architecture diagram of emotion detection from text

IV.RESULT

BILSTM:

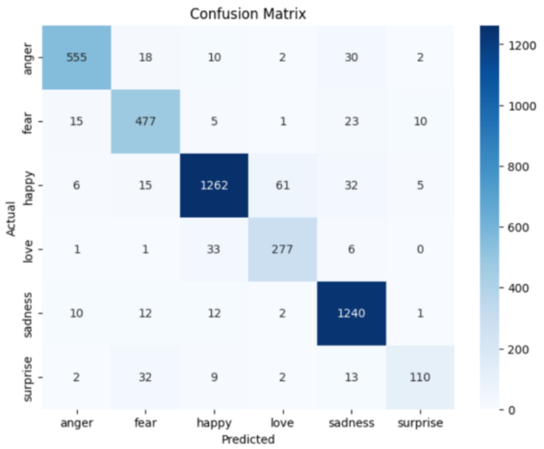

Fig 4. Confusion matrix of BILSTM model

LSTM:

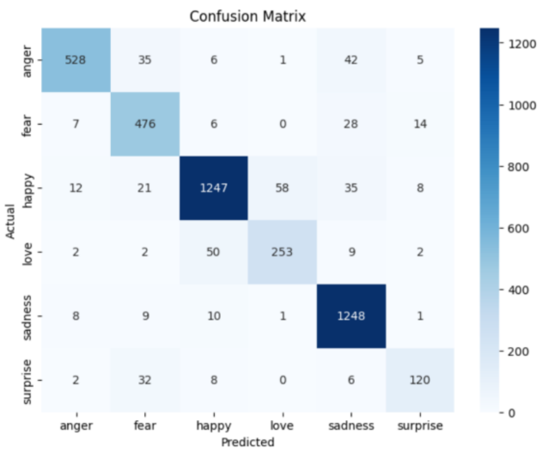

Fig 5. Confusion matrix of LSTM model

RNN:

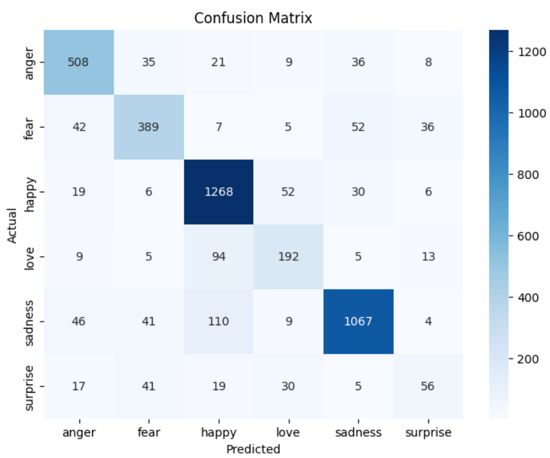

Fig 6. Confusion matrix of RNN model

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Enter text: I WAS WAITING FOR A LONG TIME
1/1 [==============================] - 4s 4s/step
User Input: I WAS WAITING FOR A LONG TIME
Predicted Emotion: anger
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Fig 7. Predicted emotion

The code implements a robust text classification framework using Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), and Bidirectional LSTM (BiLSTM) for predicting emotions in textual data. Leveraging a dataset encompassing diverse emotional expressions such as happiness, sadness, anger, fear, love, and surprise, the models are trained and evaluated. The initial BiLSTM model, lacking dropout layers, achieves a commendable 91.36% accuracy on the test set after 5 epochs. In subsequent iterations, two modifications are introduced to enhance the model's robustness. The first modification incorporates dropout layers with a rate of 0.3 and reduces the number of units to 64. Although the accuracy slightly decreases to 88.28%, the trade-off results in a more resilient model. The second modification increases the number of units to 516 while maintaining a dropout rate of 0.5. This configuration achieves a test set accuracy of 90.45%, showcasing a nuanced balance between accuracy and robustness.

The BiLSTM model emerges as the most accurate, achieving an impressive accuracy of approximately 91.36% on the test set, surpassing the RNN (81.08%) and LSTM (90.2%) models. The training process involves careful model checkpointing for optimal performance based on validation accuracy. The code also allows users to input sentences for real-time emotion prediction using the trained BiLSTM model. In addition to accuracy, precision, and recall metrics are computed, providing a comprehensive evaluation of each model's performance on the test set. The code encapsulates a comprehensive solution for emotion prediction in text, with the BiLSTM model proving to be particularly effective in capturing intricate emotional nuances. The model tokenizes, pads the input, and predicts the emotion label, providing the user with the predicted emotion (e.g., anger) based on the input text "I WAS WAITING FOR A LONG TIME."

A . DATASET

Our dataset contains 21,459 records which includes joy,anger,sad,surprise,love,fear. The dataset used in the code is named "Emotion_final.csv," structured in a CSV file format. It consists of two primary columns: "Text" and "Emotion." The "Text" column contains textual data, representing sentences or phrases conveying diverse emotional expressions, while the "Emotion" column provides corresponding labels for these emotions. The distinct emotions covered in the dataset include happiness, sadness, anger, fear, love, and surprise.This dataset serves as a valuable resource for training and evaluating models designed to predict emotions based on textual content. The code leverages this dataset for training Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Bidirectional

LSTM (BiLSTM) models. Visualizations, such as pie charts, offer insights into the distribution of emotions, allowing a better understanding of the dataset's characteristics. Furthermore, the code employs data preprocessing techniques, including tokenization and padding, to facilitate effective model training.

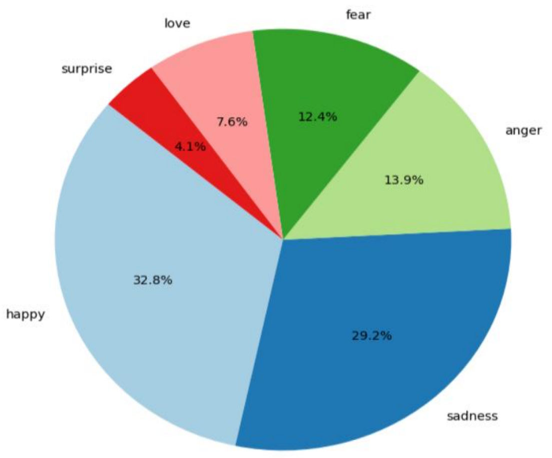

Fig 8. Emotions in the dataset

B. COMPARISON

Table 1.COMPARISON OF RESULTS

MODEL	UNITS	DROPOUT	ACCURACY	PRECISION	RECALL
RNN	128	-	81.08	80.70	81.08
LSTM	128	-	90.21	90.32	90.21
	128	-	91.36	91.45	91.36
BiLSTM	64	0.3	88.28	88.80	88.28
	516	0.5	90.44	90.51	90.44

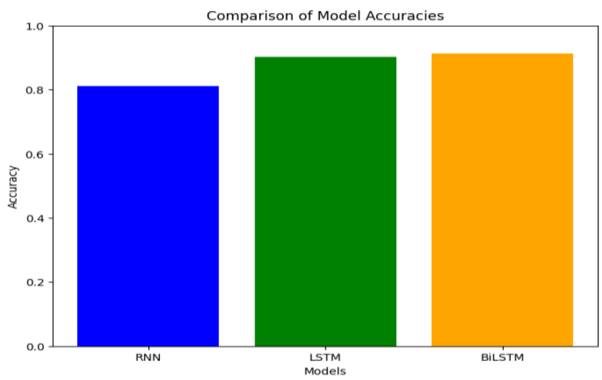

Fig 9.Comparison of model accuracies

V.CONCLUSION

In conclusion, the code creates smart models to understand feelings from written words. These models, like RNN, LSTM, and BiLSTM, are good at predicting emotions in text. The best one, BiLSTM, reaches an accuracy of around 91.36% after 5 tries. The code also handles imbalances in emotions by making sure each type is represented enough during training. Using TensorFlow and Keras makes these models work well, and saving the best version ensures top performance. Overall, these models are a solid solution for figuring out emotions in text and could be improved for even more uses.

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