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Emotion Recognition in Texts using Bidirectional Long Short-Term Memory based Neural Networks

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Abstract

Emotion Recognition from Textual data has been an open research topic in the field of Machine Learning. A lot of research has already been performed on this topic using feature engineering and Machine Learning classifiers. This paper involves the analysis of textual sentiment using deep learning techniques. The dataset undergoes preprocessing, and a sentiment classification model is developed using TensorFlow and Keras. Training, validation, and test sets are created, followed by tokenization and stemming to prepare the text for model training. A bidirectional LSTM neural network is utilized to classify sentiments into six categories: sadness, joy, love, anger, fear, and surprise. Model performance is evaluated, and a Flask web application is deployed for interactive sentiment prediction. The paper showcases the effective utilization of NLP and deep learning in sentiment analysis.

Keywords: Bidirectional LSTM, Sentiment Analysis, Text Preprocessing, Word Stemming

1. Introduction

Sentiment Analysis, a subset of Natural Language Processing (NLP), identifies emotional expressions [1] in text, categorizing them into emotions such as joy, sadness, anger, love, surprise, and fear. Techniques vary from traditional machine learning to advanced deep learning models, trained on annotated datasets for accurate emotion prediction, enhancing human-machine interactions.

Sentiment analysis interprets and categorizes emotions in textual data, combining computational linguistics, data mining, and text analytics. It aids in market analysis, customer feedback interpretation, and social media monitoring by converting unstructured text into structured data.

The inadequacy of manual methods in understanding human emotions in text drives the automation of sentiment analysis to streamline business processes, enhance customer experiences, and decision-making.

This paper aims to develop a sentiment analysis model using a bidirectional LSTM [2] network implemented using TensorFlow and Keras [3]. It also involves building a Flask web application for real-time sentiment predictions. The goal is to create an accurate and efficient sentiment analysis [4] tool for

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various NLP applications, advancing the field and offering practical solutions for text data analysis.

Sentiment analysis, a subset of natural language processing (NLP), aims to computationally determine the sentiment or opinion expressed in text. It involves understanding the attitudes, emotions, and opinions conveyed by the author through the text. This analysis finds applications in various domains, including market research, customer feedback analysis, and social media monitoring.

Early sentiment analysis techniques relied heavily on rule-based systems, using predefined rules and lexicons to classify text into different emotions such as joy, sadness, love, anger, fear, and surprise. However, these methods often struggled with language nuances like sarcasm, irony, and context-based sentiment.

Sentiment analysis, also known as opinion mining, has a rich history dating back to the early 2000s. It emerged as a subfield of computational linguistics, aiming to identify and extract subjective information from textual data. Initially, sentiment analysis focused on identifying the polarity of sentiments, categorizing text as positive, negative, or neutral. Early approaches heavily relied on rule-based systems that utilized lexicons and patterns to determine sentiment polarity.

With advancements in computing power and machine learning techniques, sentiment analysis has evolved significantly. Researchers have explored supervised and unsupervised machine learning algorithms for finer and more accurate sentiment classification. Deep learning techniques such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) have also been applied to sentiment analysis. These methods have shown promise in capturing complex linguistic patterns and contextual information, leading to further advancements in sentiment analysis methodology [5].

Moreover, sentiment analysis has found applications in various fields, including marketing, customer service, and social media analytics. It has become an essential tool for businesses and organizations to understand customer sentiment, improve products and services, and make informed decisions based on textual data analysis. Overall, sentiment analysis continues to evolve, driven by advances in technology and the growing need to understand and analyze textual data in diverse fields.

This paper is organized as follows: Section-2 discusses the work being done in this field. Section-3 introduces our proposed methodology, while in Section-4 we perform Result Analysis. We provide our concluding statements in Section 5.

2. Related Work

Kaur et. al. [6] in their paper [6] performed a comprehensive overview of sentiment analysis methods, including lexicon-based, machine learning, and hybrid approaches. The strengths and weaknesses of each approach were discussed, and insights into their applications in various fields were provided.

Zhang et.al. [7] studied the use of deep learning techniques, particularly RNNs and CNNs, for sentiment analysis. Improvements in sentiment analysis performance due to these techniques were proposed along with some future research directions in the area.

Rodriguez et. al. [8] focused on the Sentiment analysis techniques which were applied to social media data. The unique challenges of social media text analysis, such as informal language and short text, were discussed, and solutions proposed in the literature were explored.

Nazir et.al. [9] in their paper explored Aspect-based sentiment analysis techniques. Sentiment toward specific aspects or entities in a text were identified. Challenges of aspect-based sentiment analysis were discussed, and existing approaches were reviewed.

Azar et. al. in their paper [10] explored the applications of sentiment analysis in financial fields, particularly in the analysis of sentiment in news articles and stock market data. The impact of sentiment analysis on financial decision-making were discussed. Future research directions were also discussed.

Kaur et. al. in their paper [11] discussed about the various approaches to sentiment analysis in multimodal data that include text, images, and audio. The challenges and opportunities of sentiment analysis in multimodal data were discussed. Existing techniques were reviewed.

Joshi et. al. in their paper [12] performed a study on the techniques for detecting sarcasm in text, a challenging aspect of sentiment analysis due to its subtle nature. The features and linguistic cues used for sarcasm detection were discussed, Existing methods were reviewed.

Poria et. al. in their paper [13] discussed about the emotion recognition methods in conversational data. The problems of emotion recognition in conversation were discussed. Recent advances in the field were reviewed.

Lin et. al. in their paper [14] studied the applications of sentiment analysis in software. The challenges and opportunities of applying sentiment analysis in software engineering were discussed. Future research directions were explored.

Saberi et. al. in their paper [15] analyzed the various sentiment analysis techniques applied to opinion elicitation in newspaper articles. The importance of sentiment analysis in opinion analysis in journalistic content were discussed. Existing techniques were reviewed.

3. Methodology/Proposed Methodology

The objective is to develop a system capable of automatically categorizing textual content into six distinct emotions: joy, sadness, fear, anger, love, and surprise. This system will leverage advanced Natural Language Processing (NLP) techniques to accurately detect and classify these emotions, enabling applications in customer service, social media monitoring, healthcare, and marketing.

To categorize text into six emotions (joy, sadness, fear, anger, love, surprise), Long Short-Term Memory (LSTM) networks will be used. LSTMs are ideal for this task due to their ability to capture long-range dependencies and context in text.

Advantages:

- **Sequential Data Handling:** Effective for sentence flow.
- **Memory Retention:** Retains long-term contextual information.
- **Gradient Mitigation:** Overcomes vanishing gradient issues.

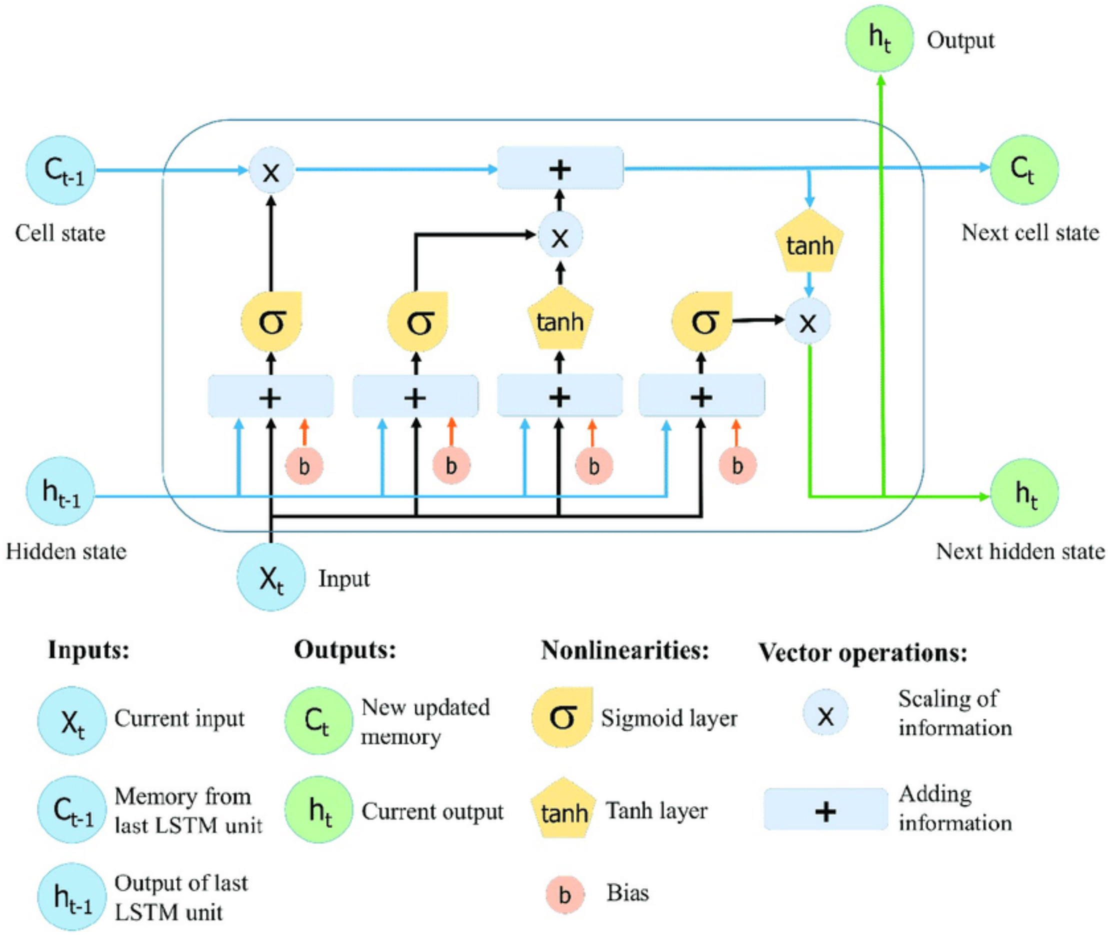


Figure 1: Architecture of Bidirectional LSTM Neural Network

3.1 The Dataset

The dataset was downloaded from Kaggle from ananthu017/emotion-detection-fer [16]. Any data sets involving sentiment analysis are binary classification problems. In this dataset, we have six different sentiments, which means we'll be treating this problem as a multiclass classification problem.

```
train = pd.read_csv('/content/training.csv')
test = pd.read_csv('/content/test.csv')
validation  = pd.read_csv('/content/validation.csv')
```

Emotions	Amount	Hashtags
sadness	214,454	#depressed, #grief
joy	167,027	#fun, #joy
fear	102,460	#fear, #worried
anger	102,289	#mad, #pissed
surprise	46,101	#strange, #surprise
trust	19,222	#hope, #secure
disgust	8,934	#awful, #eww
anticipation	3,975	#pumped, #ready

Figure 3: List of Emotions

Print first ten rows of the training dataset

```
In [3]: train.head(10)
```

Out[3]:

	text	label
0	i didnt feel humiliated	0
1	i can go from feeling so hopeless to so damned...	0
2	im grabbing a minute to post i feel greedy wrong	3
3	i am ever feeling nostalgic about the fireplac...	2
4	i am feeling grouchy	3
5	ive been feeling a little burdened lately wasn...	0
6	ive been taking or milligrams or times recomme...	5
7	i feel as confused about life as a teenager or...	4
8	i have been with petronas for years i feel tha...	1
9	i feel romantic too	2

Figure 4: First 10 Rows of the dataset

3.2 Data Preprocessing Steps

Loading Data → Adding Label Data → Data Visualization

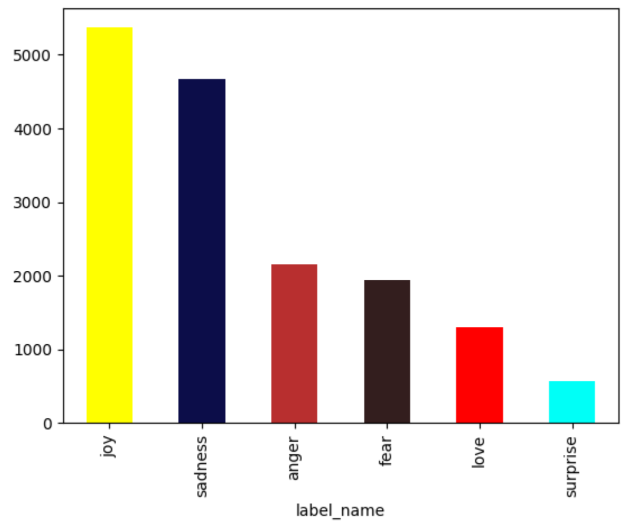
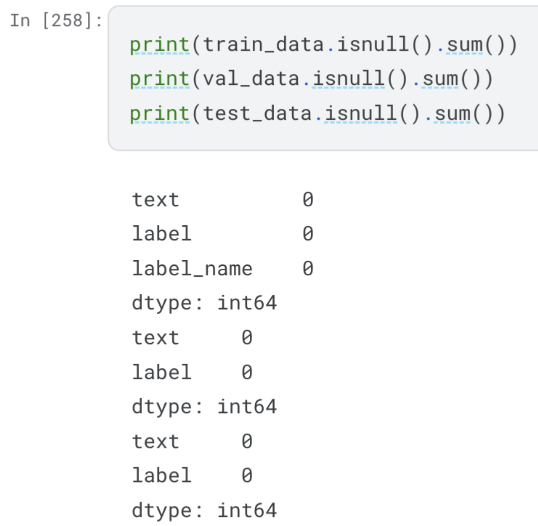


Figure 5: Data Preprocessing



```
In [258]:
print(train_data.isnull().sum())
print(val_data.isnull().sum())
print(test_data.isnull().sum())

text          0
label         0
label_name    0
dtype: int64
text     0
label    0
dtype: int64
text     0
label    0
dtype: int64
```

Figure 6: Data Cleaning

Tokenization & Stemming

- Tokenization assigns unique IDs to words, creating a word index or vocabulary.
  a. Example Sentence: "Tokenization is essential for NLP tasks."
  b. Tokenized Output: ['Tokenization', 'is', 'essential', 'for', 'NLP', 'tasks', '.']
- Stemming is a technique used to reduce an inflected word down to its word stem.
  a. Example: Original Words: running, programming, swimming, happiness, programmer (5 words)
  b. Stemmed Words: run, program, swim, happi (4 words)

3.3 Block Diagram

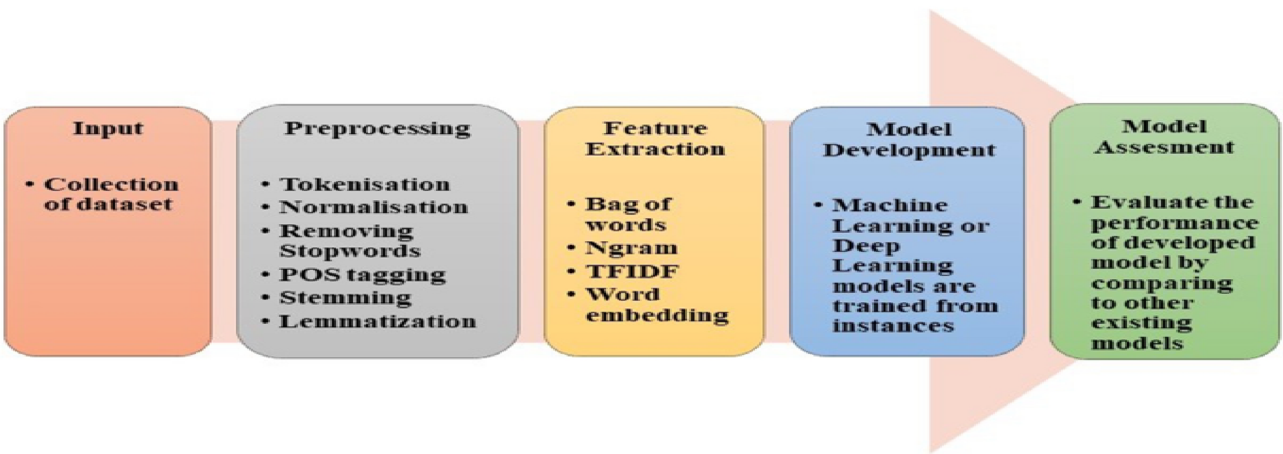


Figure 7: Key Components and Workflow

3.4 Details of each Block

Key Components and Workflow:

Data Collection:

- Gather a large, diverse dataset of text labeled with the six target emotions.

Preprocessing:

- Clean and preprocess the text data, including tokenization, removing stop words, and handling punctuation and casing.

Feature Extraction:

- Extract relevant linguistic features using techniques such as TF-IDF, word embeddings (e.g., Word2Vec, GloVe), or contextual embeddings (e.g., BERT).

Model Training:

- Train machine learning models or deep learning architectures on the preprocessed and feature-extracted data.
- Models could include Support Vector Machines (SVM), Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), or Transformers.

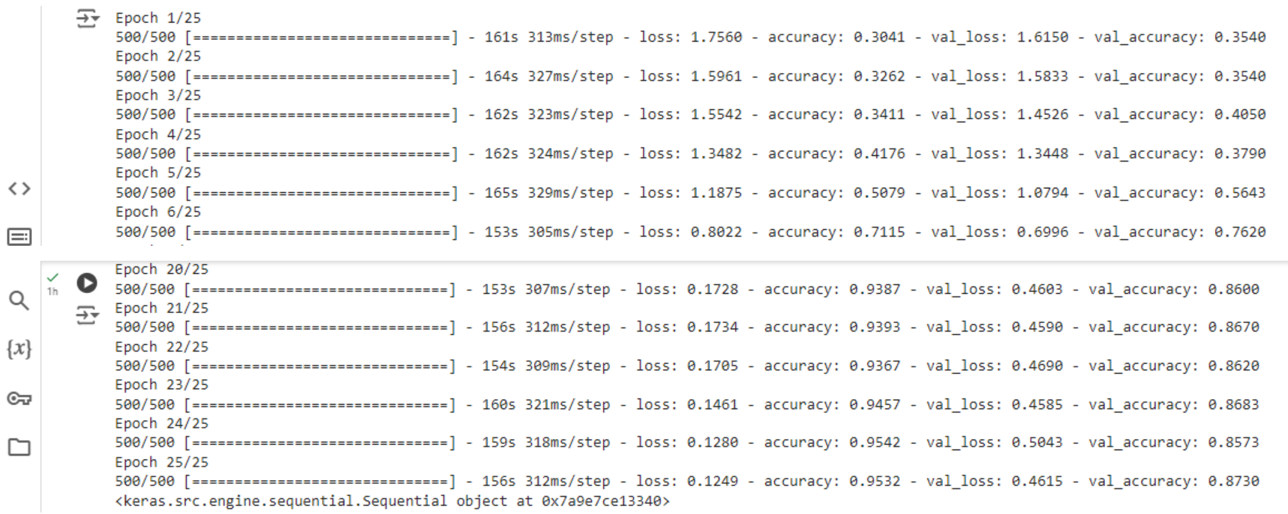
Emotion Classification:

- Implement the trained model to categorize new, unseen text into one of the six emotions.

Evaluation and Optimization:

- Evaluate the model's performance using metrics such as accuracy, precision, recall, and F1-score.
- Fine-tune the model and preprocessing steps based on evaluation results to improve accuracy.

4. Results And Discussions



```
Epoch 1/25
500/500 [==============================] - 161s 313ms/step - loss: 1.7560 - accuracy: 0.3041 - val_loss: 1.6150 - val_accuracy: 0.3540
Epoch 2/25
500/500 [==============================] - 164s 327ms/step - loss: 1.5961 - accuracy: 0.3262 - val_loss: 1.5833 - val_accuracy: 0.3540
Epoch 3/25
500/500 [==============================] - 162s 323ms/step - loss: 1.5542 - accuracy: 0.3411 - val_loss: 1.4526 - val_accuracy: 0.4050
Epoch 4/25
500/500 [==============================] - 162s 324ms/step - loss: 1.3482 - accuracy: 0.4176 - val_loss: 1.3448 - val_accuracy: 0.3790
Epoch 5/25
500/500 [==============================] - 165s 329ms/step - loss: 1.1875 - accuracy: 0.5079 - val_loss: 1.0794 - val_accuracy: 0.5643
Epoch 6/25
500/500 [==============================] - 153s 305ms/step - loss: 0.8022 - accuracy: 0.7115 - val_loss: 0.6996 - val_accuracy: 0.7620
Epoch 20/25
500/500 [==============================] - 153s 307ms/step - loss: 0.1728 - accuracy: 0.9387 - val_loss: 0.4603 - val_accuracy: 0.8600
Epoch 21/25
500/500 [==============================] - 156s 312ms/step - loss: 0.1734 - accuracy: 0.9393 - val_loss: 0.4590 - val_accuracy: 0.8670
Epoch 22/25
500/500 [==============================] - 154s 309ms/step - loss: 0.1705 - accuracy: 0.9367 - val_loss: 0.4690 - val_accuracy: 0.8620
Epoch 23/25
500/500 [==============================] - 160s 321ms/step - loss: 0.1461 - accuracy: 0.9457 - val_loss: 0.4585 - val_accuracy: 0.8683
Epoch 24/25
500/500 [==============================] - 159s 318ms/step - loss: 0.1280 - accuracy: 0.9542 - val_loss: 0.5043 - val_accuracy: 0.8573
Epoch 25/25
500/500 [==============================] - 156s 312ms/step - loss: 0.1249 - accuracy: 0.9532 - val_loss: 0.4615 - val_accuracy: 0.8730
<keras.src.engine.sequential.Sequential object at 0x7a9e7ce13340>
```

Figure 8: Epoch Performance

Epoch Performance(over 25 epochs):

- **Training Accuracy:** Increased from 30.41% to 95.32%
- **Validation Accuracy:** Increased from 35.40% to 87.30%
- **Training Loss:** Decreased from 1.7560 to 0.125
- Validation Loss: Decreased from 1.6150 to 0.462

Graph Analysis

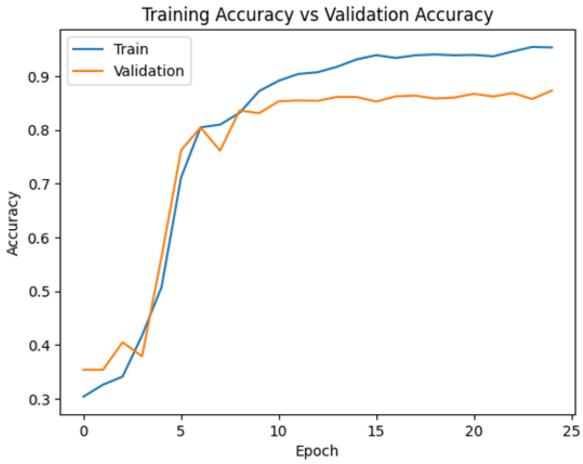


Figure 9: Training Accuracy vs Validation Accuracy

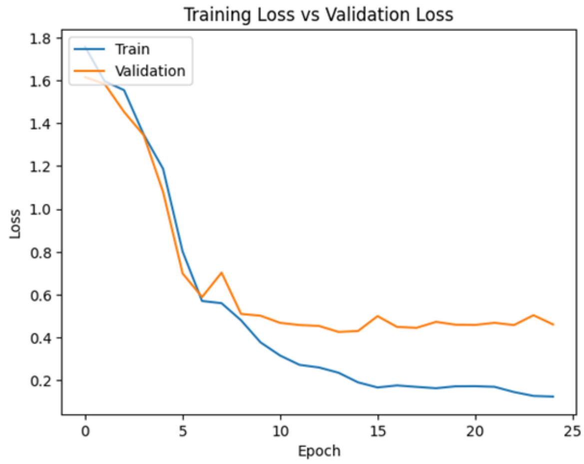


Figure 10: Training Loss vs Validation Loss

Training Accuracy vs Validation Accuracy: Both training and validation accuracy increase steadily with training accuracy reaching above 90% and validation accuracy slightly lower, indicating good generalization.

Training Loss vs Validation Loss: Training and Validation loss decreases consistently,with training loss dropping more sharply.

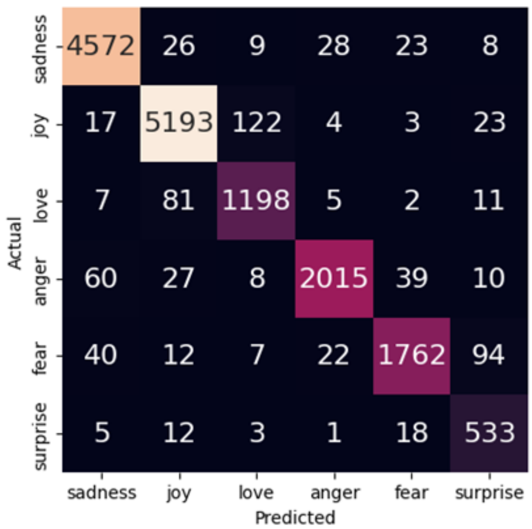


Figure 11: Confusion Matrix

Confusion Matrix

- Diagonal Values: Indicate high correct classification rates.
- Off-Diagonal Values: Suggest minimal misclassification.

```
1/1 [==============================] - 1s 928ms/step
+----+---------------------------------------------------+------------------------+---------+
|    | Text                                              | Predicted Sentiment    | Emoji   |
+====+===================================================+========================+=========+
|  0 | i felt anger when at the end of a telephone call  | anger                  | 😠      |
+----+---------------------------------------------------+------------------------+---------+
|  1 | i feel gorgeous yes                               | joy                    | 😊      |
+----+---------------------------------------------------+------------------------+---------+
|  2 | i felt loved when my friend called to check on me | love                   | ❤️      |
+----+---------------------------------------------------+------------------------+---------+
```

Figure 12: Snapshot of sample results

Textual Sentiment Analysis is on by training the model on the dataset and the model predicts the emotions such as sadness, joy, anger, fear and surprise through text. The model demonstrates strong learning and generalization. It shows high precision in classification tasks.

5. Conclusion and Future Scope

This study developed a sentiment analysis system that categorizes text into six emotions: joy, sadness, fear, anger, love, and surprise. Using advanced NLP techniques, especially a Bidirectional LSTM network, the system accurately detects and classifies emotions. Deep learning approaches effectively capture nuanced patterns in textual data, leading to high accuracy in sentiment classification. This system enhances human-computer interaction by understanding emotional context, benefiting applications like customer service, social media monitoring, healthcare, and marketing.

Future research can enhance sentiment analysis in several ways:

- Hybrid Models: Develop models combining different ML and DL algorithms for improved accuracy and robustness.
- Multimodal Data: Use multimodal data (text, visuals, audio) for a comprehensive understanding of emotions, benefiting social media monitoring and video analysis.
- Contextual Analysis: Focus on contextual and domain-specific sentiment analysis for more relevant and precise results, tailoring models to specific industries or text types (e.g., financial news, product reviews).
- Real-Time Processing: Enhance real-time sentiment analysis for immediate responses in customer service and social media monitoring.
- Cross-Language Analysis: Expand sentiment analysis to multiple languages for global applicability, considering diverse linguistic groups and cultural nuances.
- Addressing these areas can advance sentiment analysis, making it a powerful tool for understanding and responding to human emotions across various domains.

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