Analyzing Emotional Intensity of Tweets: A Deep Learning Approach

By
Mohammed Farooq Basha S
Codalab Username: Farooqasha008

Abstract:

This technical paper presents a detailed analysis of emotional intensity in tweets using a deep learning approach. The study aims to accurately predict and quantify the intensity of emotions expressed in social media conversations. The research includes data preprocessing, model development using a deep learning architecture, training, and evaluation. The findings are based on evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared (R2), Root Mean Squared Logarithmic Error (RMSLE), and Mean Absolute Percentage Error (MAPE).

1. Introduction

1.1 Background

Social media platforms, such as Twitter, have become a popular means for users to express their emotions and sentiments in real-time. Analyzing emotional intensity in tweets can provide valuable insights into the emotional responses of users and their sentiment towards different topics.

1.2 Objective

The objective of this research is to develop a deep learning model that accurately predicts the emotional intensity of tweets. By leveraging the power of deep learning algorithms, we aim to capture the complex patterns and nuances of emotional expression in social media conversations.

1.3 Contribution

This study contributes by proposing a deep learning approach to analyze emotional intensity in tweets. The developed model offers a more sophisticated and nuanced understanding of the intensity of emotions expressed in social media conversations, leading to improved sentiment analysis and emotion detection.

2. Data Collection and Preprocessing

2.1 Data Source

The data used in this study is collected from Twitter, specifically focusing on tweets related to a specific topic or event. The dataset consists of text content, emotion labels, and corresponding scores representing emotional intensity.

2.2 Text-to-CSV Conversion

To facilitate further analysis and modelling, the raw text data is converted into a structured format. The provided code snippet demonstrates the process of converting the text data into a CSV file, where each row represents a tweet with associated emotion labels and scores.

2.3 Data Preprocessing using PyCaret

The preprocessing step involves transforming the raw text data into a suitable format for modelling. PyCaret, a powerful Python library, is utilized for automating the preprocessing tasks, including text cleaning, tokenization, feature engineering, and data transformation. The preprocessed dataset is then exported for subsequent modelling steps.

3.Deep Learning Model Architecture and Hyperparameter Tuning

3.1 Hyperparameter Tuning

The hyperparameter tuning process in this study aimed to optimize the deep learning model's performance in predicting emotional intensity in tweets. The following hyperparameters were tuned: the number of hidden layers, the number of units in each hidden layer, learning rate, epochs, and batch size.

3.1.1 Initialization of Tuner

The Keras Tuner library's Bayesian Optimization tuner was used for hyperparameter tuning. The tuner was initialized with the objective function set to mean squared error (MSE), which measures the deviation between predicted emotional intensities and ground truth labels.

3.1.2 Hyperparameter Search

The tuner performed a search over the hyperparameter space to find the combination of hyperparameters that yielded the best performance. It executed 10 trials, with each trial training the model twice to ensure robustness of the results. The hyperparameters and corresponding performance metrics were saved in a specified directory and project name.

3.1.3 Retrieval of Best Model and Hyperparameters

After the hyperparameter search, the best model and its corresponding hyperparameters were retrieved. The selection of the best model was based on its performance in minimising the MSE. The hyperparameters of the best model were printed to indicate the optimal combination that achieved the best performance.

3.2 Deep Learning Model Architecture:

Based on the best hyperparameters obtained from the tuner, the deep learning model architecture was constructed to accurately predict emotional intensity in tweets.

3.2.1 Input Layer

The model began with an input layer consisting of 64 units and utilized the rectified linear unit (ReLU) activation function.

3.2.2 Hidden Layers

Four hidden layers were included in the model, with each layer consisting of 32 units and utilizing the ReLU activation function. These hidden layers aimed to capture the complex patterns and nuances of emotional expression in social media conversations.

3.2.3 Output Layer

The model concluded with an output layer containing one unit and utilizing a linear activation function. This layer provided the predicted emotional intensity for each tweet.

3.3 Model Compilation and Training

The model was compiled using the mean squared error loss function, the Adam optimizer with a learning rate of 0.0001, and the MeanSquaredError metric for evaluation. The training process involved fitting the model to the training data for 150 epochs with a batch size of 32. The validation data was utilized during the training process to monitor the model's performance and prevent overfitting.

4. Model Evaluation

Following the training process, the model was evaluated using various performance metrics to assess its accuracy and predictive power. These metrics included mean squared error (MSE), root mean squared error (RMSE), R-squared (R2), mean absolute error (MAE), root mean squared logarithmic error (RMSLE), and mean absolute percentage error (MAPE). These metrics provided insights into the deviation between the predicted emotional intensities and the actual labels.

The deep learning model's architecture and hyperparameters were determined through the hyperparameter tuning process, aiming to optimize the model's performance in predicting emotional intensity in tweets. Leveraging the power of deep learning algorithms and the fine-tuned hyperparameters, the model aimed to capture the complex patterns and nuances of emotional expression in social media conversations.

4.2 Results and Discussion

The evaluation results demonstrate the effectiveness of the deep learning model in accurately predicting emotional intensity in tweets. The findings are discussed, highlighting the model's performance, strengths, and limitations.

The evaluation metric scores are as follows:

1. Loss: [0.011815403588116169, 0.011815403588116169]
2. Mean Absolute Error (MAE): 0.06174608447512269
3. Mean Squared Error (MSE): 0.011815403851371722
4. Root Mean Squared Error (RMSE): 0.10869868376099005
5. R-squared (R2): 0.700356813488701
6. Root Mean Squared Logarithmic Error (RMSLE): 0.07315033491579366
7. Mean Absolute Percentage Error (MAPE): inf

The R-squared score is 0.70, and the rest of the scores are also in the better ranges depicting that the model's performance is good.

5. Conclusion

5.1 Summary of Findings

This research successfully applies a deep learning approach to predict emotional intensity in tweets. The developed model shows promising performance, enabling a more nuanced understanding of emotional expressions in social media conversations.

5.2 Future Work

The present study lays the foundation for further research in deep learning models for sentiment analysis and emotion detection. Future work could focus on exploring advanced architectures, leveraging transfer learning, and incorporating contextual information to enhance the prediction of emotional intensity in tweets.

References:

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