Project Report

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Deep Learning for Twitter Emotion Extraction and Classification

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***Abstract*—In the dynamic realm of social media, consider Twitter as a large platform where individuals express themselves daily. With the help of smart computers like CNN, Bi-LSTM, and BERT, this study is like a trip to learn more about these feelings.Consider these volunteers to be digital detectives, attempting to determine the emotions behind tweets, such as whether individuals are happy, startled, sad, furious, loving, or afraid. This study report is essentially a narrative about how these models, or digital detectives, examine a large number of tweets. We'll discuss the steps we took to simplify the tweets so the models could interpret them. Next, we will evaluate which model performed most well in discerning emotions.**

***Index Terms*—Emotion Detection, GloVe 6B 300d, CNN, Bi-LSTM,BERT.**

I. Introduction

In the enormous world of Twitter, where varied viewpoints meet, this study starts on a compelling journey to uncover the complexities of human emotions. This study uses advanced digital technology including CNN, Bi-LSTM and BERT to decipher the underlying emotions in tweets, which can range from anger, love, and fright to joy, surprise, and sorrow.

In contrast to binary categorizations of tweets as either positive or negative, our effort acknowledges the complex emotional range that is represented by facial expressions, where people can simultaneously express surprise and happiness. The fundamental social impact of understanding public opinion on important issues like elections and world events is at the center of this study.

The story proceeds as our heroes, the CNN, Bi-LSTM, and BERT models, take on the personas of shrewd text-analysis analysts, conducting investigative work to reveal the hidden emotional terrain within the vast Twitterverse. A thorough comparative study of these digital detectives, the technique used, and experimental results are all covered in detail in the parts that follow, which conclude with an engrossing exploration of the complex understanding of emotions on Twitter.

II. Related Work

This section summarizes previous research efforts in sentiment and emotion recognition within textual data, providing useful insights that influence the current study.

In EMOTEX: Detecting Emotions in Twitter Messages Maryam Hasan et al[1] presented a novel method that automatically categorizes individual text messages to infer emotional states. Interestingly, they used hashtags as labels, which allowed supervised classifiers to identify different emotion classes automatically—all without the need for human participation. Our research's automatic categorization methodology was influenced by this work.

In their paper Twitter Sentiment Classification using Distant Supervision Alec Go et al. [2] used Twitter text and Western-style emoticons to classify positive and negative attitudes. Using SVM, Maximum Entropy, and Naive Bayes, their study produced an astounding 80 accuracy rate. This study is essential to understanding the importance of emoticons in sentiment analysis, which is something we took into account.

Douji Yasamina et al. [3] investigated Using Youtube comments for text-based emotion recognition diving into the detection of users emotions via textual exchanges. Their work addressed the issues presented by character writing style and language change. We use their strategy as a guide as we overcome comparable difficulties in interpreting sentiment from Twitter data.

In their paper Extraction of emotions from multilingual text using intelligent text processing and computational linguistics Vinay Kumar et al. [4] used multilingual text data gathered through emotion theories based in linguistics and psychology. Our choice to include GloVe embeddings in our research is influenced by this work, which emphasizes the significance of linguistic diversity.

Darmon et al. [5] investigated the use of representation modeling to predict social media user behavior in a recent study. Their research highlighted the fact that users frequently display a small number of latent behavioral processing states—a critical discovery for comprehending and forecasting user behavior. This study contributes to our understanding of behavioral states in Twitter data processing.

III. PROJECT OBJECTIVE

Our undertaking The purpose of this project is to recognize emotions in texts. We used deep learning to identify emotions after analyzing the texts to complete this project. We have measured the models' precision in identifying emotions. As our models, we employed Bi-LSTM ,CNN and BERT. We will identify six different emotional states from the texts, including joy, surprise, sadness, anger, love, and fear.

Fig. 1. Project Workflow

IV. METHODOLOGY

A. Convolutional Neural Network (CNN)

CNN are artificial neural networks used in deep learning . There are three layers in a CNN: input, hidden, and output. Fully connected layers, embedding layers, pooling layers, dropout layers, and convolutional layers with ReLU activation are examples of hidden layers. For word embedding, we used the GloVe 6B 300d dataset. Here is the architecture:

Fig. 2. CNN

- **Embedding Layer:** First layer using GloVe 6B 300d.
- **Convolution Layer:** One Conv2D layer for feature extraction.
- **Pooling Layer:** Max pooling layer to reduce dimensionality.
- **Dropout Layer:** 0.1 dropout to prevent overfitting.
- **Fully Connected Layer:** Last layer connecting every neuron for output.

B. Bi-LSTM

Featuring both forward and backward LSTMs, Bi-LSTM is a model for sequence processing . ReLU-activated output, forward, backward, and embedding layers are among the layers. Here is the architecture:

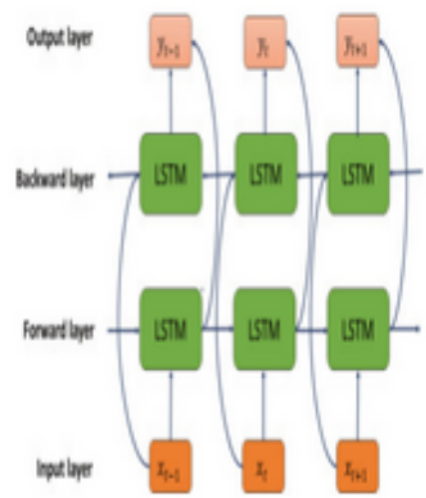

Fig. 3. Bi-LSTM

- **Embedding Layer:** First layer using GloVe 6B 300d.
- **Pooling Layer:** Average and Max pooling layers for dimensionality reduction.
- **Dropout Layer:** 0.1 dropout to prevent overfitting.
- **Fully Connected Layer:** Last layer connecting every neuron for output.

C. BERT (Bidirectional Encoder Representations from Transformers)

For bidirectional contextual comprehension, BERT is a transformer-based model . It consists of positional encodings, feedforward networks, and multi-head self-attention. Despite its complexity, the architecture is excellent at contextual understanding. Tweets are subjected to detailed emotion analysis using the pre-trained weights.

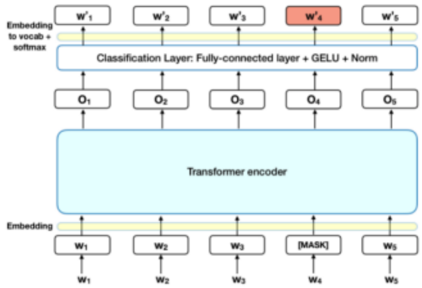

Fig. 4. BERT model

V. Experiments

A. Dataset

In this research, the Kaggle Tweet Emotion dataset is used. With the remaining 80 percent of the dataset being used for training, 20 percent is used for testing.

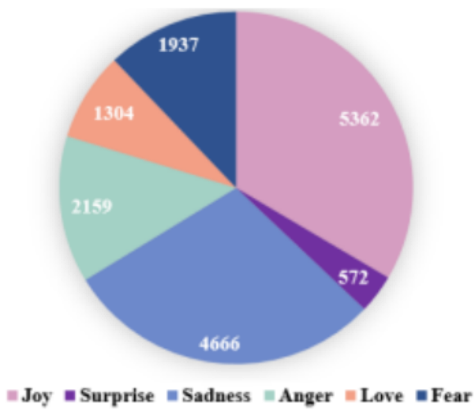

Fig. 5. Data Statistics of Emotions

B. Evaluation Metrics

Four distinct evaluation metrics have been selected by us to assess our models. Here is brief introduction of these metrics:

1) **Accuracy:** It says how close a measured value is to the actual value.

$$\text{Accuracy} = \frac{TP + TN}{P + N}$$

2) **Precision:** It measures the proximity of measured values to each other and is computed as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

3) **Recall:** It says how close a measured values are to each other.

$$\text{Recall} = \frac{TP}{P}$$

4) **F1-Score:** It is the ratio of all correctly predicted positive predictions. It measure how many the model missed.

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Here, P stands for total positive predicted class, N for total negative predicted class.

C. Confusion Matrix

Confusion matrices for CNN, Bi-LSTM, BERT models were analyzed. The confusion matrices are displayed in Figures 6, 7, 8.

Fig. 6. Confusion Matrix for CNN Model

Fig. 7. Confusion Matrix for Bi-LSTM Model

Fig. 8. Confusion Matrix for BERT Model

D. Results

1) CNN Model Performance: The loss curve of the CNN model are shown in Figure 9.

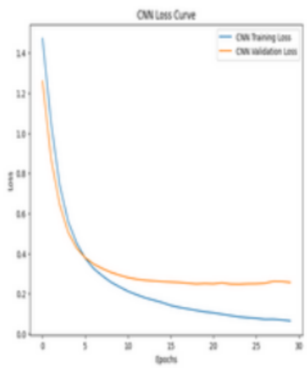

Fig. 9. Loss Curve for CNN Model

2) Bi-LSTM Model Performance: The loss curve of the Bi-LSTM model are shown in Figure 10.

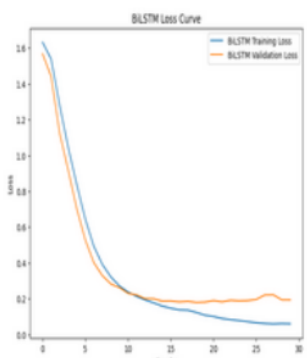

Fig. 10. Loss Curve for Bi-LSTM Model

3) BERT Model Performance: The loss curve of the BERT model are shown in Figure 11.

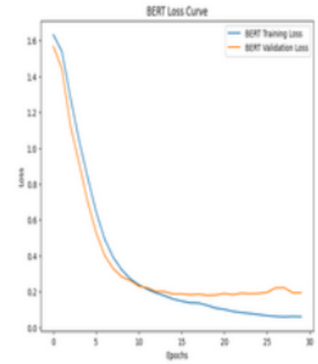

Fig. 11. Loss Curve for BERT Model

4) Precision and Recall for Different Emotions: Tables I and III show the precision and recall values for different emotions, respectively, according to CNN, Bi-LSTM, and BERT models.

	CNN	Bi-LSTM	BERT
anger	0.91%	0.91%	0.94%
fear	0.86%	0.92%	0.88%
joy	0.92%	0.95%	0.96%
love	0.80%	0.86%	0.87%
sadness	0.94%	0.94%	0.97%
surprise	0.77%	0.75%	0.77%

TABLE I
PRECISION FOR DIFFERENT EMOTIONS

	CNN	Bi-LSTM	BERT
anger	0.91%	0.94%	0.91%
fear	0.88%	0.85%	0.92%
joy	0.92%	0.93%	0.95%
love	0.84%	0.87%	0.86%
sadness	0.92%	0.97%	0.97%
surprise	0.73%	0.81%	0.83%

TABLE II
RECALL FOR DIFFERENT EMOTIONS

	CNN	Bi-LSTM	BERT
anger	0.91%	0.92%	0.93%
fear	0.87%	0.88%	0.90%
joy	0.92%	0.94%	0.96%
love	0.82%	0.86%	0.87%
sadness	0.93%	0.95%	0.97%
surprise	0.75%	0.78%	0.80%

TABLE III
F1-SCORE FOR DIFFERENT EMOTIONS

VI. DISCUSSION

High precision, recall, and F1-score are demonstrated by the BERT model in a range of emotion categories. It is particularly good at expressing subtleties in feelings like surprise, happiness, and melancholy. With an astounding 94 overall accuracy, the model is a strong performer when it comes to Twitter emotion classification. The BiLSTM model performs well, particularly when it comes to identifying emotions like surprise, joy, and melancholy. With an accuracy score of 92 overall, it shows dependable precision and recall metrics, indicating that it can handle sequential data and capture contextual dependencies. The CNN model does a good job of identifying emotions such as anger, joy, and melancholy, even though its overall accuracy of 90 is slightly lower than that of BERT and BiLSTM. The model's strength is its capacity to identify specific patterns and features in data, resulting in competitive performance.

VII. Conclusion

In conclusion, the difficult task of classifying Twitter emotions shows potential for all three models: CNN, BiLSTM, and BERT. BERT's exceptional precision and thorough comprehension of a wide range of emotions make it stand out. Although BiLSTM and CNN exhibit slightly lower accuracy, they yet yield strong performances, demonstrating the appropriateness of various architectures for this particular task.

VIII. Future Work

To enhance the accuracy of emotion identification, future research endeavors should investigate hybrid models that use both text-based information and facial expressions. Examining how emotions manifest in different species is a fascinating field that provides insights into the similarities and differences in emotional manifestation. A useful application for tracking and evaluating emotional patterns in online discussions is the creation of real-time emotion recognition algorithms for social media sites like Twitter. These initiatives seek to improve emotion recognition technologies, comprehend cross-species emotional displays, and deploy real-time systems for dynamic social media content analysis.

References

[1] M. Hasan, E. Rundensteiner, and E. Agu, "Emotex: Detecting emotions in Twitter messages," 2014.

[2] A. Go, R. Bhayani, and L. Huang, "Twitter sentiment classification using distant supervision," CS224N project report, Stanford, vol. 1, no. 12, p. 2009, 2009.

[3] V. K. Jain, S. Kumar, and S. L. Fernandes, "Extraction of emotions from multilingual text using intelligent text processing and computational linguistics," Journal of computational science, vol. 21, pp. 316–326, 2017.

[4] M. Hajar et al., "Using youtube comments for text-based emotion recognition," Procedia Computer Science, vol. 83, pp. 292–299, 2016.

[5] D. Darmon, J. Sylvester, M. Girvan, and W. Rand, "Predictability of user behavior in social media: Bottom-up v. top-down modeling," in 2013 International Conference on Social Computing, pp. 102–107, IEEE, 2013.

[6] CNN Description. https://en.wikipedia.org/wiki/Convolutionalneuralnetworkcitenote-V aluevaN agornovLyakhovV aluev2020pp.232.

[7] Bi-LSTM Description. https://paperswithcode.com/method/bilstm.

[8] BERT Model. https://towardsdatascience.com/bert-explained-state-of-the-art-language-model-for-nlp-f8b21a9b6270.

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