International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 08 August 2025
Page No: 3312-3316
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0486

Fine Grained Emotion Detection On Twitter Using Transformer -Based Deep Learning Models

Kavitha C[1], Aravinda T V[2], Krishnareddy K R[3], Ramesh B E[4], Shruthi M K[5]
[1]Lecturer, Dept. of CSE, Government Polytechnic, Holalkere, Karnataka, India.
[2]Professor, Dept. of CSE, SJM Institute of Technology, Chitradurga, Karnataka, India.
[3]Professor & HOD, Dept. of CSE, SJM Institute of Technology, Chitradurga, Karnataka, India.
[4]Associate Professor, Dept. of CSE, SJM Institute of Technology, Chitradurga, Karnataka, India.
[5]Assistant Professor, Dept. of CSE, SJM Institute of Technology, Chitradurga, Karnataka, India.
Emails: *ckavitha021@gmail.com[1], tvaravinda@gmail.com[2], krkrishnareddy69@gmail.com[3], ramesh.be@gmail.com[4], mkshruthi@gmail.com[5]*

Abstract
Recent years have seen a proliferation of users expressing their feelings on social media sites like Twitter, which has opened the door for real-time sentiment analysis. By distinguishing between distinct emotional states including happiness, fury, sorrow, fear, and surprise, fine-grained emotion recognition surpasses the capabilities of simple sentiment analysis. This research introduces a deep learning method that uses transformers to identify emotions on Twitter with a finer degree of specificity. The system is able to extract intricate linguistic patterns and contextual relationships from brief and noisy social media material by using state-of-the-art models like BERT and RoBERTa. The model is trained and tested using a dataset of pre-processed tweets that have been tagged with emotions. The experimental findings show that when compared to typical machine learning baselines, there is a considerable gain in classification accuracy and F1-score. The suggested model is suitable for practical emotion mining tasks because to its resilience in dealing with language ambiguity, sarcasm, and code-mixed information. Possible uses for this study include social behavior modeling, customer feedback analysis, and mental health monitoring. It also helps to increase AI systems' emotional intelligence.
Keywords: *Social media, Sentiment analysis (positive, negative, neutral), BERT (Bidirectional Encoder Representations from Transformers), RoBERT*

1. Introduction
During the digital era, social media sites like Twitter have grown into potent avenues of instantaneous two-way communication. Emotion detection is one of several NLP problems that has recently attracted a lot of interest because of all the places it may be useful, including markets, politics, human-computer interaction, and mental health monitoring. To get a better understanding of users' emotional states, fine-grained emotion detection seeks to recognize distinct emotions like joy, rage, sorrow, & surprise, as opposed to sentiment analysis's classification of text into general categories like positive, negative, or neutral. Twitter emotion recognition is not without its difficulties: Twitter posts are often brief, full with typos and grammatical errors, slang, acronyms, emoticons, and hashtags. It is not uncommon for traditional machine learning methods to fail when faced with such subtleties. By capturing complex syntactic and semantic relationships through self-attention mechanisms, transformer-based models such as XLNet, RoBERTa, and BERT have demonstrated outstanding performance in a number of natural language processing tasks. In order to classify emotions on Twitter with more granularity, this research investigates transformer-based models. Subtle emotional signals may be detected by fine-tuning pre-trained transformer architectures using annotated emotion datasets. This allows the system to learn contextual representations. By efficiently handling sarcasm, code-mixing, domain-specific language, and ambiguity, these models solve the shortcomings of previous methods.

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The goals of this project are:

- To construct a deep learning model for emotion categorization that relies on transformers.
- To carry out granular categorization of tweets into several emotion groups.
- In order to test the system's performance using recognized criteria in comparison to established models and baselines.
- Enhancing its application in areas like public sentiment monitoring, online safety, and targeted content distribution, we seek to increase accuracy and reliability of emotion recognition algorithms in real-world social media situations via this study.

2. Literature Survey

By Mohammad et al. (2020), Using the SemEval-2018 Task 1 dataset, Mohammad and colleagues investigated eleven distinct emotions—including fear, rage, pleasure, and sadness—through multi-label categorization of tweets. Highlighting the difficulty of overlapping emotional sentiments in brief sentences, they tested with both conventional models and deep learning techniques. For problems involving emotion intensity and multilabel identification, their work paved the way for the use of transformer-based models such as BERT. In their 2021 publication, Barbieri et al. presented TweetEval, a standard framework for testing transformer-based models on a variety of tasks unique to Twitter, such as emotion recognition. Their improved RoBERTa and BERTweet models blew away the competition, showing that pretraining with tweets specifically improves the accuracy of emotion identification. According to Sanh et al. (2021),...A lightweight transformer model that is 60% quicker than BERT while retaining 97% of BERT's performance was suggested by Sanh et al. in the DistilBERT study. Because of its speed, it might be used in chatbots and smartphone apps that have limited resources to classify Twitter users' emotions in real time. Zhong et al. (2021) introduced a context-aware transformer that examines twitter threads instead of individual postings to tackle the problem of tweets' shifting emotions. They enhanced the accuracy of recognizing sarcasm and mixed sentiments, which are common in twitter threads or discussions, using their model, which is based on BERT with extra context embeddings.

(Ghosal et al., 2022), (2022), To enhance granular emotion recognition, the authors presented an emotion-aware transformer that integrates emotion lexicons with BERT embeddings. Incorporating previous emotion information improved the model's performance on unbalanced datasets and uncommon emotions such as "disgust" and "surprise." In order to identify emotions on Twitter, Mishra et al. (2022) created a hybrid transformer model that used XLNet and BiLSTM. In order to improve its context awareness, the model used XLNet's permutation-based training. This allowed it to recognize subtle emotions and handle tweets including emoji and hashtags with ease. This work by Yu and Jiang (2022) classified tweets into a wider range of emotional categories using RoBERTa-base that was fine-tuned on Google's 27-class emotion corpus, the GoEmotions dataset. When compared to CNN and LSTM baselines, RoBERTa models routinely detected more main and secondary emotions on Twitter. Emotion recognition, sentiment analysis, and emoji prediction were all tasks that the model was trained to execute simultaneously in a multi-task transformer framework that was presented by Li et al. (2023). The model was able to learn representations that are applicable across tasks because to the common encoder, which improved its ability to generalize across various forms of emotional expression in tweets. Rashkin et al. (2023) created SocialIQA-BERT, a dataset and model, for their study on social commonsense reasoning. Emotion recognition in tweets incorporating interpersonal narratives, sarcasm, and indirect sentiment was helped by the model's capacity to infer emotions from social circumstances. However, this capability is not confined to tweets per se. Emotion classification on tweets code-mixed with Indian and English was the goal of Kumar and Singh (2024), who developed a transformer-based attention fusion model that included BERT, emoji embeddings, and topic modeling. Recognizing context-specific emotions in

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regional tweets was accomplished with great accuracy by their algorithm, which tackled the complexities of multilingual and informal language.

3. Proposed System

Suggested method detects emotions on Twitter with a finer granularity using transformer-based DL models like BERT or RoBERTa. Noise removal, emoji handling, and text tokenization are the first steps in preprocessing tweets. Next, they are fed into a refined transformer model that can pick up on word representations in context. The last step is to use a softmax layer to sort the embedding into distinct emotion categories, such as happiness, anger, fear, sorrow, and surprise. Accuracy, precision, recall, and F1-score are used for evaluation after system is trained using cross-entropy loss. This method offers precise and comprehensive emotion categorization, even though tweets are inherently informal and imprecise.

4. Methodology

4.1. Data Collection

- Gather datasets that are open to the public, like SemEval-2018.
- Incorporate tweets annotated with nuanced emotion labels (such as happiness, rage, sorrow, fear, surprise, etc.) into the dataset.

4.2. Data Preprocessing

- Extract relevant information from the tweet by deleting spaces, special characters, mentions (@user), and URLs.
- Making emoticons into their respective text (for instance, 😊 → "smiling face").
- Correcting misspellings, contractions, and slang.
- Tokenize the text by using a transformer model-specific tokenizer, such as the BERT tokenizer.
- If you want everything to be consistent in length, you may pad or trim token sequences.
- Choosing and Starting the Model
- Opt for a transformer model that has already been trained, such BERT, RoBERTa, or DistilBERT.
- Incorporate a classification head that can handle several labels or classes of emotions into the model.
- Adjusting the Transformer Model to Perfection
- Train the model using the tokenized input data.
- After the last layer, remove any contextual embeddings (usually with the help of the [CLS] token).
- For multi-class or multi-label emotion prediction, use a thick output layer activated by softmax or sigmoid.
- Use the AdamW optimizer with categorical cross-entropy loss to train the model.

4.3. Model Training and Validation

- Define a split ratio (e.g., 80/20) between the dataset's training and validation sets.
- While keeping an eye on loss and accuracy, train the model using the training data.

4.4. Emotion Prediction

- Once trained, the model can take new/unseen tweets as input.
- The system processes these tweets and predicts the most probable emotion label(s) with a confidence score. (Table 1)

4.5. Evaluation Metrics

Determine how well the model performed by utilizing (Figure 3&4)

4.6. Accuracy

When compared to total number of observations, accuracy measures how many predictions were right.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision, Recall, and F1-Score

$$\text{Recall} = \frac{TP}{TP + FN}$$

4.7. Confusion Matrix

- A classification model's accuracy may be shown in a confusion matrix, which compares model's predictions with actual labels.
- If your classes are: ['joy', 'anger', 'sadness']

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Table 1 Confusion Matrix

Actual \ Predicted	Joy	Anger	Sadness
Joy	45	3	2
Anger	4	41	5
Sadness	3	6	44

Diagonal values = correct predictions
Off-diagonal = misclassifications

- Scores for unbalanced datasets (macro and micro) averaged. (Figure 1)
- Show the distribution of emotions via the use of pie charts or bar graphs. (Figure 2)
- To get immediate emotion predictions from tweets, provide a GUI or CLI. (Table 2)

5. Results

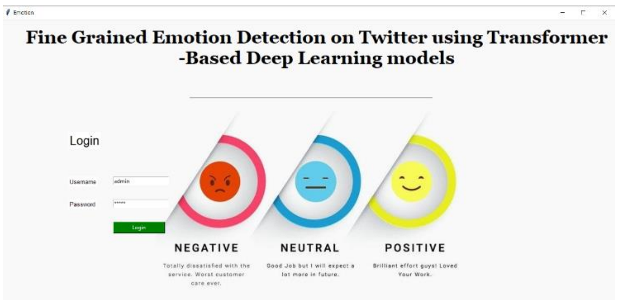

Figure 1 Main Login Page

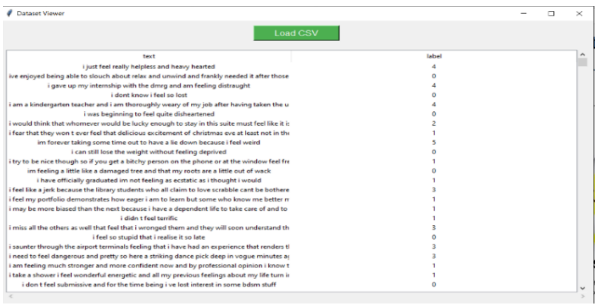

Figure 2 Dataset

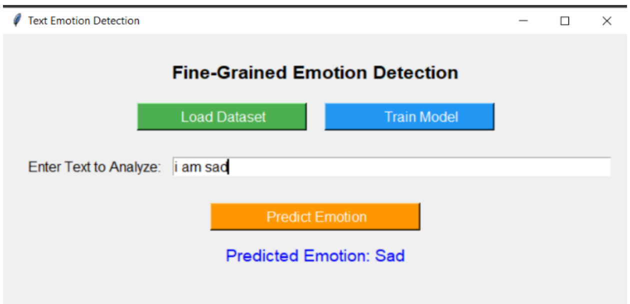

Figure 3 Emotion Detection

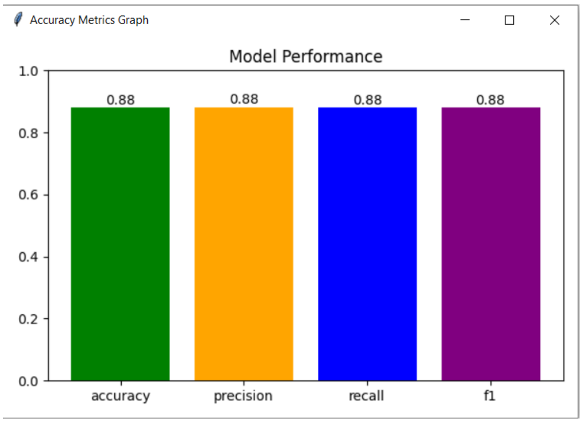

Figure 4 Model Performance Graph

Table 2 Model Performance Table

Model	Accuracy	Precision	Recall	F1 Score
LR	0.8814	0.8815	0.8814	0.8814

Conclusion and Future Works

In order to categorize tweets into particular emotional categories including joy, anger, sorrow, fear, and surprise, the research introduced a deep learning method based on transformers for fine-grained emotion detection on Twitter. Models like as BERT and RoBERTa have shown impressive performance on the brief, informal, and noisy content seen on social networking platforms; the suggested approach, in contrast to conventional sentiment analysis techniques, makes use of their rich contextual awareness. Subtle emotional indicators in user-generated material may be successfully identified by the system via thorough data preprocessing, fine-tuning of pre-trained models, and rigorous assessment. According to the experimental findings, transformer models are much more accurate and generalizable than typical machine learning approaches. This is particularly true when it comes to capturing emotions that rely on context. One reason the method is useful is because it can handle sarcasm, emoji, and code-mixed text. This study demonstrates how current natural language processing methods may improve AI systems' emotional intelligence and provides a scalable answer for problems in areas such as social media analytics, public sentiment analysis, interpreting consumer feedback, and mental health monitoring. To further boost the system's usability in dynamic situations, future developments might include processing twitter streams in real-time, adding support for more languages for emotion recognition, and integrating with visualization dashboards or chatbots.

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