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# IMPLEMENTATION OF TRANSFORMER MODEL FOR FINE-GRAINED EMOTION DETECTION ON SOCIAL MEDIA "X"

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**Abstract:** Fine-grained emotion detection on social media text is one of the challenges in the field of Natural Language Processing (NLP), particularly due to the unstructured and multi-label nature of the data. This study aims to evaluate the performance of three Transformer-based models—EmoBERT, RoBERTa, and EmoRoBERTa—in classifying emotions on tweets from the SenWave dataset. The dataset consists of 10,001 English-language tweets annotated into ten emotion categories, but this study focuses on four primary labels: anxious, annoyed, empathetic, and sad. The research process involves data preprocessing, tokenization, data splitting for training and testing, model training, and evaluation using accuracy, precision, recall, and F1-score metrics. The evaluation results show that EmoBERT and EmoRoBERTa achieved the best performance with an F1-score of 0.81, while RoBERTa achieved an F1-score of 0.73. These findings suggest that Transformer architectures specifically adapted for emotion-related tasks can improve the accuracy of emotion classification on social media text.

**Keywords:** emotion detection; multi-label classification; natural language processing; social media; Transformer

**Abstrak:** Deteksi emosi secara fine-grained pada teks media sosial merupakan salah satu tantangan dalam bidang pemrosesan bahasa alami (Natural Language Processing/NLP), terutama karena sifat data yang tidak terstruktur dan multi-label. Penelitian ini bertujuan untuk mengevaluasi performa tiga model berbasis arsitektur Transformer, yaitu EmoBERT, RoBERTa, dan EmoRoBERTa, dalam tugas klasifikasi emosi pada teks dari dataset SenWave. Dataset ini terdiri dari 10.001 tweet berbahasa Inggris yang telah dilabeli ke dalam sepuluh kategori emosi, namun penelitian ini berfokus pada empat label utama: anxious, annoyed, empathetic, dan sad. Proses penelitian meliputi prapemrosesan data, tokenisasi, pembagian data latih dan uji, pelatihan model, serta evaluasi menggunakan metrik akurasi, presisi, recall, dan f1-score. Hasil evaluasi menunjukkan bahwa model EmoBERT dan EmoRoBERTa memiliki performa terbaik dengan nilai f1-score sebesar 0,81, sedangkan RoBERTa memperoleh nilai f1-score sebesar 0,73. Temuan ini menunjukkan bahwa penyesuaian arsitektur Transformer khusus untuk emosi dapat meningkatkan akurasi klasifikasi emosi pada teks media sosial.

**Kata kunci:** deteksi-emosi;klasifikasi-multi label;media sosial;pemrosesan Bahasa alami;transformer

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## INTRODUCTION

Social media has become one of the main spaces for humans to interact and express feelings, habits, and motions openly in the digital era. One of the most popular social media platforms with hundreds of millions of monthly active users is "X"[1], [2], [3]. With each day generating quotes that reflect different forms of emotions, the app is rich in generating a large amount of rich data to perform *fine-grained emotion analysis*, as well as a rich platform for understanding emotions in digital communication[1], [2], [3].

It faces specific challenges that are complex and multidimensional. One of the biggest obstacles is the limitation of data that has been manually annotated or labeled. Until now, various machine learning and deep learning models have been developed and encouraged research to classify a person's emotions.

To overcome this problem, it is also necessary to use several emotional elements such as emojis, emoticons, acronyms, and hashtags (e.g., #happy #sad #angry #anxious) which are used in the remote supervision method approach as an alternative to giving emotional labels. Phenomena such as language mixing, variation and typos also need to be important aspects that need to be considered[4]. This allows for the training of models that are expected to be more effective and accurate in detecting emotions in fine-grained emotion detection in a platform environment that has language complexity[1], [3], [5].

In recent years, the development of several models such as BERT, EmoBERT, RoBERTa, EmoRoBERTa, and sharing variants has brought significant and successful impact in natural language processing[4], [6]. This includes tasks related to tasks that have to do with the analysis and detection of user emotions. Research such as "Detecting Fine-Grained Emotions on Social Media during Major Disease Outbreaks: Health and Well-being before and during the COVID-19 Pandemic" by Adugraba et al. (2023), discussing the development of EmoBERT. This study combines emotional knowledge in the BERT architecture to improve the accuracy of *fine-grained emotion detection*. EmoBERT has proven to be superior to common models such as BERT and XLNET in various categories of emotions, such as *anxious, sad, empathetic, annoyed,* and happy as well as several other emotion labels[4].

BERT and XLNET in various categories of emotions, such as *anxious, sad, empathetic, annoyed,* and happy as well as several other emotion labels[3], [5], [7]. However, until now there has still been little research that specifically utilizes emotion-based knowledge in *fi*ne-grained emotion detection. Since sentiment analysis is closely related to emotion detection, this means that it integrates emotional knowledge into other models that will result in better performance in emotion detection[8]. Therefore, this study will compare the performance of three models, namely EmoBERT, RoBERTa, and EmoRoBERTa, in detecting emotions in depth from social media texts, especially on the "X" platform.

## METHOD

The methodology in this study encompasses various steps previously undertaken by researchers, including planning, implementation, data processing, drawing conclusions, and disseminating research findings. This re-

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search follows several stages, which are illustrated in the following image:

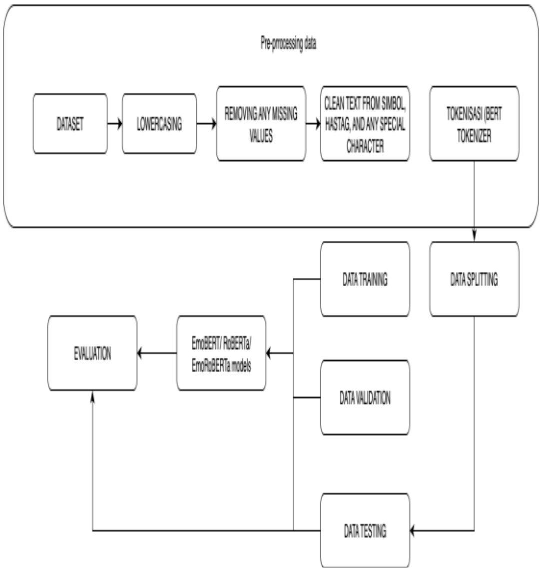


Image 1. Research Stages

## Dataset

The dataset used in this study comes from previous research and focuses on labeling posts that come from platform "X". Durham University's data consists of 10,001 English-language tweets published during the COVID-19 pandemic and has been *fine-grained* emotional labels into 10 categories, namely optimistic, thankful, empathetic, pessimistic, anxious, sad, annoyed, denial, official report, and joking[5].

Each entry in the dataset will represent one upload in the "X" platform that has been labeled or annotated for various categories of emotions. The main features available include IDs, Tweets, and Emotion labels represented in binary form (0 or 1), which indicate the presence and absence of certain emotions in each post. The Senwave dataset is publicly available and has been manually annotated. It's also multi-label, meaning a single upload can contain more than one type of emotion at a time. Designed to support fine-grained emotion detection tasks in social media[8], [9].

## Data Preprocessing

Data preprocessing is the most important stage for analyzing data and building models[4], [10]. In this study, the data used was in the form of a collection of tweets from the "X" platform. Several stages of pre-processing are carried out to improve the quality of the data. First, the text will be converted to lowercase to maintain consistency. Then the removal of elements that are not very important and relevant, such as URLs, hashtags, user mentions (@username), and symbols or other special elements, need to be removed.

To ensure consistency and eliminate ambiguity in the labeling and analysis phases, the emotion labels within this dataset will undergo standardization. Subsequently, the data was filtered to retain only those "X" quotes that featured at least one primary emotion, as defined by the study parameters. Given that a single upload might encompass multiple emotional categories, a multi-label classification methodology was employed. This filtering process enhances the data's specificity and relevance, thereby preparing it for the model training phase, with the expectation of facilitating more precise and contextually aware fine-grained emotion detection.

## Data Splitting

This stage will be used to divide a dataset into several subsets, generally into data that will be trained on validation data, and test data. The main goal is to ensure that the built model can generalize

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the data properly, thereby reducing the risk of overfitting[11], [12].

The models used in this study are based on the BERT architecture, namely EmoBERT, RoBERTa, and EmoBERT. In contrast to classical approaches such as LSTM or Bi-LSTM, which will read text sequentially, BERT utilizes a transformer architecture that allows the model to comprehensively understand the relationships between words in a sentence[6], [13], [14].

A number of studies have also shown superior performance in various natural language processing tasks. An example shown in this study is that BERT shows better results in demonstrating the effectiveness of transformer-based models in capturing contextual constraints. In the context of deep semantic understanding, the RoBERTa model has proven to be very effective in translation tasks and sentiment analysis, it allows the model to perform better contextual understanding as well as produce more accurate and coherent predictions[13], [15], [16].

In this study, the dataset was devided by three parts: 80% for training, 10% for validation and 10% for testing. This divition allows us to build the model and then evaluate how well it works on new unseen data. This data sharing is not done just once. The process was repeated several times using *the stratified sampling* technique with random *seed settings*, so that the distribution of data between the studied emotion labels remained balanced in each subset. The goal is to ensure that the model gets a proportionate learning experience of different types of emotions. With this approach, the resulting model is expected to be stronger, adaptive, and able to understand emotional expressions more deeply (*fine-grained*) in the context of communication on social media, especially on the "X" platform.

**Model Architecture and Fine- Tuning**

The model used in this study is based on the BERT (Bidirectional Encoder Represntations from Transformers) architecture which compares 3 transformer architectures for fine-grained emotion detection, namely EmoBERT, RoBERTa, and EmoRoBERTa. These three models are the ones that have proven to excel in a wide range of natural language processing tasks due to their ability to understand bidirectional contexts[17].

**EmoBERT**

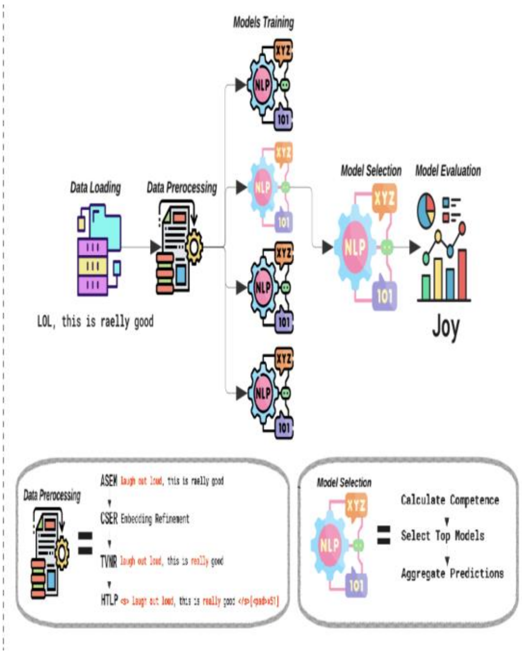


Image 2. EmoBERT Architecture

As a development of the BERT model, EmoBERT specifically *fine-tunes* in order to understand the emotional context contained in posts on the "X" platform. EmoBERT is trained using *emotion word masking strategies.* Where in this

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concept, words that contain emotional labels on tweets will be disguised so that the model is trained to guess the words[18], [19]. With this process, the training involves an AdamW optimizer (*learning rate 5e-5, batch size 8, 6 epoch)* From this study, it turns out that EmoBERT has a profound ability to identify emotional patterns, especially capturing feelings that are not explicitly conveyed or uploaded by the users[20], [21].

**RoBERTa**

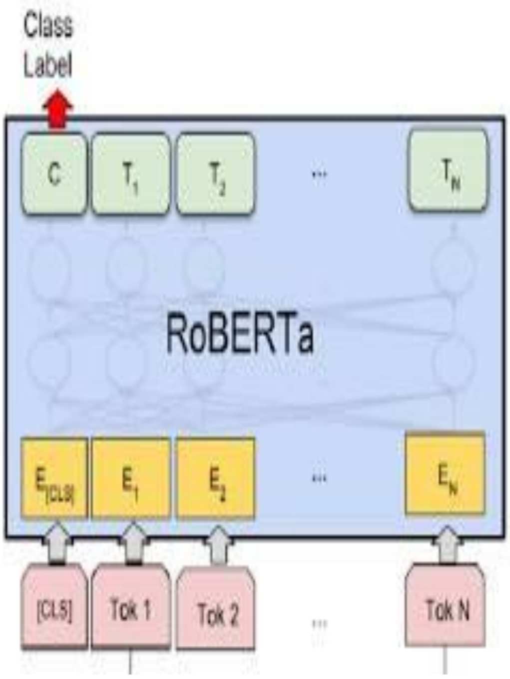


Image 3. RoBERTa Architecture

In this study, RoBERTA was chosen as a strong basic model to compare the accuracy of fine-grained detection results[19]. RoBERT is one of the optimizations of the BERT model, where it is trained with much more data and without *sentence prediction strategies* that make this model more focused on intra-text comprehension[22]. Faced with the problem of multilingual and multi-label classification on a single post, this model adapts and adds a linear classification layer to the sentence output (per token (CLS)). *Fine-tuning* at this stage will be optimized using *binary cross-entropy loss,* which is a logical approach to multi-label classification[23], [24].

**EmoRoBERTa**

This model combines an emotional approach with the power of the RoBERTa architecture in mind. EmoRoBERTa was built with the aim of understanding texts that imply multiple labels or multiple emotions at once. Architecture[25]. This model takes RoBERT's proprietary foundation and then takes an emotion-focused approach like EmoBERT does[22]. This model will use a special grouping layer and dropout regulatory mechanism to be more sensitive to emotions. The goal is for this model to be able to unravel the complexity of emotions contained in uploads on the "X" platform, which often cannot be represented by a single emotion label alone[14], [17], [23].

**RESULT AND DISCUSSION**

Each entry in this study includes one uploaded text along with a number of binary labels that indicate the existence of certain emotions, such as empathetic, sad, anxious, and annoyed. A single upload can also be worth more than one emotion, so this dataset is multi-label. In data processing, several adjustments are made to improve the consistency and relevance of the data to the purpose of analysis. Fields that are not used or irrelevant to the classification process such as the "ID" attribute are retained only as mark-

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ers, while the main information analyzed is focused on the text of the tweet itself. Emotion labels are also uniformly named so as not to cause confusion during the labeling and model training process. Then, the data was filtered to include only tweets that contained at least one of the four main emotions that the study focused on, namely *anxious*, *empathetic*, *sad*, and *annoyed*.

## Model Training Evaluation

The model used in this study is based on transformer architectures, namely EmoBERT**,** RoBERTa**,** and EmoRoBERTa, each of which has gone through a fine-tuning process of emotion data from tweets. Each model was trained using a multi-label classification technique, with the goal of detecting more than one emotion that might be contained in a single upload. During the training process, these models were tested in 15 epochs with a data share of 80% for training and 20% for validation, using a batch size of 8. To prevent overfitting, techniques such as dropouts were applied, and evaluations were carried out on separate test data.

The results of the evaluation showed that the EmoRoBERTa model had the best performance with a macro F1-score of 0.81, followed by EmoBERT with a score of 0.78, and RoBERTa with 0.73. These results show that the integration of emotional knowledge in transformer architectures significantly improves the model's accuracy and sensitivity in recognizing emotions, especially subtle emotins such as empathetic or anxious.

In this study, evaluation was carried out for each emotion label separately. Such as *anxious, empathetic, sad, annoyed,* and other emotional labels. Based on the evaluation results, the EmoRoBERTa model showed the most stable performance with the highest F1-score consistently on almost all emotion labels. Meanwhile, EmoBERT excels at more complex and contextual emotions such as *empathetic*, while RoBERTa tends to have average performance.

Table 1. EmoBERT Evaluation Table

| Emosi | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Annoyed | 0.81 | 0.81 | 0.82 | 0.81 |
| Anxious | 0.80 | 0.80 | 0.80 | 0.72 |
| Empathetic | 0.81 | 0.84 | 0.84 | 0.76 |
| Sad | 0.80 | 0.77 | 0.84 | 0.76 |

Table 2. RoBERTa Evaluation Table

| Emosi | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Annoyed | 0.79 | 0.78 | 0.71 | 0.77 |
| Anxious | 0.70 | 0.72 | 0.72 | 0.77 |
| Empathetic | 0.78 | 0.71 | 0.75 | 0.77 |
| Sad | 0.78 | 0.71 | 0.81 | 0.77 |

Table 3. EmoRoBERTa Evaluation Table

| Emosi | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Annoyed | 0.79 | 0.81 | 0.82 | 0.81 |
| Anxious | 0.79 | 0.72 | 0.73 | 0.72 |
| Empathetic | 0.79 | 0.84 | 0.79 | 0.81 |
| Sad | 0.79 | 0.71 | 0.84 | 0.76 |

**Final Evaluation Results**

Table 4. Overall models Evaluation Table

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| EmoRoBERT | 0.81 | 0.77 | 0.82 | 0.81 |
| RoB-ERTa | 0.77 | 0.74 | 0.72 | 0.73 |
| EmoRoBERTa | 0.79 | 0.82 | 0.81 | 0.81 |

## CONCLUSION

This study was conducted to see how well the transformer-based models EmoBERT, RoBERTa, and EmoRoB-ERTa are in understanding and detecting fine-grained emotions from user uploads on the "X" social media platform. Using a dataset of 10,001 "X" quotes that had been annotated in a multi-label manner, each model was trained and tested to recognize emotions such as *sad*, *empathetic*, *anxious*, and *annoyed*. The results of the evaluation showed that EmoRoBERTa recorded the highest performance with an F1-score of 0.81 and an accuracy of 0.79, making it the most reliable model in recognizing emotions precisely and consistently. EmoBERT ranks second with an F1-score of 0.78 and an accuracy of about 0.775, excelling especially in subtle emotions such as *empathetic* and *sad*. Meanwhile, RoBERTa recorded an F1-score of 0.73**,** indicating good but suboptimal performance in capturing complex emotional nuances.

From these findings, it can be concluded that adding emotional understanding into the model architecture actually helps the model in understanding the increasingly complex context of human communication on social media. An approach like this has great potential not only for emotion detection, but also to support other applications such as mental health analysis, content moderation, and the study of user behavior more broadly.

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