Multi-Label Emotion Detection Using BERT, T5 Transformers, and *(mBERT).*

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*Abstract*—Emotion detection is a vital area of natural language processing (NLP), with applications in sentiment analysis, mental health monitoring, and human-computer interaction. This paper presents two multi-label emotion detection models: one based on the BERT Transformer architecture and another using the T5 Transformer. Both models predict the presence of five emotions—Anger, Fear, Joy, Sadness, and Surprise—in textual data. The study involves preprocessing, fine-tuning of pre-trained models, and dataset balancing. We evaluate both models using macro-average and micro-average F1 scores, highlighting their capability to detect multiple emotions within a single text input. The results show the strengths and challenges of each model in real-world emotion detection tasks. Keywords—Emotion detection, BERT, T5 Transformer, multi-label classification, NLP, fine-tuning, F1 score, LLaMA 3B, emotion intensity detection, multi-label classification, few-shot learning, quantization.

# Introduction

*Emotion detection from text is an important task in NLP, as it enables machines to understand and respond to human emotional expressions. This task is particularly challenging due to the overlapping and context-dependent nature of emotions. Unlike single-label classification, multi-label emotion detection models can identify multiple emotions simultaneously, which often co-occur in real-world texts. Use the enter key to start a new paragraph. The appropriate spacing and indent are automatically applied. In this paper, we explore two Transformer-based architectures, BERT and T5, to address the problem of multi-label emotion detection. We describe the preprocessing pipeline, dataset balancing, and the fine-tuning process for both models. Additionally, we evaluate the models using F1 scores to assess their performance in detecting the presence of multiple emotions in textual data.*

### II. Dataset and Preprocessing

### 2.1 Dataset

### The dataset used consists of textual data annotated with binary labels indicating the presence (1) or absence (0) of five emotions: Anger, Fear, Joy, Sadness, and Surprise. The dataset includes both training and development datasets, each with text samples labeled for each emotion.

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### 2.2 Preprocessing

### Text Cleaning: Conversion to lowercase, removal of special characters, URLs, and extra spaces.

### Handling Missing Values: Rows with missing emotion labels were replaced with zeros.

### Normalizing Labels: Emotions were encoded as binary values (0 or 1) for multi-label classification.

### Text Normalization: A custom function was implemented to ensure uniformity across text inputs, preparing them for tokenization.

*Case Normalization: Converted all text to lowercase.*

*Feature Engineering: Applied keyword extraction or other feature transformations, if any.*

*2.3 Dataset Balancing*

*To address class imbalance, we used the resample method from Scikit-learn to oversample minority classes, ensuring that all emotions were equally represented in the training dataset.*

* III Model Architecture

*3.1 BERT Transformer*

*BERT (Bidirectional Encoder Representations from Transformers) is a pre-trained model optimized for NLP tasks. We fine-tuned the BERT base uncased model to predict the presence of five emotions in text. A custom classification head was added to map the BERT hidden states to emotion labels, allowing multi-label predictions.*

*3.2 T5 Transformer*

*T5 (Text-to-Text Transfer Transformer) is a versatile model designed to perform various text-based tasks. We fine-tuned the Google Flan-T5 base model for multi-label emotion detection. The input text was prefixed with "predict emotions:" to guide the model's learning process. The tokenized inputs were padded and truncated to fixed lengths for consistency across samples.*

* 1. *Tokenization and Input Representation*

*For both models, tokenization was done using the respective model-specific tokenizers (BERT tokenizer and T5 tokenizer). Input sequences were padded and truncated to ensure a consistent length of 128 tokens. For T5, the emotion labels were combined into a string format, aligning with the text-to-text paradigm.*

*3.4 LLaMA 3B*

*LLaMA 3B is a generative model optimized for few-shot learning. While it excels in text generation tasks, its performance on structured classification tasks has been less explored. LLaMA's architecture requires significant computational resources, and its effectiveness in tasks like emotion intensity detection may be limited by its generative nature*

* 1. *mBERT and Translation Techniques*

*Multilingual BERT (mBERT) to perform cross-lingual emotion detection. By utilizing pre-trained models and language translation techniques, the system aims to predict emotion labels across languages effectively. The detected emotions include anger, fear, joy, sadness, and surprise.*

*3.6 Model Training: Multilingual BERT*

*The bert-base-multilingual-cased model was selected as the base for fine-tuning. This model is pre-trained on multiple languages and is designed to handle cross-lingual tasks.*

### IV. Experimental Setup

*4.1 Training Configuration*

*We fine-tuned both models using the HuggingFace Trainer API with the following parameters:*

*BERT Model:*

*Learning rate: 1e-4*

*Batch size: 32*

*Epochs: 10*

*Optimizer: AdamW*

*Loss Function: Binary cross-entropy for multi-label classification*

*T5 Model:*

*Learning rate: 5e-5*

*Batch size: 8*

*Epochs: 5*

*Optimizer: AdamW*

*Weight decay: 0.01*

*4.2 multilingual BERT (mBERT)*

*Fine-tuning was performed over 3 epochs with the following parameters:*

*Learning rate: 2e-5*

*Batch size: 16*

*Weight decay: 0.01*

##### *4.3 Evaluation Metrics*

##### *We used macro-average and micro-average F1 scores to evaluate the performance of both models. These metrics are suitable for multi-label classification tasks, as they account for class imbalance by averaging the F1 scores across all labels.*

### V. Results and Discussion

*5.1 Quantitative Results*

*The models were evaluated on a held-out test dataset.*

*The F1 scores for the models are as follows:*

*BERT Model:*

*Validation F1 Score: [0.7149425287356321]*

*Micro-Average F1 Score (micro): [0.7149425287356321]*

*T5 Model:*

*Weighted F1 Score: [0.7481661533650893]*

*Micro-Average F1 Score: [0.7554479418886199]*

*(mBERT):*

*Macro-average F1 score: 0.6628*

*Class-wise performance (Precision, Recall, F1):*

*Anger: Precision = 1.00, Recall = 0.098, F1 = 0.179*

*Fear: Precision = 0.828, Recall = 0.908, F1 = 0.866*

*Joy: Precision = 0.821, Recall = 0.754, F1 = 0.786*

*Sadness: Precision = 0.711, Recall = 0.719, F1 = 0.715*

*Surprise: Precision = 0.912, Recall = 0.663, F1 = 0.768*

*Emotion Intensity Detection:*

*BERT achieved an F1 score of 0.7*

*LLaMA 3B recorded an F1 score of 0.3*

*5.2 Visualization*

*We visualized the F1 scores using bar charts for both models, highlighting their performance across the five emotion labels.*

*5.3 Qualitative Analysis*

*Both models were able to effectively capture multiple emotions in complex sentences. For example, the sentence "The sudden success left me feeling thrilled but also a bit anxious" was correctly classified as having Joy and Fear. However, misclassifications were observed, especially in cases of overlapping emotions like Joy and Surprise.*

*5.4 Comparative Analysis*

*When compared to single-label emotion models, both BERT and T5 demonstrated superior performance in identifying multiple emotions. The T5 model, in particular, showed promise in handling more complex, text-to-text interactions, while BERT was efficient in capturing the contextual relationships between emotions in the text.*

*VI. Conclusion and Future Work*

*This study demonstrates the effectiveness of both BERT and T5 transformers for multi-label emotion detection. While both models showed promising results, future work could involve:*

*Expanding the Dataset: Incorporating a more diverse range of emotional states.*

*Exploring Alternative Architectures: Investigating other Transformer models, such as GPT-3 or DeBERTa, for multi-label emotion detection.*

*Integrating Contextual Information: Using external contextual features, such as speaker intent or dialogue history, to improve model performance in complex scenarios.*

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