

# Emotion Detection — Deep Learning & NLP Based Project

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## 1. Executive Summary

This project is based on the Kaggle competition where the task was to detect emotions from text. Each sentence could contain one or more of the following emotions: anger, fear, joy, sadness, and surprise, so it was a multi-label text classification problem.

I implemented and compared three different models:

1. TF-IDF + Logistic Regression (scratch baseline)
2. Fine-tuned RoBERTa Transformer
3. DistilBERT multilabel classifier with custom training loop

All training experiments were tracked using Weights & Biases (W&B).

Among all models, RoBERTa performed the best, with the highest macro F1, micro F1 and accuracy.

## 2. Introduction

In this challenge, the goal was to automatically identify emotional meaning from a text post. The dataset contained a “text” column and five separate binary columns, one for each emotion.

Problem Statement

Given a sentence, predict which of the five emotions are present.

Objectives of the Project

- Understand and compare traditional ML and transformer-based NLP methods
- Use different tokenization strategies and loss functions
- Improve model performance through fine-tuning techniques
- Track and compare all experiments using W&B visualizations

The report is organized in the order: dataset → preprocessing → modelling → results → conclusion.

## 3. Dataset & Preprocessing

The dataset provided on Kaggle had the following columns:

| Column | Description    |
|--------|----------------|
| text   | Input sentence |

anger, fear, joy, sadness, surprise Binary emotion labels

Total rows: (6827,8)

## Observations from EDA ([Notebook Link](#))

- Dataset has ~6.8k samples with 5 emotion labels.
- Imbalanced dataset — fear is most frequent, anger is least frequent.
- Multi-label nature — many texts contain 2 or more emotions together.
- Most common co-occurrences: fear + sadness and fear + surprise.
- Average text length: ~15–16 words (256 token limit is enough).
- Texts with multiple emotions usually describe stressful or negative events.

## Preprocessing Steps Applied

| Step                      | Status               |
|---------------------------|----------------------|
| Remove missing text rows  | yes                  |
| Convert labels to integer | yes                  |
| Tokenization              | Per model            |
| Max token length          | 256 for transformers |

I did not apply aggressive text cleaning because transformer models usually perform better with raw text.

## 4. Tokenization Strategy

| Model                        | Tokenizer                |
|------------------------------|--------------------------|
| TF-IDF + Logistic Regression | Bag-of-Words / TF-IDF    |
| RoBERTa                      | Byte-Pair Encoding (BPE) |
| DistilBERT                   | WordPiece                |

BERT-family tokenizers break text into sub-words which helps handle spelling variations and unseen words.

TF-IDF captured frequency information but couldn't understand the meaning of the text, while transformer models could understand context.

## 5. Modelling & Experimentation

### 5.1 Model-1 — TF-IDF + Logistic Regression (Scratch Model) [[Notebook Link](#)] [[W&B](#)]

- Convert text to TF-IDF matrix
- Train 5 binary logistic regression models (one per emotion)

- Convert probability to label using a threshold
- Fast and lightweight but low performance because it doesn't understand semantics

## 5.2 Model-2 — Fine-Tuned RoBERTa (Best Model)[\[Notebook link\]](#) [\[W&B\]](#)

- Used roberta-base model from HuggingFace
- Added a linear classification head on top
- Loss: BCEWithLogitsLoss
- Used scheduler, warm-up and gradient clipping
- RoBERTa could understand context and long-range relationships, so it performed the best

## 5.3 Model-3 — DistilBERT Multi-Label Model[\[Notebook link\]](#) [\[W&B\]](#)

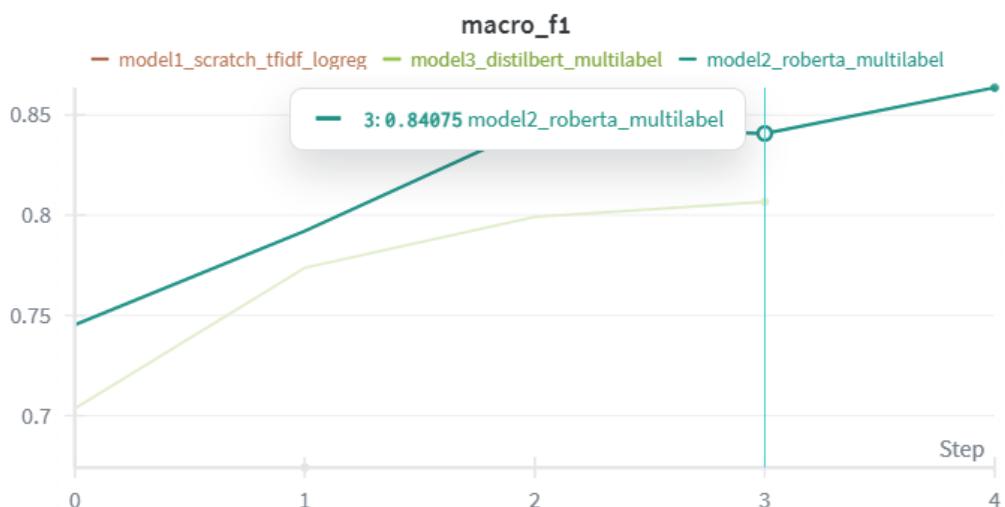
- DistilBERT backbone + Dropout + Linear classifier
- Full manual training loop (optimizer + scheduler + early stopping)
- Handled class imbalance using pos\_weight
- Good model, slightly faster than RoBERTa, but accuracy was a bit lower

## 6. Performance & Comparative Analysis

Metrics used

- Macro F1 (primary)
- Micro F1
- Accuracy
- (ROC-AUC also tested for DistilBERT)

## Final Results



| Model                        | Macro-F1 | Micro-F1 | Accuracy | Notes                                     |
|------------------------------|----------|----------|----------|---|
| TF-IDF + Logistic Regression | 0.67     | 0.75     | 0.53     | Scratch baseline                          |
| DistilBERT                   | 0.80     | 0.82     | 0.59     | Good trade-off between speed and accuracy |
| RoBERTa (Best)               | 0.86     | 0.87     | 0.71     | Final submission model                    |

## W&B Insights

- For the **TF-IDF + Logistic Regression** model, the graphs in W&B were almost flat. This means the model could not learn much and its accuracy and macro-F1 did not improve.
- For both **DistilBERT** and **RoBERTa**, the W&B curves showed clear improvement. The macro-F1 and micro-F1 kept increasing, and the validation loss went down and then became stable. This shows that training was going smoothly.
- When comparing models, **RoBERTa performed better than DistilBERT** on all main metrics like macro-F1, micro-F1, and accuracy.
- The W&B comparison also showed that **RoBERTa did not overfit too much**. The training and validation curves were close, which means the model learned properly without memorizing the data.

## Inference Pipeline

For inference, the final RoBERTa model was loaded using PyTorch. The test dataset was tokenized using the same tokenizer settings (max\_length=256, truncation=True).

The model outputs logits, which were passed through sigmoid functions and then converted to binary predictions using a threshold of 0.5. The final output was saved as submission.csv for Kaggle upload.

## 7. Conclusion & Future Work

### Key Learnings

- Transformers perform much better than classical ML for NLP tasks
- Tokenization choice has a huge impact on model performance
- Scheduler + gradient clipping + early stopping improved training stability
- W&B helped a lot in visually comparing model performance

### Challenges Faced

- Limited GPU time restricted experimentation
- Debugging tokenization and tensor shape mismatches took time
- Scratch model was hard to tune for multilabel settings

## Future Improvements

- I can try using an **ensemble** of RoBERTa and DistilBERT to see if combining both models gives better results.
- I want to experiment with **bigger models** like DeBERTa or Longformer, which may understand text even better.
- I can run **hyperparameter tuning** (like learning rate finder or W&B sweeps) to get better training settings.
- I can also try adding **more training data** or using **data augmentation** to help the model learn more patterns.

## 8. Environment and Dependencies

- The models were trained on Google Colab T4 GPU.
- Libraries used: torch, transformers, scikit-learn, pandas, numpy, datasets, wandb.
- The exact versions are listed in requirements.txt stored in the GitHub repository.

## 9. Model Deployment

The final RoBERTa emotion-detection model was deployed on **Hugging Face Spaces** using a simple Gradio UI.

**Live Demo:** <https://huggingface.co/spaces/Ashish4129/roberta-emotion-detection-demo>

### Benefits of Deployment

- Shows practical real-world usability.
- Provides an instant prediction interface.
- Confirms model performance outside training.
- Completes the pipeline from training to deployment.

## 10. References

- Vaswani et al., “Attention Is All You Need”, 2017
- Liu et al., “RoBERTa: A Robustly Optimized BERT Pretraining Approach”, 2019
- Sanh et al., “DistilBERT: Smaller, faster, cheaper and lighter BERT”, 2019
- Hugging Face Transformers Documentation
- Kaggle Competition Dataset – official data source for this project.
- YouTube (general ML/NLP learning resources):
  - StatQuest – for easy explanations of ML concepts.
  - Hugging Face YouTube Channel – for tutorials on Transformers and tokenization.
  - Simplilearn / CodeEmporium – for basic NLP and deep learning explanations.