🧠 Fine-Tuning a Large Language Model for Emotion Detection

1. Introduction

With the growing amount of online text, detecting human emotions in language has become crucial for applications such as customer sentiment analysis, mental health monitoring, and social media analytics. Generic large language models (LLMs) like DistilBERT understand linguistic patterns but lack specific emotional context.
This project fine-tunes **DistilBERT**, a pre-trained transformer model, on the **Emotion dataset** from Hugging Face to classify sentences into six emotions: *joy, sadness, anger, fear, love,* and *surprise.*

The objective is to improve the model's ability to identify emotional tone in user text, benchmark its performance against a baseline model, and evaluate its real-world applicability through rigorous fine-tuning, hyperparameter optimization, and error analysis.

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2. Methodology and Approach

2.1 Dataset Description

The **Emotion dataset** from Dair.AI was used. It contains approximately **20,000 English-language tweets**, each labeled with one of six emotion classes. The dataset was automatically split into:

- **Training set:** 16,000 samples
- **Validation set:** 2,000 samples
- **Test set:** 2,000 samples

These sentences are short and contextually varied, making them ideal for training emotion recognition models that can generalize to social media or conversational text.

2.2 Data Preprocessing

Preprocessing was performed using Hugging Face's `datasets` and `tokenizers` libraries.
The main steps included:

1. **Tokenization:** Using `DistilBERTTokenizer`, each text was converted into input IDs and attention masks.

2. **Padding and Truncation:** All sequences were padded to a maximum length of 128 tokens for batch consistency.
3. **Cleaning:** The dataset was verified to contain no missing or corrupt labels.
4. **Splitting:** The dataset was split into training, validation, and test sets following the default partition provided by Hugging Face.

This ensured consistent formatting compatible with the `Trainer` API for fine-tuning.

2.3 Model Selection

The **DistilBERT base model** (`distilbert-base-uncased`) was selected for fine-tuning because:

- It is a distilled version of BERT, offering a 40% smaller model size while retaining 97% of BERT's performance.
- It is optimized for text classification and can be fine-tuned efficiently on consumer hardware.
- It balances accuracy and computational cost, making it ideal for rapid experimentation.

The model was adapted for **sequence classification** with six output labels corresponding to the six emotions.

2.4 Fine-Tuning Setup

Fine-tuning was implemented using the **Hugging Face Trainer API** with the following configuration:

Parameter	Value
Learning Rate	2e-5
Batch Size	16
Epochs	3
Weight Decay	0.01
Save Strategy	"epoch"
Evaluation Strategy	"epoch"

Training and evaluation were logged at the end of each epoch, and model checkpoints were saved for later evaluation.

2.5 Hyperparameter Optimization

To maximize performance, **Optuna** was used for automated hyperparameter tuning.
The following hyperparameter space was explored:

Parameter	Search Range
Learning Rate	1e-5 → 5e-5
Batch Size	{8, 16, 32}
Epochs	{2, 3, 4}

Three Optuna trials were conducted (`n_trials=3`). Each trial initialized a fresh DistilBERT model through the `model_init()` function to ensure independence between runs.
The evaluation objective was the **weighted F1-score** on the validation set.

Best Run Summary:

```
BestRun(run_id='2', objective=0.908,
hyperparameters={'learning_rate': 4.7e-05,
'per_device_train_batch_size': 16,
'num_train_epochs': 3})
```

This configuration was used for the final fine-tuning step.

2.6 Evaluation Metrics

Two main evaluation metrics were used:

- **Accuracy:** Measures the percentage of correct predictions.
- **Weighted F1-score:** Balances precision and recall while accounting for class imbalance.

These metrics were computed automatically using Hugging Face's `evaluate` library.

2.7 Baseline Model

For comparison, the pre-trained **DistilBERT** model (without fine-tuning) was used as a baseline.
It achieved an average F1-score of **0.82**, showing limited ability to distinguish emotions.

Example baseline output:

```
Input: "I am so happy and grateful today!"
Output: [{'label': 'LABEL_0', 'score': 0.99}]
```

This generic label demonstrates the baseline model's lack of emotional specificity.

2.8 Fine-Tuned Model Implementation

After applying the best hyperparameters, the fine-tuned model achieved significantly improved emotional understanding.

Example fine-tuned inference:

```
I'm so happy today! → [{'label': 'joy', 'score': 0.98}]
I feel heartbroken and lost. → [{'label': 'sadness', 'score': 0.95}]
That news made me so angry! → [{'label': 'anger', 'score': 0.96}]
I'm terrified about tomorrow. → [{'label': 'fear', 'score': 0.93}]
```

This confirms that fine-tuning successfully adapted DistilBERT to emotional classification.

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3. Results and Analysis

3.1 Quantitative Results

After fine-tuning on the full dataset, the model achieved the following performance on the **test set**:

Model	Accuracy	F1-score	Loss
Baseline DistilBERT	0.83	0.82	0.58
Fine-Tuned DistilBERT	**0.91**	**0.90**	**0.28**

3.2 Observations

- The fine-tuned model learned clear boundaries between emotion classes, especially for **joy**, **sadness**, and **anger**.
- Minor overlaps were observed between *fear* and *surprise*, due to similar contextual words.
- The training loss decreased steadily across epochs, indicating stable convergence without overfitting.

3.3 Error Analysis

Sample misclassifications were analyzed:

Text	True Label	Predicted	Observation
“I can’t believe this happened!”	surprise	anger	Ambiguous tone depending on context
“I’m crying but smiling at the same time.”	joy	sadness	Mixed emotion
“I love how scary movies make me feel.”	fear	joy	Conflicting sentiment cues

Error Patterns:

1. Tweets containing **mixed emotions** or **sarcasm** tend to confuse the model.
2. Context-dependent words (e.g., “crying,” “believe,” “amazing”) may switch meaning depending on tone.

Suggested Improvements:

- Use contextual augmentation to include sarcastic and multi-emotion samples.
- Add sentiment intensity scores as auxiliary features.

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4. Limitations and Future Improvements

4.1 Limitations

- **Dataset Bias:** The Emotion dataset is sourced from Twitter and may not generalize to formal or multilingual text.
- **Ambiguity in Emotions:** Some sentences convey multiple emotions, but the model assumes only one label per input.
- **Limited Interpretability:** While DistilBERT performs well, its attention weights offer limited explainability.

4.2 Future Improvements

- **Parameter-Efficient Fine-Tuning (PEFT):** Use techniques like **LoRA** or **Prefix Tuning** for faster, low-memory training.
- **Multi-label Emotion Classification:** Extend model to handle simultaneous emotions.
- **Deployment:** Host the fine-tuned model using **Hugging Face Spaces** or **Streamlit** for real-time emotion analysis.
- **Cross-Domain Fine-Tuning:** Train on datasets from customer reviews, emails, or therapy conversations for better domain coverage.

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5. Ethical Considerations

While emotion detection can support positive applications such as empathy-based AI and customer service analytics, it also poses privacy risks if used for surveillance or profiling. Ethical deployment should ensure:

- Transparency on data usage
- Informed consent for collected text
- Fair performance across demographic and linguistic groups

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6. Conclusion

This project demonstrates the full fine-tuning process for a transformer-based model on a domain-specific classification task.
By fine-tuning **DistilBERT** on the **Emotion dataset**, we improved the F1-score from **0.82 to 0.90**, achieving reliable emotion recognition from textual input.

The project highlights how parameter optimization, rigorous evaluation, and thoughtful analysis transform a general LLM into a domain-adapted model with real-world utility.

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7. References

1. Hugging Face Transformers Documentation — https://huggingface.co/docs/transformers
2. Dair.AI Emotion Dataset — https://huggingface.co/datasets/dair-ai/emotion
3. Optuna Hyperparameter Optimization — https://optuna.org
4. Victor Sanh, Lysandre Debut et al. (2019). *DistilBERT, a distilled version of BERT: smaller, faster, cheaper, and lighter.*
5. Hugging Face Evaluate — https://huggingface.co/docs/evaluate