SemEval 2025-Task 11: Bridging the Gap in Text-Based Emotion Detection

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https://github.com/emotion-analysis-project/SemEval2025-Task11

Motivation

- **Human communication**
  is deeply emotional

- **Multilingual and cultural challenges**
  Emotional expression varies across **languages, cultures,** and **contexts** (perceived subjectively).

- **Our task**
  Text-based emotion detection across cultures and language

SemEval 2025 Task 11: Text-Based Emotion Detection

Focuses on **perceived emotions**

Predict… *what emotion most people will think the speaker may be feeling, given a sentence or a short text snippet uttered by the speaker.*

Task Setup

- **Track A (Multi-label Emotion Detection)**
  Classes: *joy, sadness, fear, anger, surprise, and disgust*

- **Track B (Emotion Intensity Detection)**
  Classes: 0, 1, 2, or 3

- **Track C (Cross-lingual Emotion Detection)**
  Classes: *joy, sadness, fear, anger, surprise, and disgust*

Evaluation Metrics

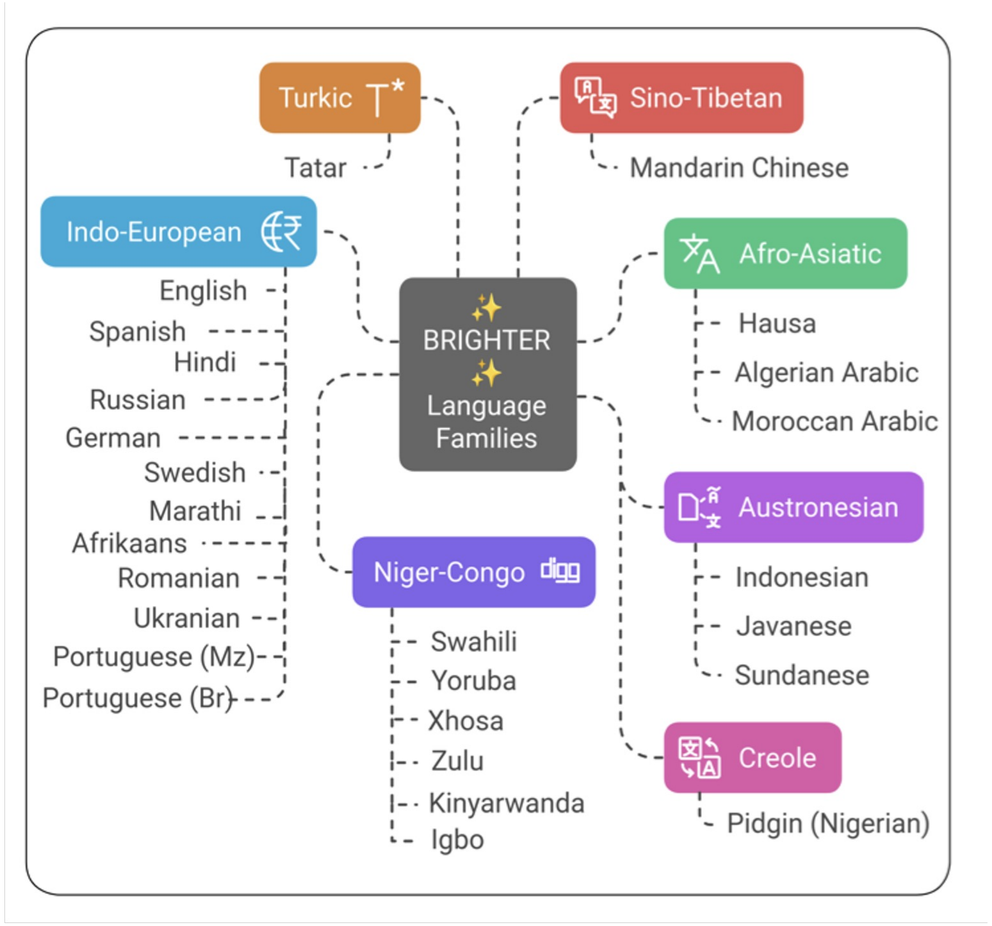
1. Average macro F1 score
2. Pearson correlation coefficient

Baseline

1. Majority class
2. Fine-tuned RoBERTa

Languages

32



Dataset Example

32

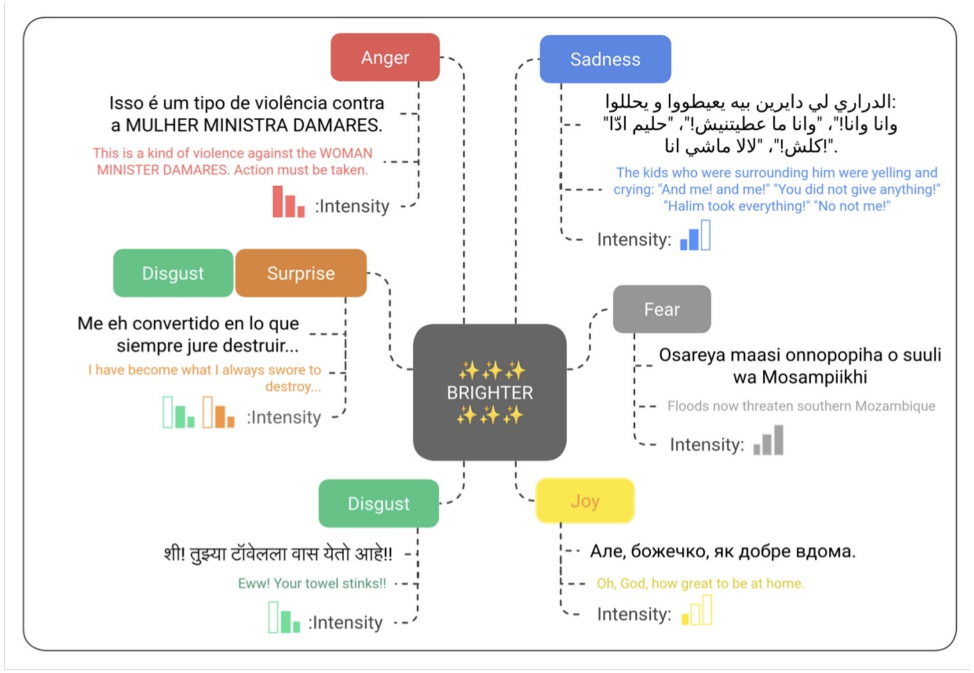
Emotion labels

Anger, Disgust, Sadness,
Joy, Fear, Surprise, Neutral

12

Emotion intensity

0 → no emotion
1 → low intensity
2 → moderate intensity
3 → high intensity



BRIGHTER: BRIdging the Gap in Human-Annotated Textual Emotion Recognition Datasets for 28 Languages
Evaluating the Capabilities of Large Language Models for Multi-label Emotion Understanding

Dataset Quality

Inter-Annotator **Agreement** (IAA) vs Annotation **Reliability**

- Split-Half Class Match Percentage (SHCMP)

  ↳ extends the concept **of Split-Half Reliability** (SHR), traditionally used for continuous scores to discrete categories (i.e., intensity scores).

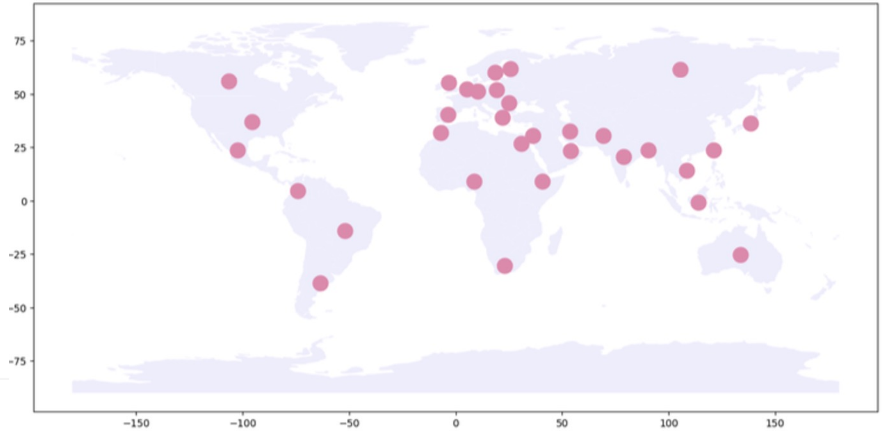
- SHMP scores vary from **60%** to more than **90%**, indicating that our datasets are of high quality.

WorryWords: Norms of Anxiety Association for over 44k English Words (Mohammad, EMNLP 2024)

Tasks Summary

Our task was the most popular
competition on Codabench in 2024

Codabench Newsletter 2024



700+
Registered Participants

362
Submitted system during evaluation phase

93
Submitted system description paper

220
Task A: Multi-label Emotion Detection

96
Task B: Emotion Intensity Detection

46
Task C: Cross-lingual Emotion Detection

Top Systems

	Team	# Languages
Task A Multi-Label Emotion Detection	**Pi** Ping An Life Insurance Company of China	20 out of 28 languages
Task B Emotion Intensity Detection	**Pi** Ping An Life Insurance Company of China	10 out of 11 languages
Task C Cross-lingual Emotion Detection	**DeepWave** Tomorrow Advancing Life (China)	25 out of 32 languages

Best System (Tracks A and B)

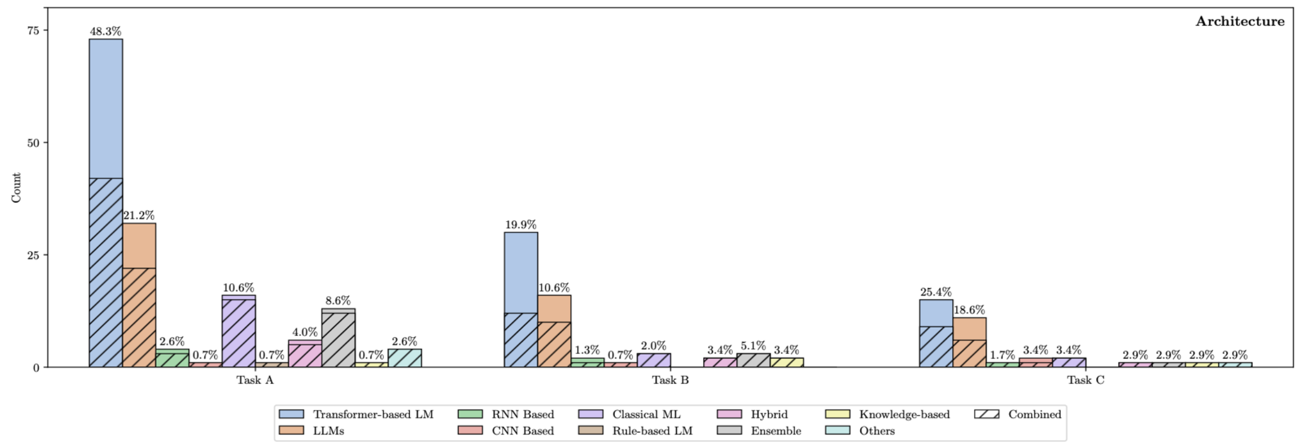
Track A & B

PAI at SemEval-2025 Task 11: A Large Language Model Ensemble Strategy for Text-Based Emotion Detection

Ping An Life Insurance Company of China

Approach

*CSECU-Learners ranked at the top in **Amharic** by fine-tuning language-specific transformers for Amharic with a classification layer and multi-sample dropout.*



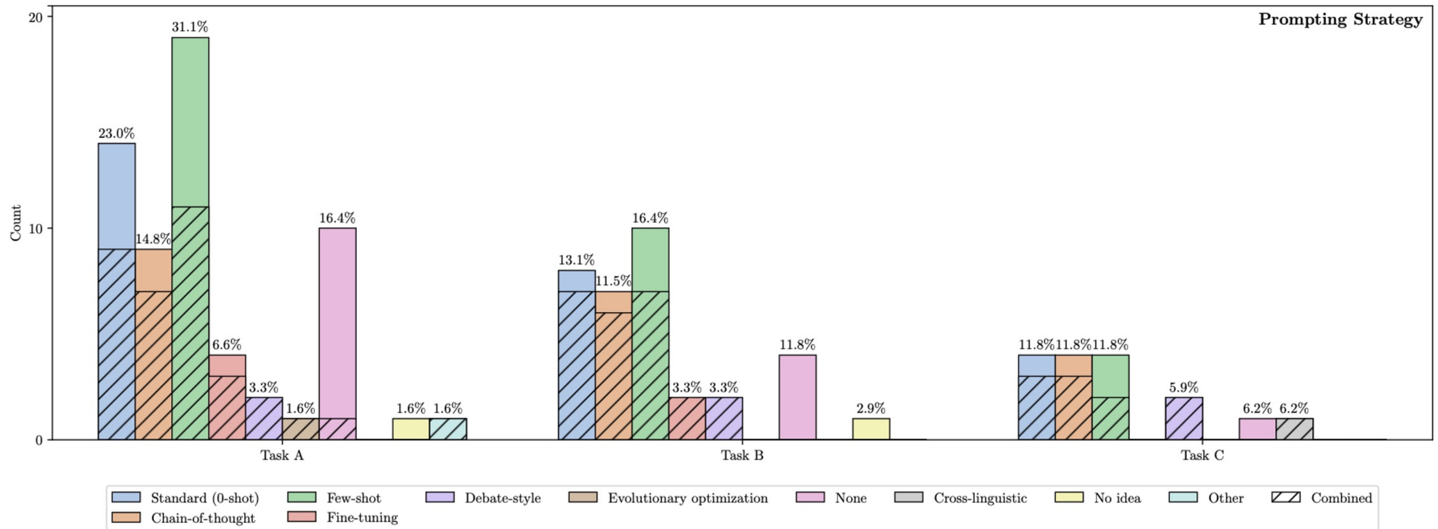
Best System (Track C)

Track C

PAI at SemEval-2025 Task 11: A Large Language Model Ensemble Strategy for Text-Based Emotion Detection

Ping An Life Insurance Company of China

- *Supervised fine-tuning (SFT) Google Gemma 2 large language model*
- *data augmentation, Chain-of-Thought (CoT) prompting, and model ensembling techniques.*



Takeaways: Popular Methods

- Most top-performing teams favored fine-tuning and prompting **LLMs**
- **Full fine-tuning** and **parameter-efficient fine-tuning** were the most commonly used strategies to enhance performance
- For prompting, **few-shot**, **zero-shot**, and **chain-of-thought** prompting were the most frequently used techniques.
- Traditional transformer-based models, particularly **XLM-RoBERTa**, **mBERT**, **DeBERTa**

Takeaways: Best Performing Systems

- **LLMs** achieve strong overall performance; however, their effectiveness is heavily dependent on **prompt engineering** techniques and **wording**.
- Performance varies significantly by language.
    - Better in **high-resource languages** such as English and Russian
    - Dropped on low-resource languages such as **Swahili** and **Emakhuwa**
- Most teams did not incorporate **additional datasets** to enhance performance, as **few-shot** and **zero-shot** approaches proved highly effective.

SemEval 2025 Task 11: Text-Based Emotion Detection

Thanks to all participants

Thanks to the SemEval Chairs

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