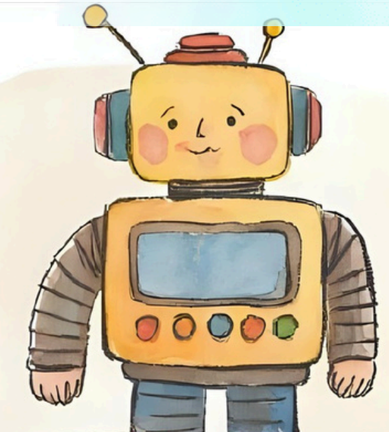
MKSSS's Cummins College of Engineering for Women, Pune

Department of Computer Engineering

TY Div-B, AIML – AY 2025-26

Emotion Detection and Mood Analysis through Conversational AI



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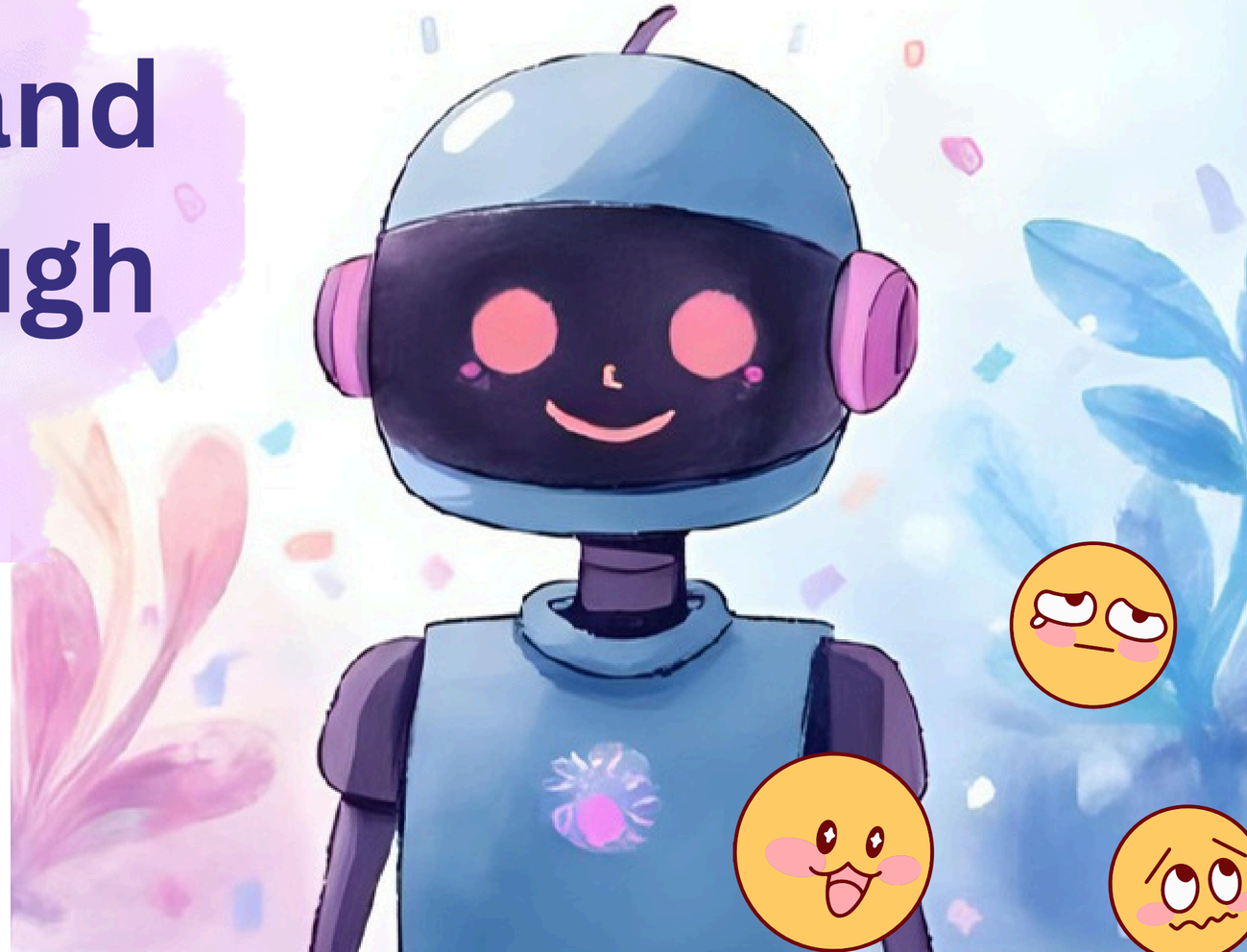
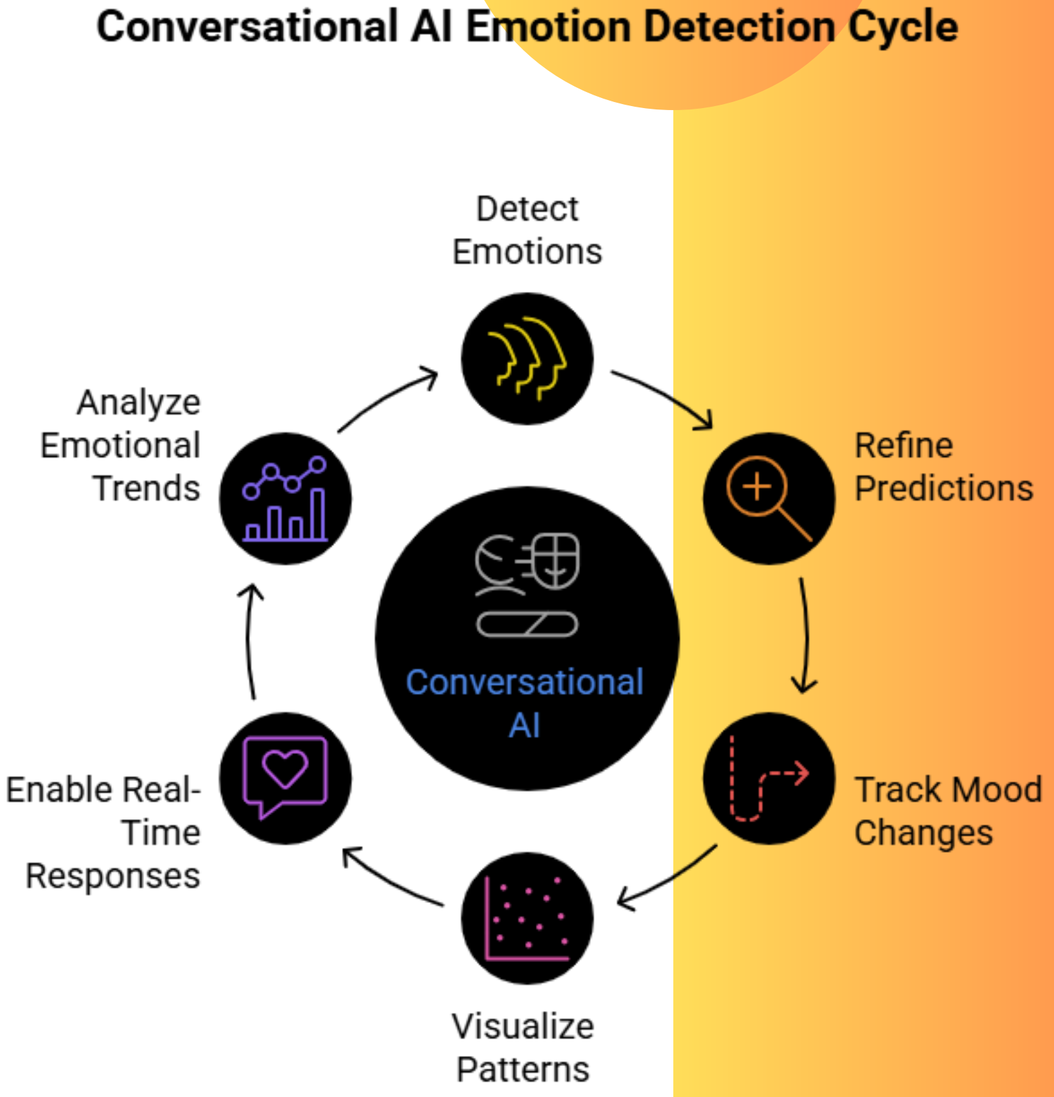


Abstract

- Conversational AI is now expected to **understand user emotions**, not just respond to text.
- Our project builds a **chatbot** that **detects emotions** (anger, joy, sadness, fear, disgust, neutral, surprise) using DistilRoBERTa.
- Sentiment checks and rule-based refinement **improve prediction accuracy**.
- The system tracks mood changes using a **transition matrix** and **visualizes patterns** using **K-Means clustering + PCA**.
- A **Flask backend** and **web UI** enable real-time responses and empathetic interaction.
- The system helps analyze emotional trends and supports more natural human–computer communication.

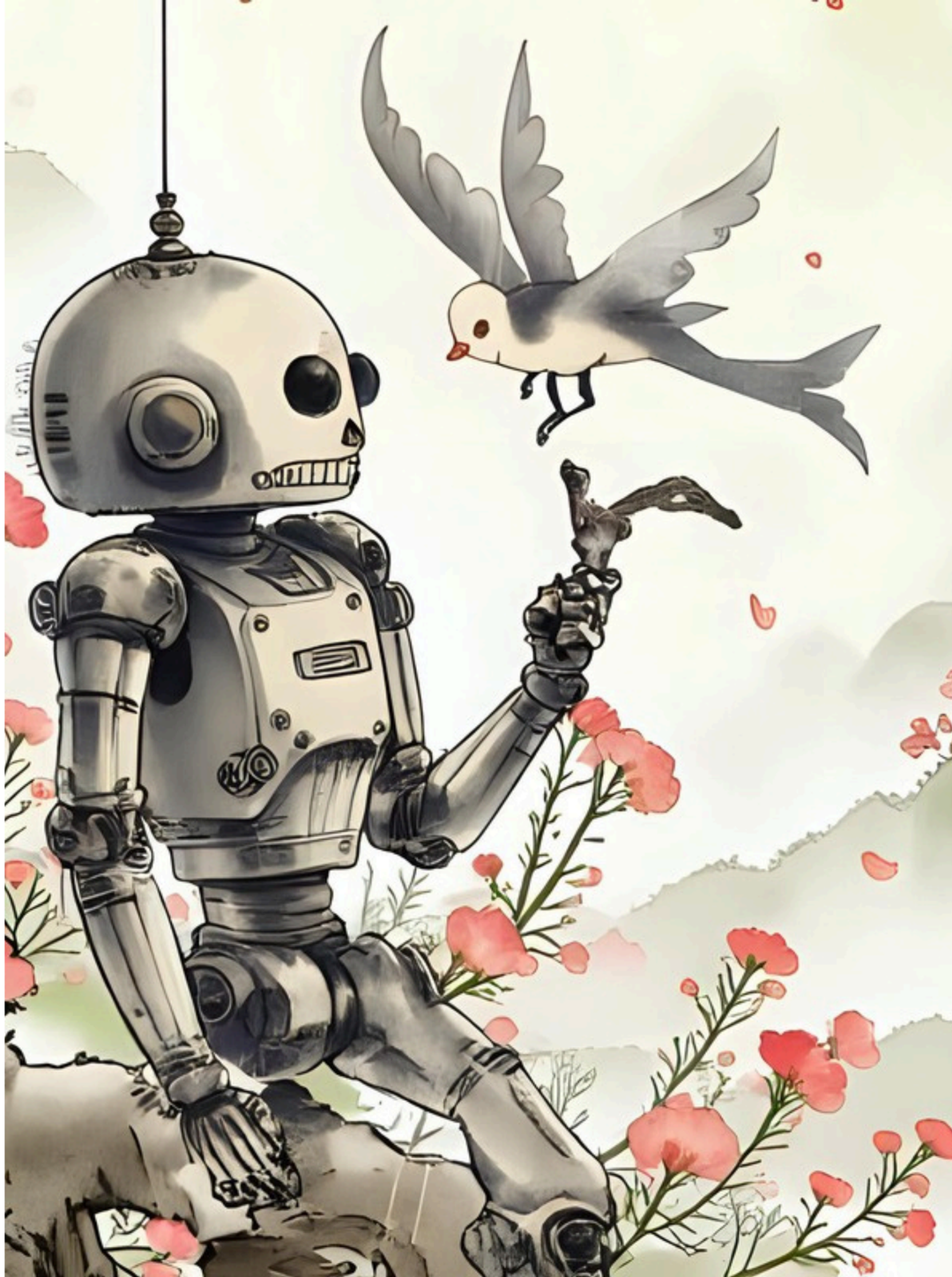


Problem Statement

Existing chatbots struggle to detect emotions or track mood changes.

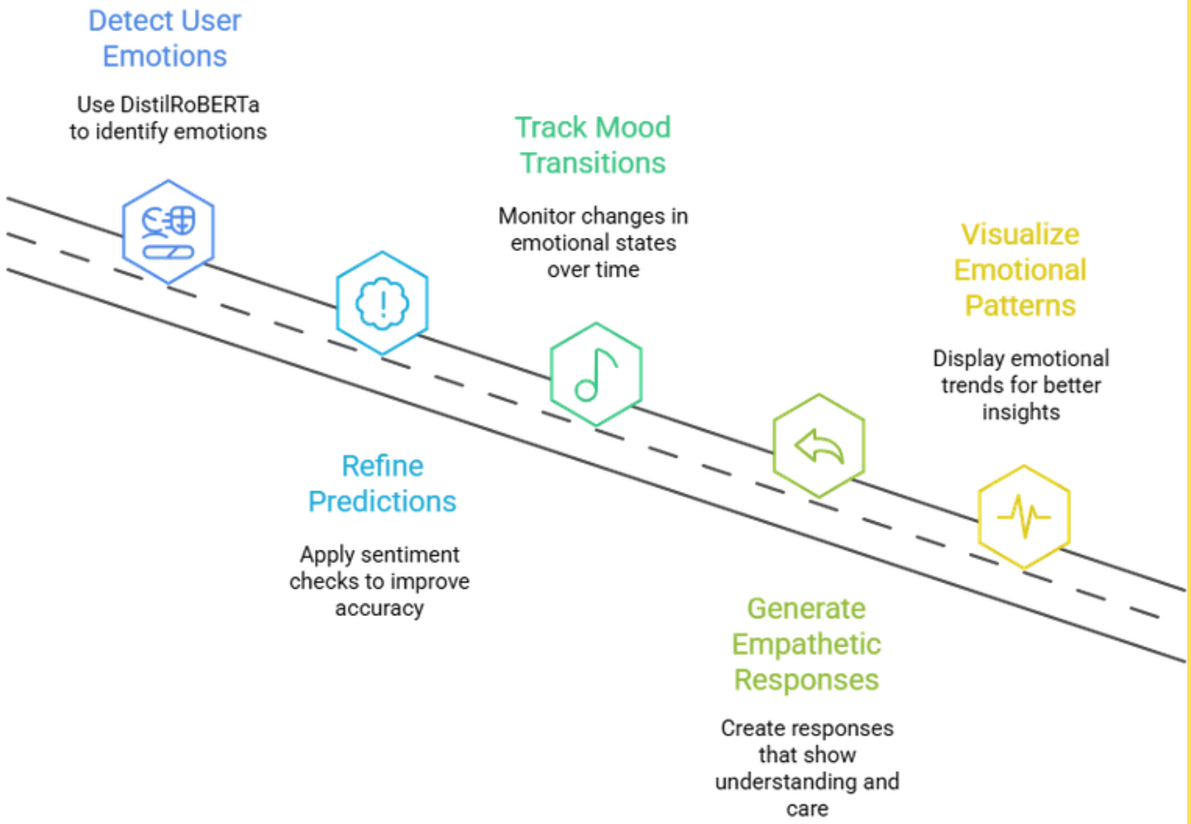
Problem Background

- Users often express emotions through text, but simple chatbots fail to recognize them.
- Rule-based systems cannot detect mood shifts or emotional cues.
- This leads to disconnected interactions and poor user experience.



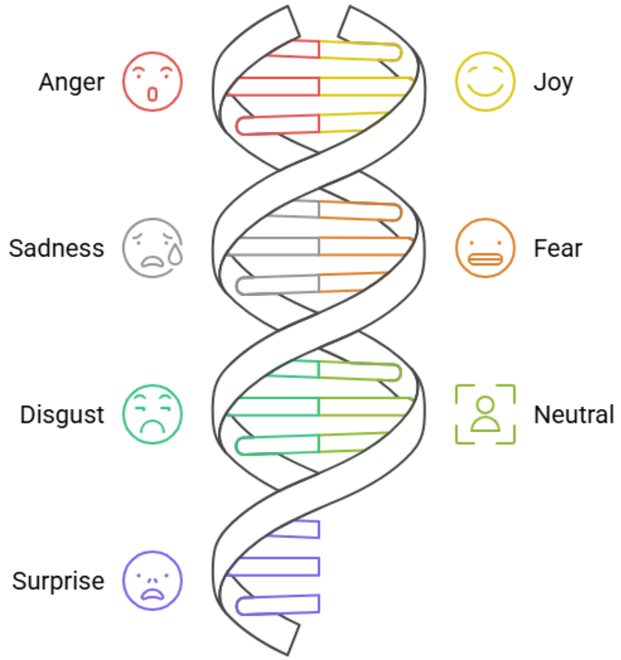
Objective

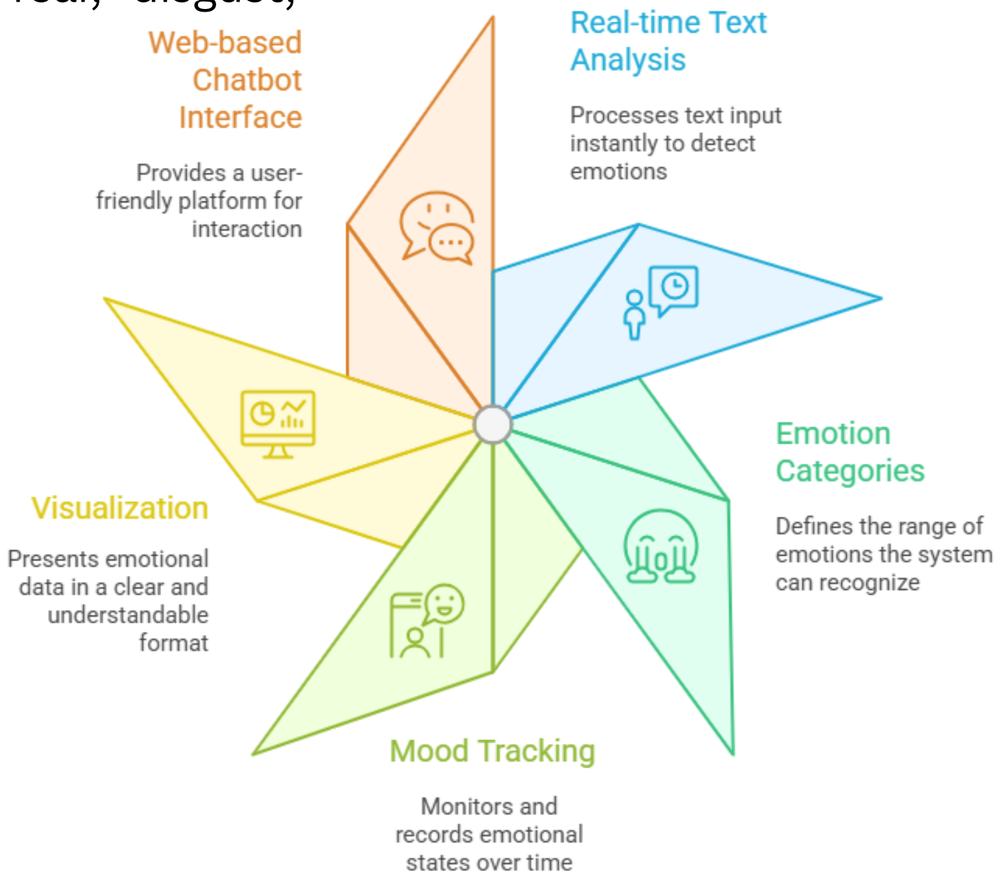
- Detect user emotions accurately using DistilRoBERTa.
- Provide refined predictions using sentiment checks.
- Track mood transitions and generate empathetic responses.
- Visualize emotional patterns for better understanding.



Scope of Project

- Real-time text emotion detection.
- Seven emotion categories (anger, joy, sadness, fear, disgust, neutral, surprise).
- Mood tracking and visualization.
- Web-based chatbot interface.





Literature Survey

Traditional and Transformer-Based Approaches

SR. NO.	TITLE	AUTHOR	YEAR	METHODOLOGY	FINDING
1	Emotion recognition using chatbot system	A. Pophale et al.	2021	Rule-based chatbot system	Traditional chatbots fail to respond appropriately; interactions seem robotic.
2	Emotion recognition-based mental healthcare chat-bots	J. Antony et al.	2021	Classical ML (SVMs, Naïve Bayes)	Early methods used handcrafted features but lacked deep contextual understanding.
3	Knowledge-enriched transformer for emotion detection	P. Zhong et al.	2019	Transformer with self-attention	Transformers revolutionized emotion recognition through contextual understanding.
4	Exploring transformers: BERT, RoBERTa, DistilBERT	C. Cortiz	2021	Comparative transformer analysis	Transformers outperform classical approaches; ideal for real-time use.

Why DistilRoBERTa Selected ?

Pre-trained for Emotions

Ready for 7-emotion classification out of the box

High Accuracy

Maintains performance levels close to RoBERTa

Fast and Lightweight

Enables real-time processing for immediate responses

Contextual Understanding

Interprets tone, expressions, and context accurately

Embedding Vectors

Provides data for clustering and mood analysis

Balanced Performance

Achieves a balance between speed, accuracy, and practicality

Emotion Categories (7-Class Model)

-Our bot classifies messages into seven core emotions:

- Anger
- Disgust
- Fear
- Joy
- Neutral
- Sadness
- Surprise

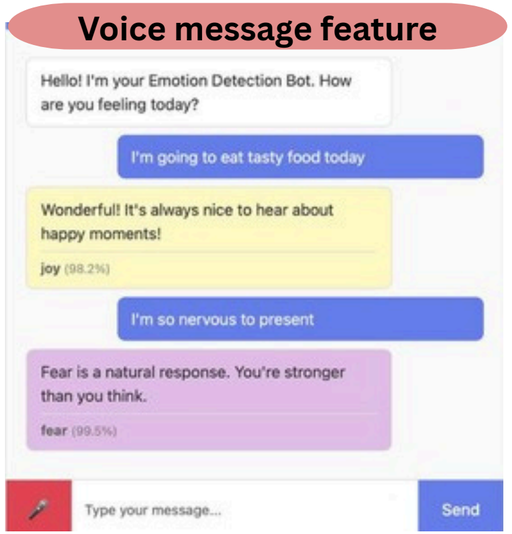
-Widely used in emotion research and datasets.
-Covers most everyday emotional expressions.
-Helps in tracking emotional flow over a conversation.

Project Flow

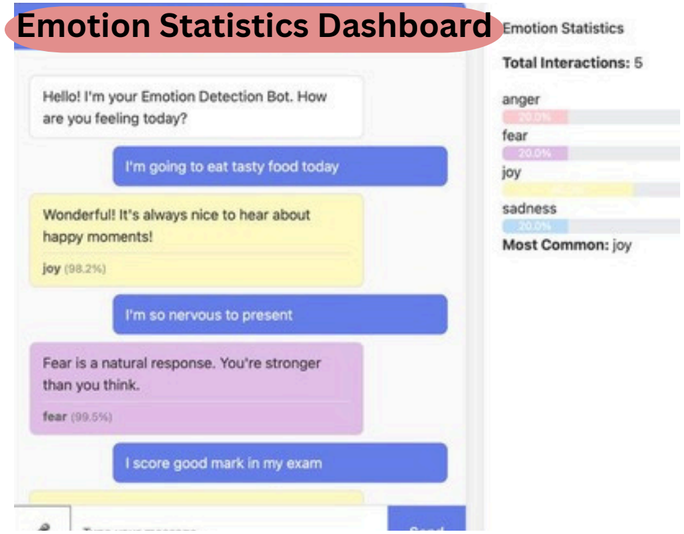
Initial Landing Screen

First Interaction - Joy Detection

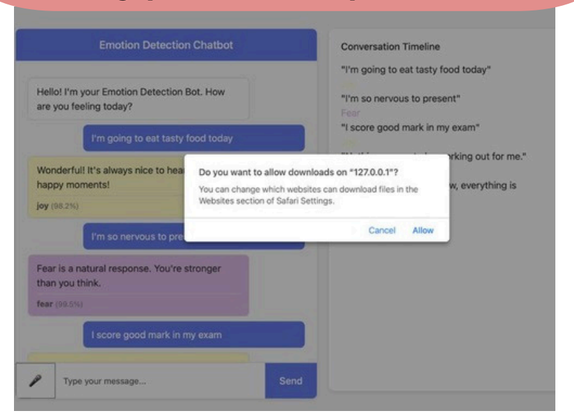
Voice message feature



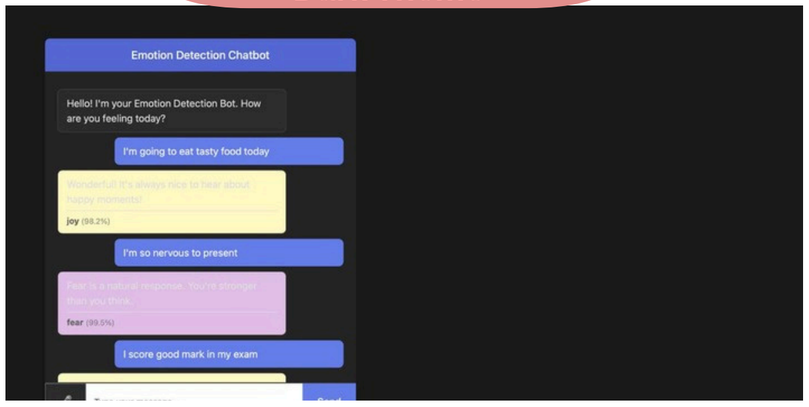
Emotion Statistics Dashboard



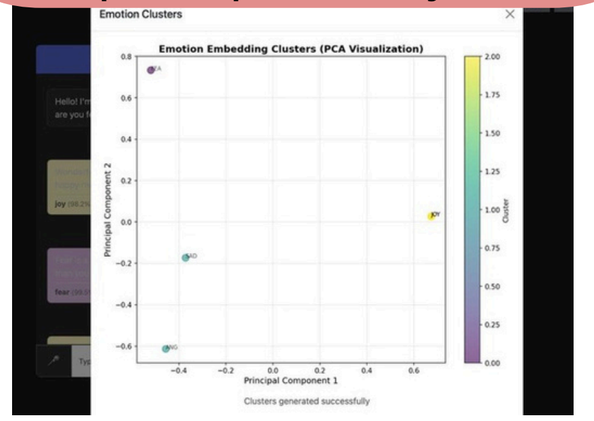
History panel and export feacture



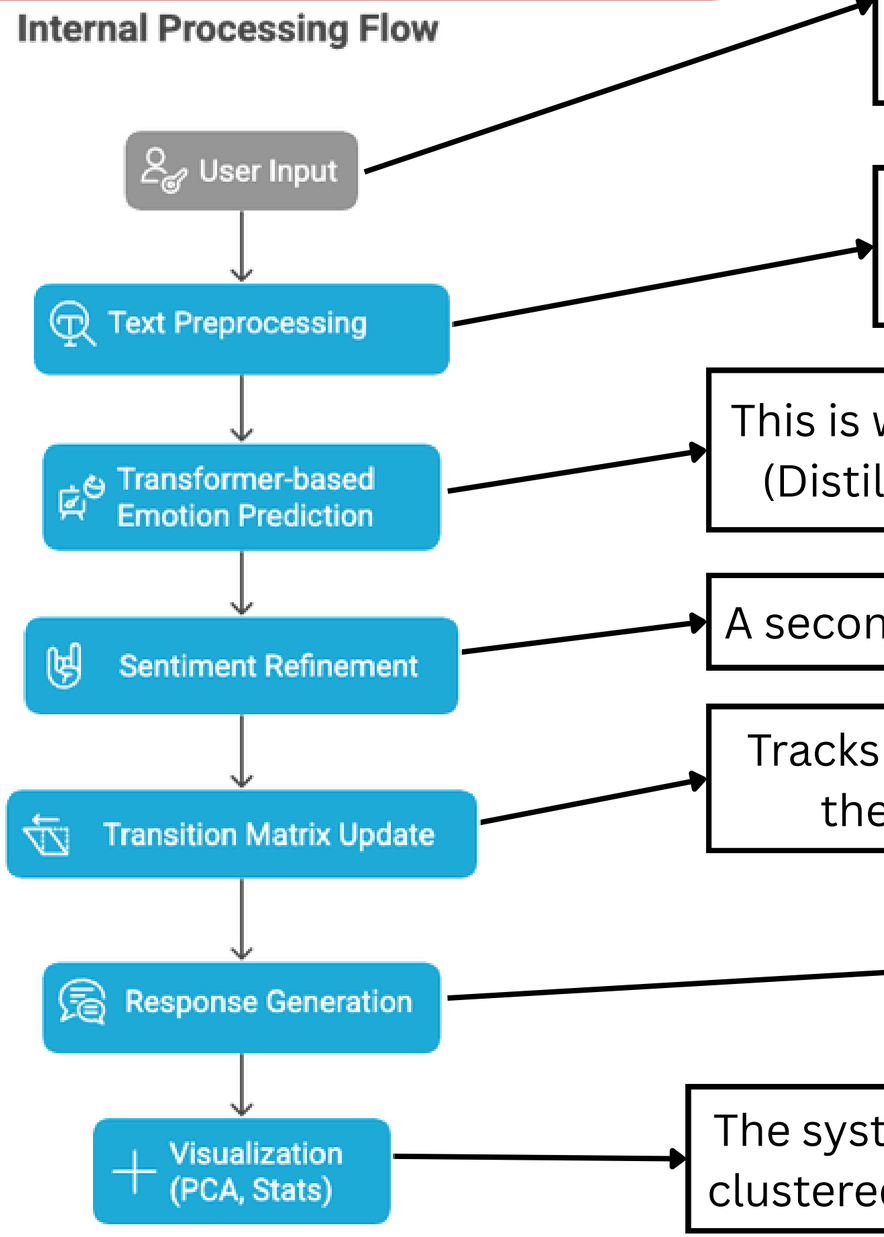
Dark Theme



Principal Component Analysis (PCA)



System Working



User enters text (e.g., “I’m feeling nervous aBout my exAm”).

The text is cleaned so the model can understand it.

This is where the main emotion classifier (DistilRoBERTa) predicts the emotion.

A second check to correct the model’s prediction.

Tracks emotion changes across the whole conversation.

The bot selects an empathetic reply based on the final predicted emotion.

The system shows emotion stats and clustered mood patterns for the user.

Emotion Prediction & Refinement

1. Transformer Model (DistilRoBERTa)

- Generates probability scores for 7 emotions
- Highest-score emotion selected as prediction

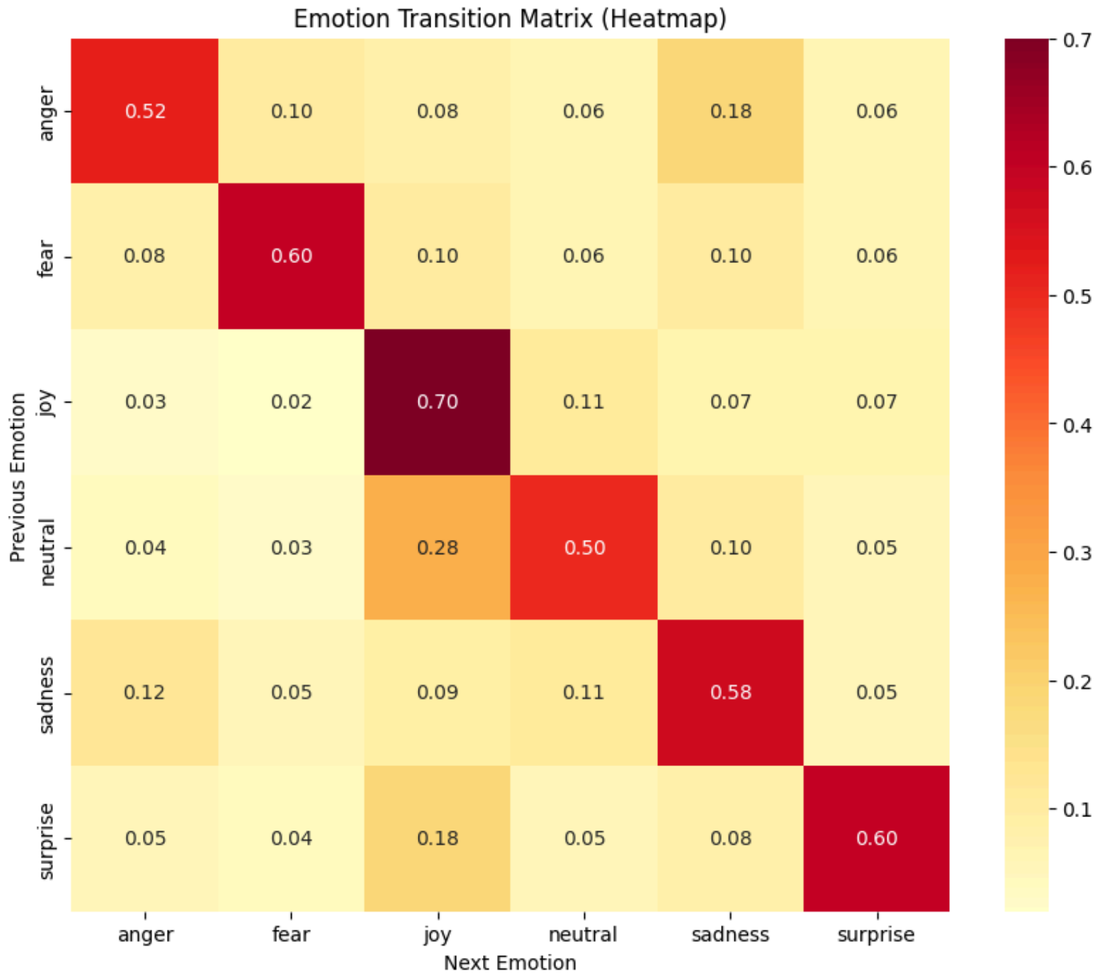
2. Sentiment Polarity Adjustment

- TextBlob checks whether text is positive/negative/neutral
- Corrects transformer output for short/ambiguous messages

3. Rule-based Keyword Tuning

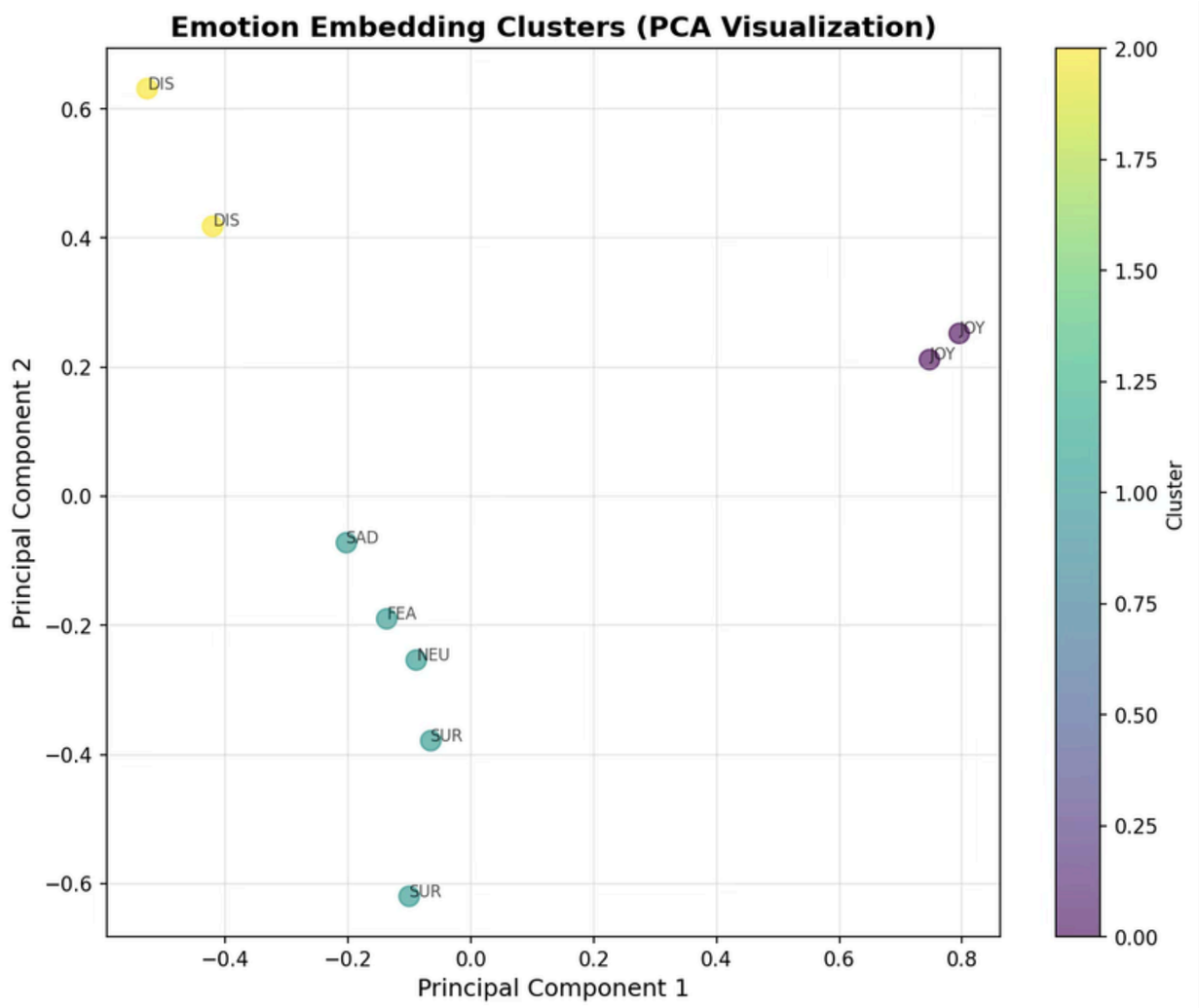
- Keywords help fix edge cases (e.g., “okay”, “fine”, “whatever”)
- Ensures more accurate final emotion

Mood Tracking Using Transition Matrix



- Each prediction updates previous → current emotion
- Stored in a 7×7 probability matrix
- Displays emotional flow patterns such as:
  - ✓ Consistency (joy→joy, sadness→sadness)
  - ✓ Common shifts (neutral→joy, anger→sadness)
  - ✓ Rare transitions (joy→anger)
- Helps understand the overall mood trend during the conversation

Emotion Cluster Visualization



Observations from the cluster plot:

- Emotions with similar tone formed close clusters (e.g., fear and surprise appeared near each other).
- Positive emotions (joy) were visibly separated from negative ones (sadness, anger, disgust).
- Neutral messages formed a spread-out region, reflecting their broad range.

Experiments & Evaluation Setup

Models Evaluated

- Baseline: TF–IDF + Logistic Regression
- Transformer: DistilRoBERTa

Dataset: Emotions Dataset for NLP (Kaggle)

- 2000 unseen text samples
- 6 emotion categories: anger, fear, joy, love, sadness, surprise

Evaluation Metrics

- Accuracy
- Precision
- Recall
- F1-score
- Confusion Matrix

Objective

- Compare performance and identify strengths/weaknesses

Baseline Model: TF–IDF + Logistic Regression

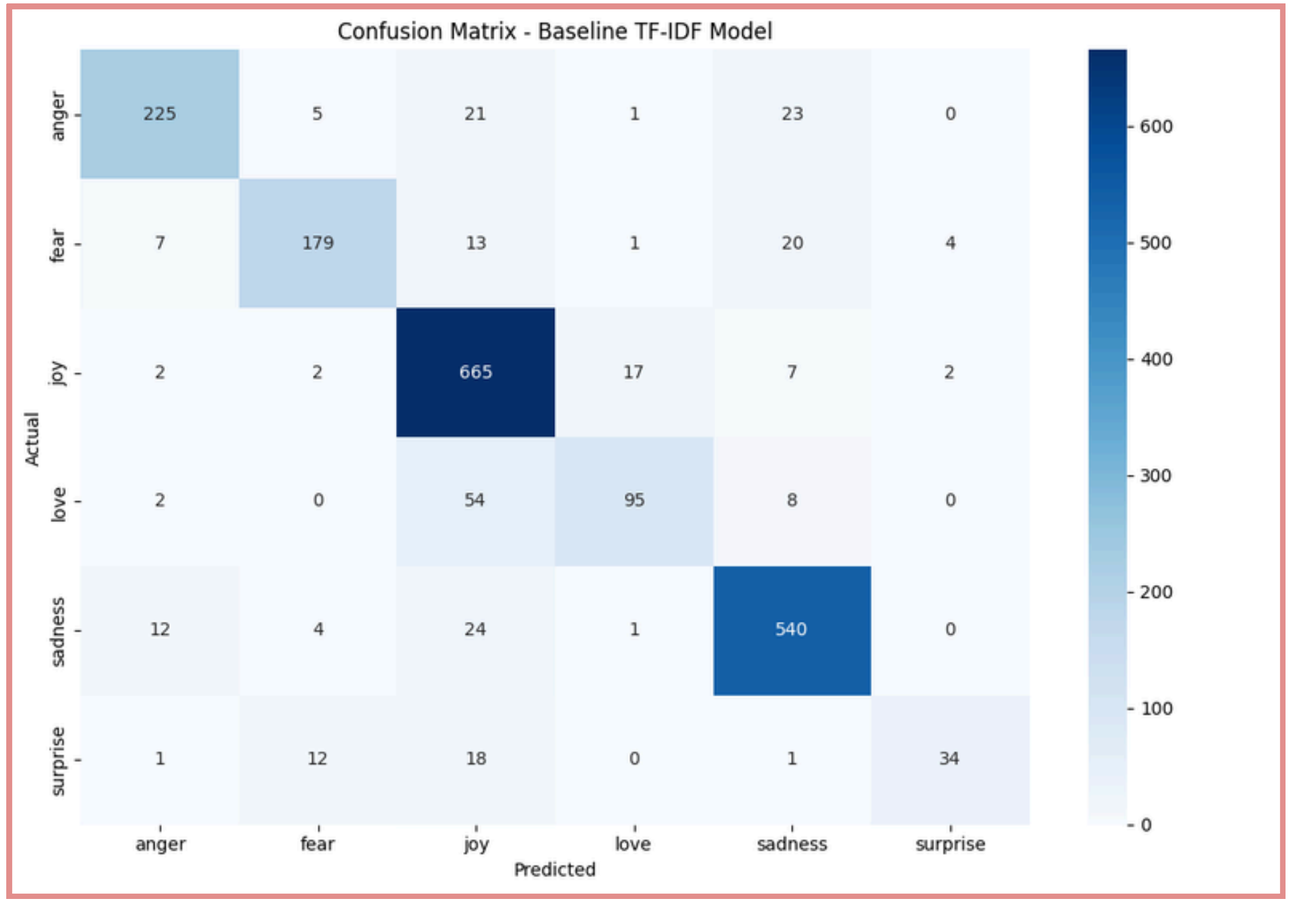
Accuracy: 86.9%
Weighted F1-score: 0.865
Macro F1-score :0.807

Performs strongly on:

✓ Joy(0.893)
✓ Sadness(0.915)
✓ Anger(0.872)

Struggles with:

✗ Love(0.693)
✗ Surprise(0.642)



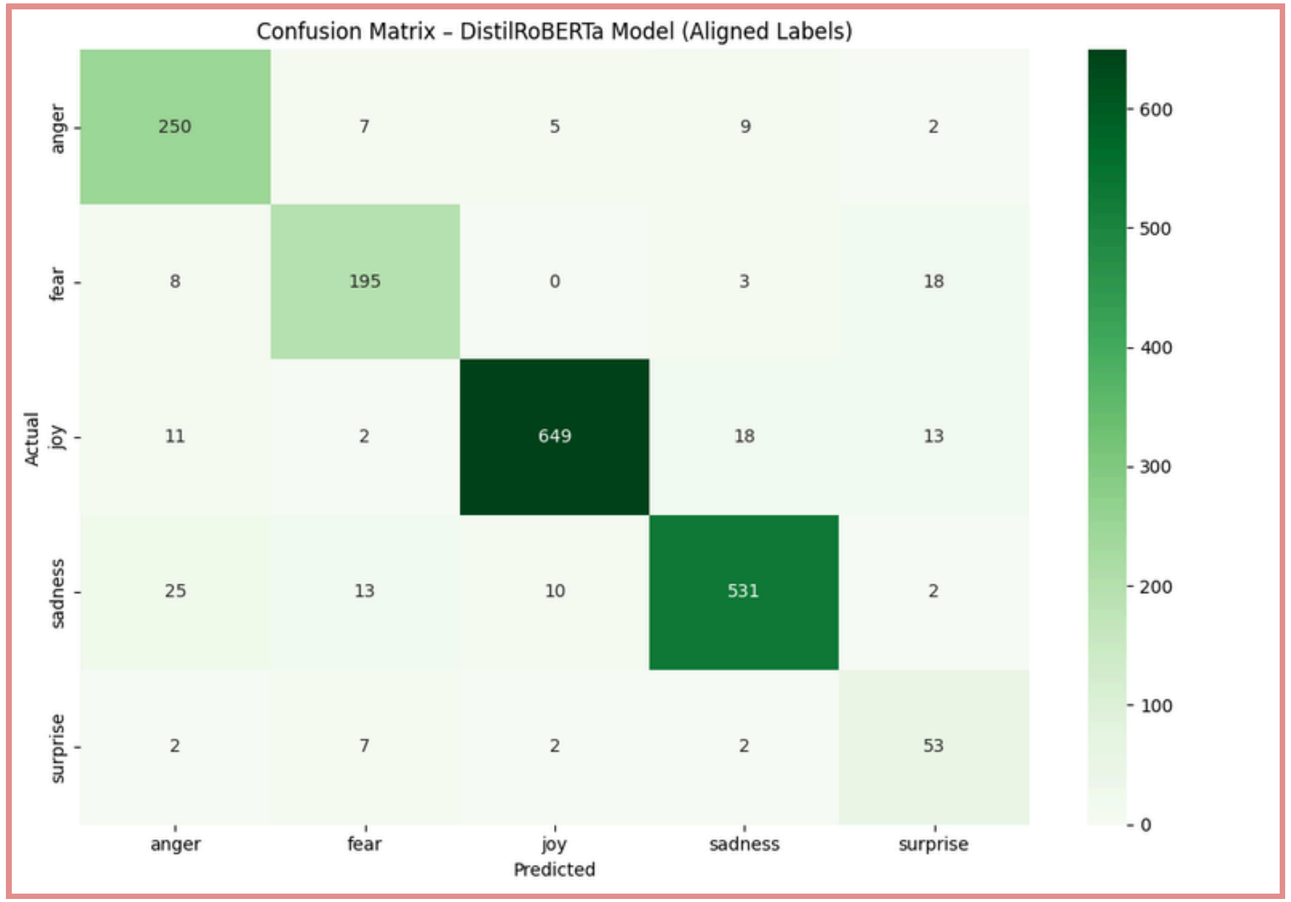
Often confuses similar emotions: joy ↔ love, fear ↔ sadness

DistilRoBERTa Model Performance

Accuracy: 84.1%
Weighted F1-score: 0.876
Macro F1-score:0.838

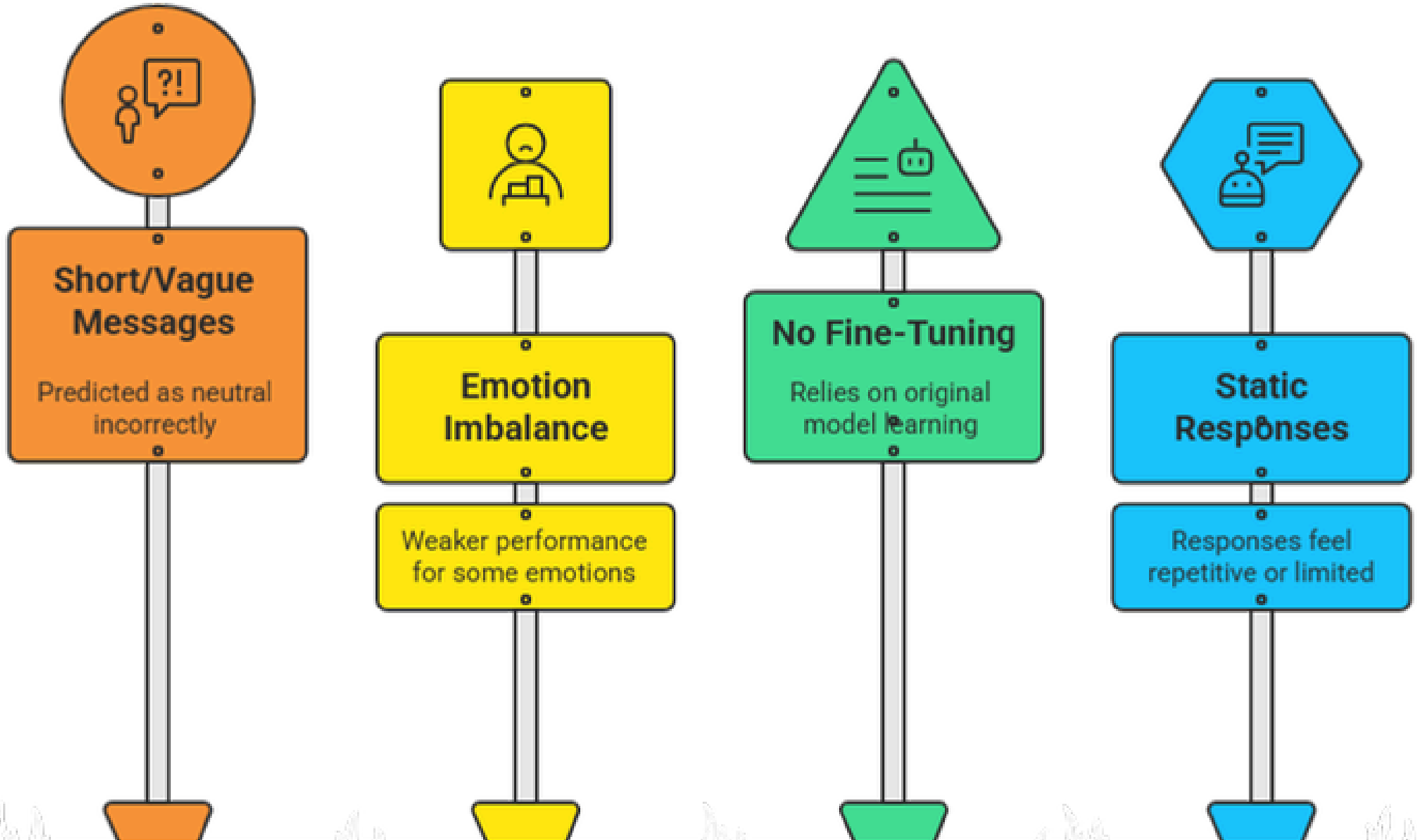
Performs well on:

- ✓ Sadness(0.907)
- ✓ Joy(0.877)
- ✓ Fear(0.832)
- ✓ Anger(0.845)



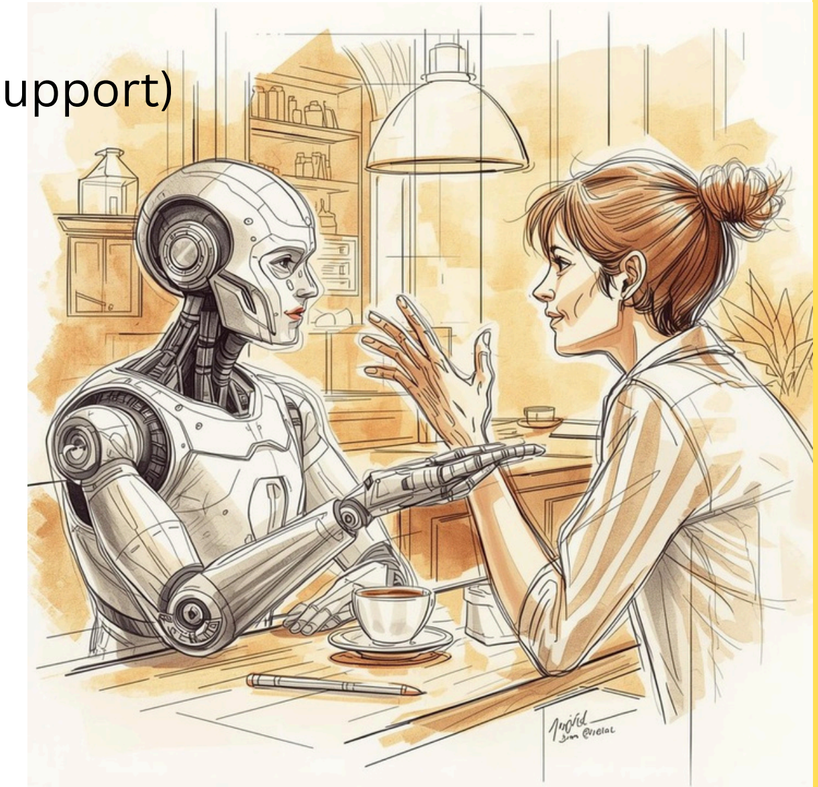
Understands context, not just keywords
Better with subtle or indirect emotional expressions

Limitations of Our System



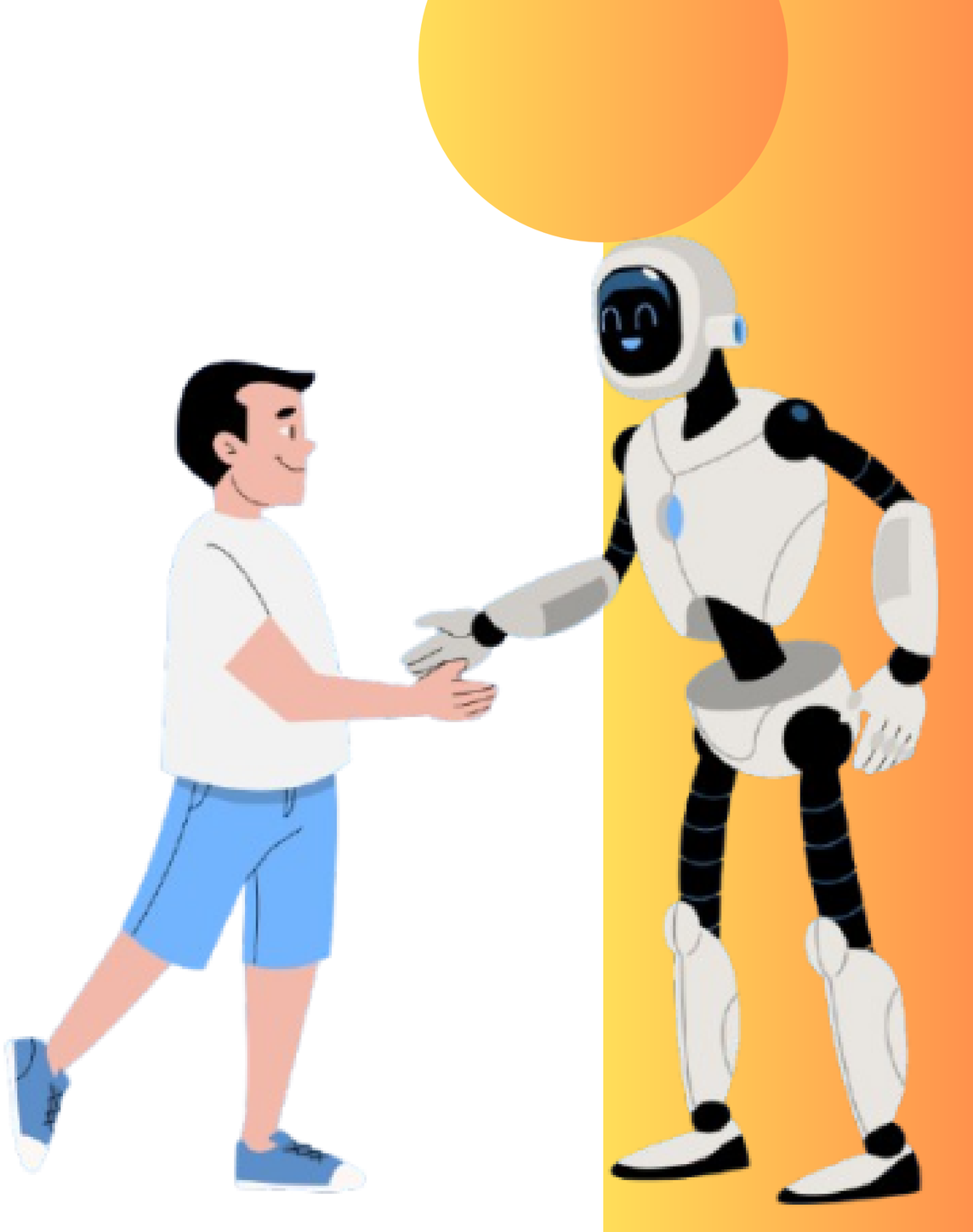
Future Scope

- Add multimodal emotion detection (voice + face)
- Fine-tune transformer on our custom dataset
- Add fully dynamic AI-generated responses
- Deploy as mobile & web application
- Add emotional intensity scoring (0–100 scale)
- Mood-based recommendations (songs, quotes, support)
- Long-term personalized mood analytics



Conclusion

While the baseline TF–IDF model performs well on clear emotional keywords, the DistilRoBERTa transformer excels at capturing subtle emotions and contextual nuances, making it the superior choice for real-world emotion detection



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THANK YOU