

Detecting Emotion Drift in Mental Health Text Using Pre-Trained Transformers

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Abstract

This study investigates emotion drift: the change in emotional state across a single text, within mental health-related messages. While sentiment analysis typically classifies an entire message as positive, negative, or neutral, the nuanced shift of emotions over the course of a message is often overlooked. This study detects sentence-level emotions and measures emotion drift scores using pre-trained transformer models such as DistilBERT and RoBERTa. The results provide insights into patterns of emotional escalation or relief in mental health conversations. This methodology can be applied to better understand emotional dynamics in content.

1. Introduction

Understanding human emotions in written communication has become increasingly important, especially in the context of mental health. More traditional methods to understand sentiment classify whole texts for being positive, negative, or neutral and provide a high level overview of the emotional tone (Dilmegani, 2024). However, these algorithms do not consider the change or drift in emotional state within a single text. These types of large emotion shifts, or drifts in emotions can be indicative of emotion escalation or instability, which is particularly relevant in mental health (Mitchell, 2021).

Recent improvements in natural language processing such as pre-trained transformer models (e.g., DistilBERT and RoBERTa) make it possible to analyze emotions which are more subtle on the sentence level (Acheampong et al., 2020). By using these models, the ability to examine subtle emotional transitions and measure changes of emotions in texts is made possible. Comprehending these dynamics can increase early detection of emotional distress, improve automated mental health care systems, and offer deeper insights into users' emotional experiences.

In this study, I propose a framework for detecting emotion drift in mental health texts. I have analyzed sentence-level emotions using transformer models, compute emotion drift scores, and evaluate their ability to capture emotional variability. Our results demonstrate how emotional analysis can uncover patterns of emotional escalation that are not captured by traditional sentiment analysis. A lightweight Streamlit application was also developed to demonstrate the practical use of emotion drift analysis, allowing users to input any text and instantly view sentence-level emotions, the emotion timeline, drift score, and overall sentiment in an intuitive and interactive interface.

2. Literature Review

Emotion analysis in text has become a relevant area of research from natural language processing (NLP), particularly within areas related to human welfare, online communication and mental health (Plaza-del Arco et al., 2024). Most of the existing sentiment analysis models are built in such a way that they assign one global sentiment (positive, negative or neutral) to an entire message. This has worked well in various scenarios such as product review, social media polarity classification but does not model the fine-grained emotional dynamics commonly observed in user-generated content (Pang & Lee, 2008). Psychological evidence suggests

that people often experience ambivalent or contradictory feelings when listening to a single story, especially when participants are discussing something negative about their life or psychological problems (Liu, 2024). The recent advancements in the field, such as transformers and deep learning architectures, have allowed for classification of these fine-grained emotions.

The utilization of pre-trained models such as BERT (Devlin et al., n.d.), RoBERTa and their distilled versions can improve the recognition performance of different emotion types, including joy, anger, sadness, fear and surprise. The availability of such rich annotations has also expanded the information available for emotion classification research, by modularization problems that benefit from richer annotations like those found in GoEmotions (GoEmotions: A Dataset for Fine-Grained Emotion Classification, n.d.) with 27 emotion labels. Other data sets such as the Emotion dataset used in this work include a selected few core emotions, allowing for simpler benchmarking while maintaining emotional variety. However, most of these models and datasets still evaluate emotions at the document level, leaving sentence-level emotional transitions largely unexplored.

The concept of emotion drift, defined as the change in emotional state across different segments of a single piece of text, has only recently started receiving attention. A few studies have explored emotional trajectories in narratives and long-form posts, showing that measuring emotional progression can uncover latent psychological indicators and provide deeper insights into user behaviour (Christ et al., 2024). In mental health contexts, emotional fluctuations have been linked to stress, anxiety, mood instability, and coping mechanisms, making them valuable for early detection and support frameworks. Despite this, there is limited work on operationalising emotion drift using pre-trained transformer models, particularly in real-time, user-facing applications.

To address this gap, recent research efforts have focused on applying transformer-based emotion classifiers at the sentence level to compute emotional trajectories and drift scores. Models such as DistilBERT and DistilRoBERTa provide a computationally efficient alternative to their full-sized versions while retaining high accuracy, making them suitable for practical applications like conversational agents and mental health monitoring tools (Sajid, 2018). The increasing emphasis on explainability and transparency in AI systems has further highlighted the importance of visualising emotional sequences, not merely reporting a single sentiment label. This study builds upon this emerging line of research by applying distilled transformer models to detect sentence-level emotions, quantify emotional volatility, and visualise emotion drift in a user-friendly interface.

3. Methodology

This study follows a multi-stage methodology designed to detect sentence-level emotions, measure emotional drift within a text, and evaluate the performance of multiple pre-trained transformer models. The methodology consists of four major components: dataset preparation, model selection, emotion drift computation and application integration.

Dataset Preparation

The performance of different transformer-based emotion classification models were benchmarked using the publicly available Emotion Dataset provided by Hugging Face Datasets library. This collection comprises 20,000 text samples with one of six basic emotions: joy, anger, sadness, fear, love and surprise (Datasets at Hugging Face, 2023). I choose the dataset because of its balanced quantity, clear label structure, and popularity in emotion recognition.

The dataset was split into training, validation, and test sets as provided. For evaluation purposes, only the test set (2,000 samples) was used, ensuring that performance metrics reflect the models' generalisation to unseen data. All text samples were preprocessed by lowercasing and removing extraneous whitespace, while preserving semantic content to maintain the integrity of emotion cues.

Model Selection

Three widely used transformer models were selected to evaluate their effectiveness in sentence-level emotion classification:

- DistilRoBERTa
- DistilBERT
- DeBERTa

The models selected for evaluation were chosen based on their demonstrated effectiveness in emotion classification and their suitability for sentence-level analysis. DistilRoBERTa was included for its balance of accuracy and efficiency, making it well-suited for interactive applications. DistilBERT was selected for its consistent and interpretable predictions, which are particularly valuable for real-time emotion drift analysis. DeBERTa Base represents a more recent architecture with advanced attention mechanisms capable of capturing subtle emotional nuances, included to assess whether it could improve accuracy over the distilled models. Together, these models provide a comprehensive comparison across efficiency, consistency, and state-of-the-art performance, enabling an informed selection for the application.

The Hugging Face text-classification pipeline was used to perform emotion prediction, enabling consistent inference across all models.

Each model was evaluated using the same test set and identical processing pipeline to ensure fairness. For every sample in the test set, the predicted emotion label was compared with the ground truth label.

Accuracy was used as the comparison metric due to its interpretability and relevance for choosing a model for deployment.

The evaluation results showed that DistilBERT achieved the highest accuracy (92.7%), outperforming DistilRoBERTa (83.9%) and GoEmotions RoBERTa (19.6%). Based on this high accuracy and excellent computational efficiency, DistilBERT was chosen as the foundational model for the final emotion drift analysis application.

Emotion Drift Computation

After selecting the best-performing model, a custom emotion drift pipeline was developed:

1. Sentence Segmentation
User input text is split into individual sentences using regex-based segmentation.
2. Emotion Classification
Each sentence is passed through the DistilBERT classifier to obtain the predicted emotion label.
3. Emotion Timeline Construction
The sequence of predicted emotions is arranged chronologically to form an emotion timeline, allowing users to visually track emotional transitions.

Emotion Timeline:

	Sentence	Predicted Emotion
0	I am very happy today!	joy
1	I feel anxious about tomorrow.	fear
2	This is frustrating and disappointing.	sadness
3	I am calm and relaxed.	joy
4	Why does everything go wrong?	anger
5	I love this!	joy
6	I don't know what to feel anymore.	sadness

Figure 1: Emotion timeline of sample text

4. Drift Score Calculation

Emotion drift is computed as the number of emotion changes divided by the total number of transitions. A score of 0 indicates no change in emotional state, while a score close to 1 represents high emotional volatility.

$$\text{Drift Score} = \frac{\text{Number of Emotion Changes}}{\text{Number of Sentences} - 1}$$

5. Overall Sentiment Estimation

The final sentiment of the passage is obtained using the DistilBERT model fine-tuned for sentiment analysis (Hugging Face, 2024) to understand general tone.

Emotion Drift Score: 1.00
Overall Sentiment: POSITIVE

Figure 2: Emotion Drift Score and Overall Sentiment of text

Application Integration

The above pipeline was integrated into a Streamlit web application. Users can input any text, view the predicted emotion timeline, observe the drift score, and receive the overall sentiment. This makes emotion drift analysis accessible and interpretable to users.

4. Model Evaluation

I evaluated three pre-trained transformer models for sentence-level emotion detection. To assess the suitability of transformer-based architectures for emotion classification, I benchmarked three pre-trained models sourced from the Hugging Face Model Hub. This phase focused on understanding how different encoder variants perform when applied to sentence-level emotion detection tasks.

Model Name	Pre-trained Source	Description
roberta_distil	j-hartmann/emotion-english-distilroberta-base	A distilled version of RoBERTa trained specifically for emotion classification, offering a strong balance between accuracy and computational efficiency.
bert_distil	bhadresh-savani/distilbert-base-uncased-emotion	A compact DistilBERT model fine-tuned for multi-class emotion detection, optimized for speed and resource efficiency.
deberta_base	ihabiko/deberta-v3-base-emotion-model	Based on DeBERTa-v3 Base architecture, which introduces disentangled attention and enhanced mask decoding for superior context modeling.

Figure 3: overview of models selected

Each model was loaded using the Hugging Face transformers pipeline for text classification, predicting multiple emotions per sentence. The predicted labels were then converted to a simplified representation for drift analysis.

Distil RoBERTa

This is a distilled version of RoBERTa, which means it is a smaller, faster version of the original RoBERTa model that has been optimized to maintain the majority of its performance. Compared to RoBERTa-base, which has 125M parameters, the model contains 82M parameters with 6 layers, 768 dimensions, and 12 heads (Hugging Face, 2023). RoBERTa itself is based on the transformer architecture, using self-attention to create contextualized embeddings for each token in a sentence (Gandhi, 2025).

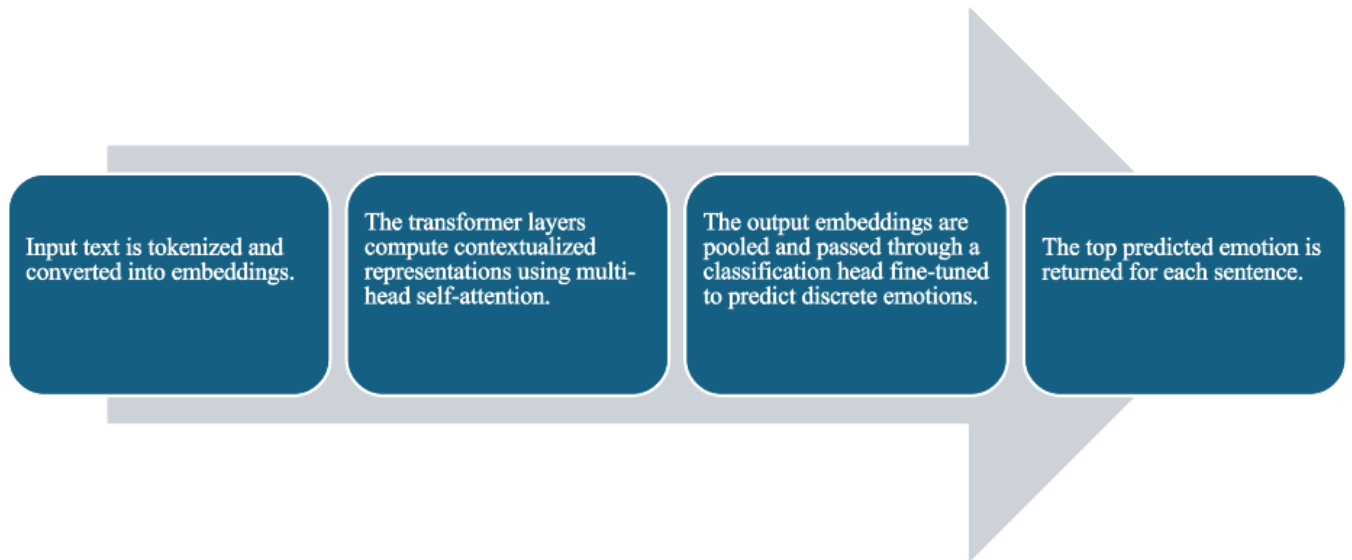


Figure 4: Workflow for Distil RoBERTa model

The distilled form retains a high level of general-purpose understanding of language, but it may be less sensitive to subtle emotional cues due to its diminished depth and representational ability. Because of this, it excels at main or high-frequency emotions (such as joy, sadness, and anger), but it may have trouble with more complex or ambiguous emotions like anticipation or confusion. However, this model is a great choice for real-time emotion detection pipelines.

Distil BERT

This model(distilbert-base-uncased-emotion) is a DistilBERT variant, a lighter version of BERT that reduces parameters and speeds up inference. The “uncased” version ignores capitalization, making it robust to case variations. It is fine-tuned for emotion detection, providing reliable sentence-level predictions(GeeksforGeeks, 2025).

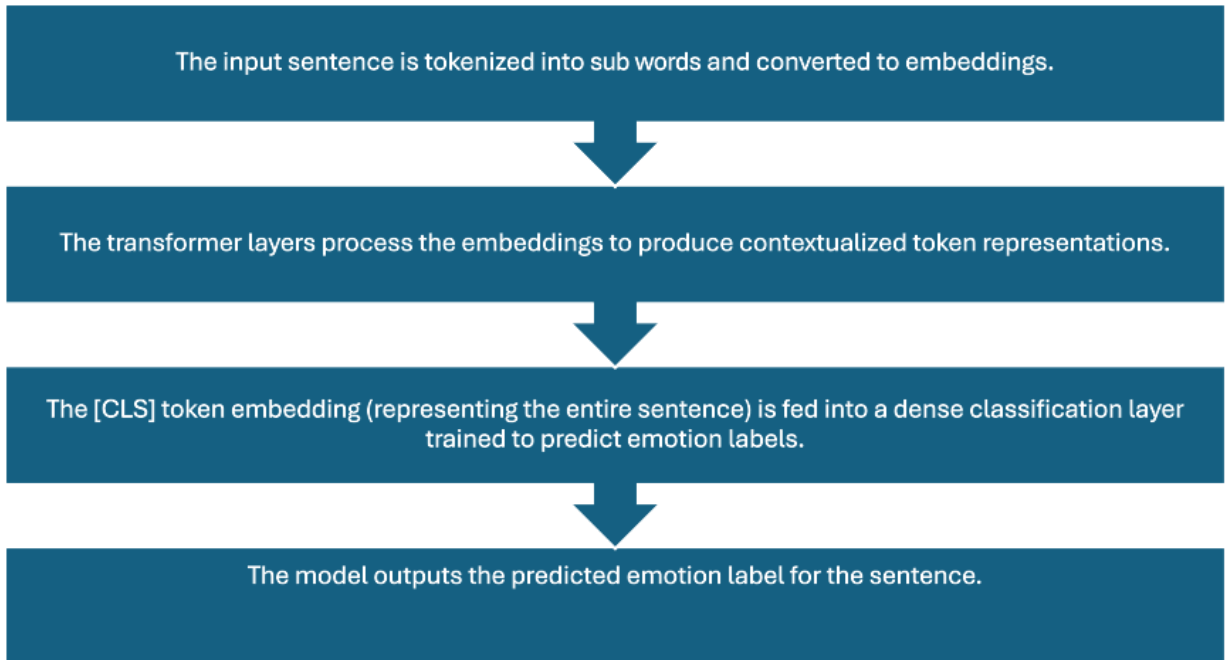


Figure 5: Workflow for Distil BERT model

DistilBERT maintains the fundamental advantages of the BERT architecture, such as robust semantic representation and bidirectional contextual awareness, despite being lightweight(GeeksforGeeks, 2025). This allows it to detect subtle emotional cues in short text segments, making its predictions both stable and reliable across consecutive sentences. In the context of emotion drift analysis, this stability ensures that the model captures genuine emotional transitions rather than producing noisy or inconsistent classifications.

DeBERTa

This model uses the DeBERTa-v3 Base architecture, which improves on BERT or RoBERTa by employing disentangled attention and using enhanced mask decoders (Hugging Face, n.d.). This allows it to capture subtle nuances in text and produce richer contextual embeddings. The model is fine-tuned for emotion classification, making it suitable for primary emotion detection.

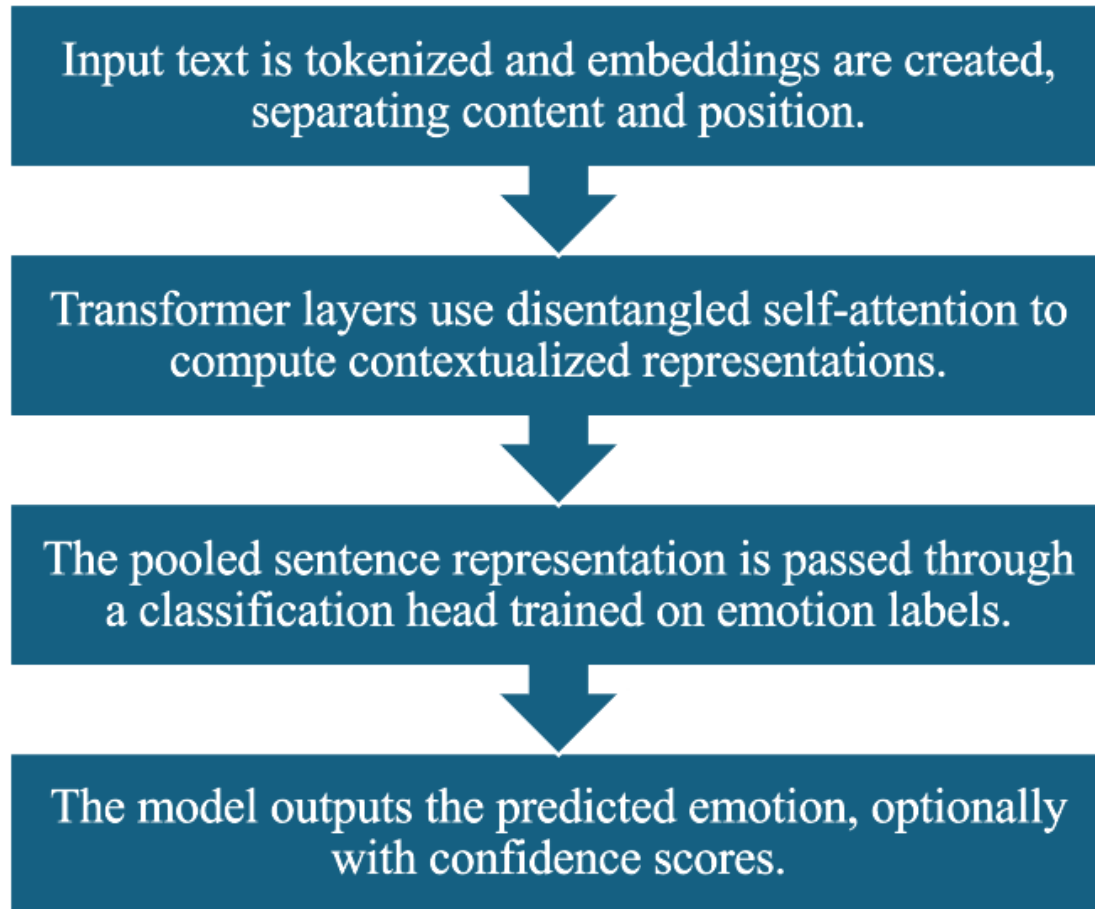


Figure 5: Workflow for DeBERTa Base model

While DeBERTa often achieves slightly higher accuracy than distilled models, its predictions can occasionally be inconsistent for ambiguous sentences due to differences in fine-tuning datasets and label distribution.

5. Experiments & Results

To evaluate the performance of different pre-trained transformer models for sentence-level emotion detection, I choose a series of text samples and compared their predictions between the three models on sentence-level emotion detection. The following figure shows the predicted emotions for each sentence across the models:

text	roberta_distil	bert_distil	deberta_base
I am very happy today!	joy	joy	joy
I feel anxious about tomorrow.	fear	fear	fear
This is frustrating and disappointing.	sadness	sadness	anger
I am calm and relaxed.	joy	joy	joy
Why does everything go wrong?	anger	anger	anger
I love this!	joy	joy	joy
I don't know what to feel anymore.	sadness	sadness	joy

Figure 6: predicted emotions for sample sentences across models

The performance of each model was subsequently validated on a bigger benchmark dataset, and the following results were obtained:

Accuracy Scores:
roberta_distil: 0.8390
bert_distil: 0.9270
deberta_base: 0.9315

Figure 7: Accuracy scores of models

- roberta_distil: 0.8390
- bert_distil: 0.9270
- deberta_base: 0.9315

From the evaluation results, deberta_base achieved the highest overall accuracy (0.9315), slightly outperforming bert_distil (0.9270), while roberta_distil scored 0.8390. Despite a strong accuracy, DeBERTa does indeed misclassify test sentences sometimes in ways that appear strange or counter-intuitive. For example, categorizing “This is annoying and disappointing” as anger (rather than sadness) or “I don’t know what to feel anymore” as joy. These inconsistencies are likely due to differences in fine-tuning datasets, label schemes, and sensitivity to subtle emotional cues.

In contrast, bert_distil produces slightly lower overall accuracy but demonstrates more consistent and intuitive sentence-level predictions, which is particularly important for real-time emotion drift analysis in interactive applications. That is why I chose Distil BERT for the Streamlit application as its predictions are more trustworthy to calculate sentence-level emotional differences.

Example of Model Predictions and Drift Score

In this experiment, I analyzed a short text passage to demonstrate emotion drift detection using three pre-trained transformer models: roberta_distil, bert_distil, and deberta_base.

This was the example text used: “I feel overwhelmed today. I tried to reach out for help. Nobody is responding, and I am frustrated.”

The input text was first split into individual sentences, and each sentence was analyzed to predict its dominant emotion. The emotion drift score was then computed by calculating the proportion of consecutive sentences that exhibited a change in emotion. For the example passage, the roberta_distil model predicted the emotions ['surprise', 'sadness', 'anger'] with a drift score of 1.0, indicating a complete change in emotion across sentences. The bert_distil model predicted ['fear', 'fear', 'anger'] with a drift score of 0.5, showing that the first two sentences maintained the same emotion before changing. The deberta_base model predicted ['fear', 'joy', 'anger'] with a drift score of 1.0, again indicating high emotional volatility. This comparison demonstrates how different models capture emotional transitions, highlighting both the strengths and limitations of each model in detecting nuanced emotional changes. The drift score effectively quantifies the sequence of emotional changes.

```
Model: roberta_distil
Sentences: ['I feel overwhelmed today.', 'I tried to reach out for help.', 'Nobody is responding, and I am frustrated.']
Emotions: ['surprise', 'sadness', 'anger']
Emotion Drift Score: 1.0

Model: bert_distil
Sentences: ['I feel overwhelmed today.', 'I tried to reach out for help.', 'Nobody is responding, and I am frustrated.']
Emotions: ['fear', 'fear', 'anger']
Emotion Drift Score: 0.5

Model: deberta_base
Sentences: ['I feel overwhelmed today.', 'I tried to reach out for help.', 'Nobody is responding, and I am frustrated.']
Emotions: ['fear', 'joy', 'anger']
Emotion Drift Score: 1.0
```

Figure 8: emotional drift detection across models for a sample text

The figure below illustrates the emotion drift across three sentences from an example post, as detected by three different pre-trained models: RoBERTa Distil, BERT Distil, and DeBERTa Base. Each model's detected emotion for every sentence is mapped on the y-axis, while the x-axis represents the sentence sequence (S1-S3). The lines show how emotions change throughout the text, providing a clear visual representation of emotional transitions. For instance, RoBERTa Distil identifies a progression from surprise → sadness → anger, indicating a high emotional drift. BERT Distil shows fear → fear → anger, reflecting a more gradual escalation. DeBERTa Base detects fear → joy → anger. This visualization highlights how different models interpret emotional changes in text.

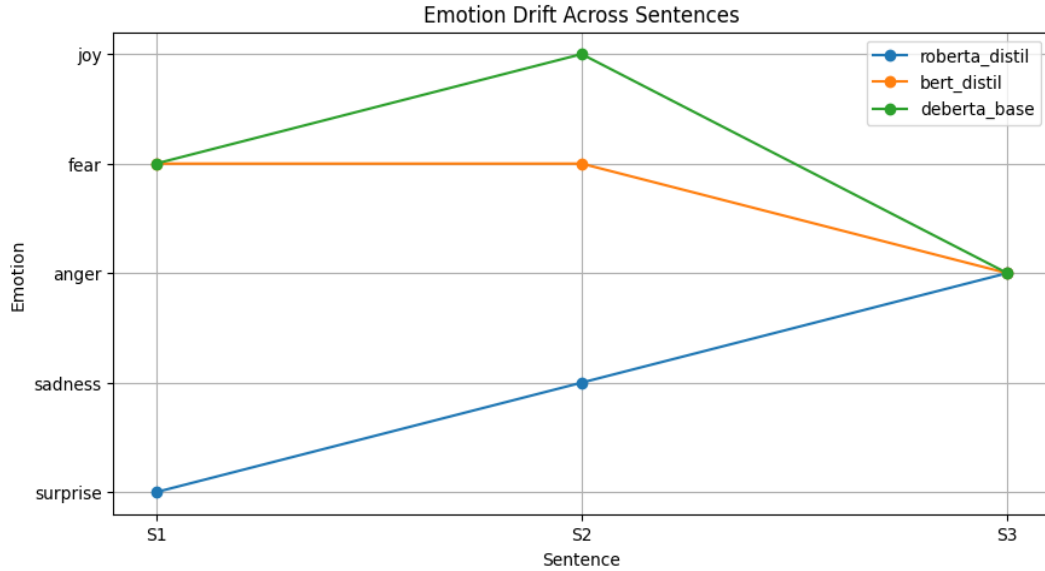


Figure 9: graph of emotion drift across sentences

6. App Development

A Streamlit application was developed to provide an interactive environment for analyzing emotion drift within user-submitted text. The app can be accessed here: <https://emotion-drift-app.streamlit.app/>. The system takes a text passage as input, and it divides the text into sentences automatically and uses pre-trained emotion classifier DistilBERT to obtain sentence-level emotions. Based on performance evaluation, DistilBERT was considered as the main model for deployment which reported a good accuracy (92.7%) and presented reliable and efficient response time for real-time analysis. The application evaluates how emotions change throughout a piece of text. The input text is broken into smaller segments, and each segment is classified to generate an Emotion Timeline, showing the sequence of feelings expressed by the writer.

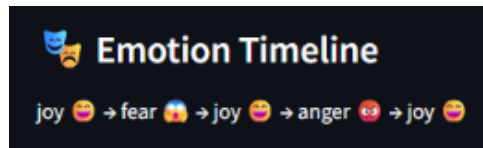


Figure 10: Emotion Timeline generated in web application

The degree of emotional fluctuation is then measured using a Drift Score, where higher scores suggest more emotional volatility.

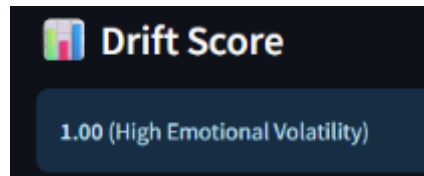


Figure 11: Drift score generated in web application

Alongside this, the app also provides an overall sentiment (positive, negative, or neutral) to summarise the dominant tone of the entire passage. This allows users to visualise both the emotional flow and the general mood of the text in a clear and intuitive way.



Emotion Drift Analyzer

Enter your text:

I was happy to start the new project. Then I felt a bit anxious about the deadlines. The team was supportive, which made me feel relieved. Sometimes, small mistakes frustrated me. By the end of the week, I felt content and satisfied.

Analyze



Emotion Timeline

joy 😊 → fear 😨 → joy 😊 → anger 😡 → joy 😊



Drift Score

1.00 (High Emotional Volatility)

Overall Sentiment

POSITIVE

Figure 12: screenshot of web application

7. Conclusion & Future Work

The study shows that DeBERTa Base and DistilBERT achieve high accuracy in primary emotion detection, with DeBERTa slightly outperforming DistilBERT in terms of accuracy. However, DistilBERT offers more consistent and easily interpretable sentence-level predictions and is a good candidate for real-time usage. Our models both illustrate how emotion drift scores can capture variation in emotion within a text, while providing more detailed analysis than traditional sentiment analysis. This approach is applicable to mental health texts, online forums, or social media, providing a quantitative way to assess emotional dynamics across sequences of sentences.

However the limitation is that the models are trained on general-purpose datasets and may not fully capture domain-specific emotional expressions in mental health posts. In conclusion, this paper discusses how to apply transformer models for sentence-level emotion detection to identify emotion drift in textual data. By computing drift scores, it is easier to quantify emotional variability and highlight patterns of escalation or relief within posts.

Future work includes:

- Fine-tuning transformer models on domain-specific datasets (e.g., mental health forums) to improve accuracy.
- Extending emotion drift analysis to multi-modal data (text + audio/video).
- Incorporating temporal analysis to study emotion evolution over multiple posts or interactions.

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