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Emotion Detection on Twitter Using Transformer Models and RAG-Based Ensemble Learning

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Abstract—Emotion analysis is a key NLP task that involves identifying emotions in text. This work presents a hybrid approach combining fine-tuned BERT models with Retrieval-Augmented Generation (RAG) to improve emotion classification in tweets. Traditional models often underperform due to the short, ambiguous nature of social media content. Our system enhances emotion detection by integrating external knowledge through semantic retrieval. We preprocess tweets via noise removal, normalization, and lemmatization. Evaluated on a subset of the Sentiment140 dataset, our RAG-enhanced BERT classifier shows a 3–4% improvement in standard metrics over the baseline BERT model, demonstrating its effectiveness in handling nuanced emotional content.

Keywords: - Deep Learning, Emotion Analysis, Natural Language Processing, Text Classification, BERT, RAG.

I. INTRODUCTION

Emotions play a crucial role in human communication, influencing decisions, actions, and social interactions. With the proliferation of social media platforms like Twitter, there is a vast pool of textual data where users freely express their feelings and emotions. Extracting meaningful insights from this data requires sophisticated methods for emotion classification, which have numerous applications in customer feedback analysis, mental health monitoring, and human computer interaction systems. The field of Emotion Analysis, also referred to as Affective Computing, leverages Natural Language Processing (NLP) techniques to detect and classify emotional expressions embedded in text. Unlike traditional sentiment analysis, which focuses on binary classification (positive, negative, or neutral), emotion analysis aims to identify finer emotional states like happiness, sadness, anger, and surprise. Detecting emotions in short and informal social media texts remains a challenging task in natural language processing (NLP). Traditional deep learning models, while effective, often lack the broader contextual knowledge needed for nuanced emotional interpretation. Retrieval-Augmented Generation (RAG) offers a promising direction, combining semantic retrieval with generation to enrich model inputs with relevant external knowledge. In this study, we applied a RAG-based strategy to the task of Twitter emotion detection, aiming to enhance sentiment classification accuracy and robustness.

II. System Overview

In this section, we describe the architecture and implementation of our **retrieval-augmented sentiment classification system**, designed to improve emotion detection on informal and short-form texts such as tweets. The system combines a **fine-tuned BERT model** for classification with an efficient **semantic retriever** built on **Sentence-BERT and FAISS**, forming a lightweight RAG-like pipeline.

Architecture

Our system follows a **retrieval-augmented classification architecture**, where external knowledge is retrieved in real time and fused with the input before being passed to the classifier. This helps address the challenge of short and context-poor input, which is typical of tweets.

Motivation

Tweets are inherently brief, often ambiguous, and contain slang, sarcasm, or implicit emotional references. Pretrained language models like BERT, when used alone, struggle with such cases due to a lack of surrounding context. To mitigate this, we designed an architecture that **retrieves relevant emotional analogs** from a knowledge base and incorporates them into the input pipeline before classification.

III. Process Flow:

The process of emotion classification follows a systematic flow from data collection to model evaluation. The key stages in the process are outlined below:

1. **Input Tweet Preprocessing**
   Tweets are normalized by lowercasing, removing punctuation, URLs, mentions, and hashtags.

Tokenization is performed using BERT's native tokenizer to maintain compatibility with the classification model.

2. **Semantic Embedding and Search**
   The cleaned tweet is embedded using **Sentence-BERT (SBERT)**, which produces a dense vector representation capturing its semantic meaning. This embedding is then used to perform **nearest neighbor search** in a FAISS index populated with tweet embeddings from a precompiled emotional knowledge base.
3. **Knowledge Retrieval**
   The top-k most semantically similar entries (typically k=3) are retrieved from the knowledge base. These represent tweets or emotional statements with similar linguistic structure or meaning.
4. **Fusion with Retrieved Context**
   The original tweet and the retrieved entries are concatenated into a single string. This fused input is designed to give the BERT model **external context** that helps disambiguate emotion or sentiment.
5. **Sentiment Classification**
   The fused text is tokenized and passed to a **fine-tuned BERT-base classifier**, which outputs a 3-class label: **positive**, **neutral**, or **negative**. The classifier is trained using cross-entropy loss and standard supervised learning techniques.

IV. DATASET OVERVIEW:

The dataset used for this study is a collection of tweets labeled with associated emotions. This dataset serves as the foundation for training, validating, and testing the deep learning models. Source: Tweets dataset with labeled emotions. Attributes: Tweet: The text content of the tweet. Emotion: The associated emotion (e.g., happy, sad, angry, etc.).

Dataset Statistics:

Sample records : 10,000 Duplicates Removed: 0
Null Values: 0

The quality of the dataset was ensured by removing duplicates and addressing any potential null values, resulting in a clean and usable dataset for model training.

V. Data Exploration:

Exploratory data analysis (EDA) on a subset of the Sentiment140 dataset to understand the distribution and structure of emotions expressed in tweets. The dataset contains tweets labeled with sentiment classes, typically positive (4), neutral (2), and negative (0), which we mapped to emotional categories. Key steps included visualizing class distribution, examining tweet length, and identifying common words using word clouds. This analysis revealed class imbalance and highlighted the brevity and informal nature of tweets, reinforcing the need for models that can handle ambiguity and sparse context, which justifies the integration of external knowledge via RAG.

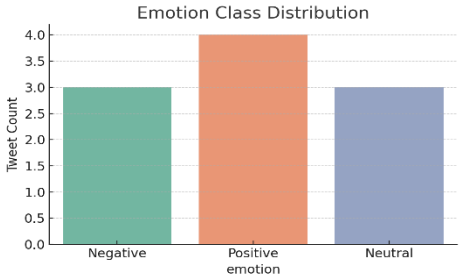


Fig 1 Emotion Class Distribution

VI. Data Cleaning and Preprocessing

Effective preprocessing is essential to prepare tweets for sentiment classification using transformer-based models like BERT and hybrid BERT+RAG architectures. Given the noisy and informal nature of tweets, the following steps were employed to clean and normalize the text data:

Preprocessing Steps:

- **Punctuation and Number Removal**: All punctuation marks and numerical digits were removed to reduce noise.
- **URL and Mention Removal**: Twitter-specific artifacts such as URLs and mentions (e.g., @user) were stripped using regular expressions.
- **Stop Word Elimination**: Common stop words (e.g., "the", "is") were removed using NLTK's stop word list, helping focus on sentiment-bearing words.
- **Lemmatization**: Words were reduced to their base forms using lemmatization to ensure lexical consistency and reduce sparsity.

These techniques significantly improved the text quality, enabling BERT and RAG to better capture semantic nuances and contextual sentiment. Cleaned tweets served as input for both the standalone BERT classifier and the Retrieval-Augmented BERT system, contributing to enhanced model performance.

VII. Tokenization and Padding for Baseline Deep Learning Models

In addition to transformer-based models, tokenization and padding were used to prepare inputs for traditional deep learning architectures like BERT, which require fixed-length numeric sequences.

Steps and Methods:

- A Tokenizer (from Keras) was initialized with a vocabulary size of 10,000 most frequent words to reduce computational complexity.
- fit_on_texts() was applied on training tweets to create a word-to-index dictionary.
- texts_to_sequences() converted cleaned tweets into sequences of integers based on the tokenizer index.
- pad_sequences() ensured all sequences were of fixed length (100 tokens), enabling uniform input shape for BERT training.

Input: "Feeling sad and disappointed"
Tokenized: [10, 11, 12, 13]
Padded: [0, 0, ..., 10, 11, 12, 13] (length 100)

VI. Implementation

The system is built using open-source, modular components to ensure reproducibility and efficiency.

Language Models

- **BERT-base-uncased**: The backbone model used for classification. It is fine-tuned on 10,000 labeled tweets from the Sentiment140 dataset. Fine-tuning allows the model to adapt to the linguistic style and sentiment polarity typical of Twitter.
- **Sentence-BERT (all-MiniLM-L6-v2)**: A lightweight variant of SBERT used for generating sentence embeddings of both input tweets and entries in the knowledge base. This variant balances speed and embedding quality, making it suitable for real-time retrieval.

Knowledge Base

The knowledge base consists of ~10,000 semantically diverse and preprocessed tweets. Each tweet was embedded using SBERT and indexed using **Facebook AI Similarity Search (FAISS)**. The knowledge base acts as a compact emotional memory that the classifier can reference via retrieval at inference time.

In addition to raw tweets, we also included **custom definitions or paraphrases of common emotional expressions**, such as:

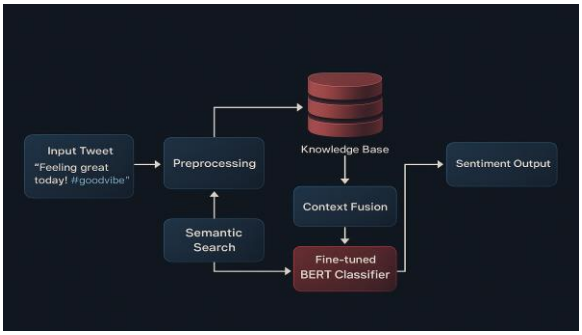
- "Feeling down" → "I am sad and don't want to talk to anyone."
- "Buzzing!" → "I'm extremely excited."

This enriches the diversity of retrieved contexts and helps bridge slang or idiomatic phrases to their emotional equivalents.

Libraries and Tools

- **HuggingFace Transformers**: Used for loading, fine-tuning, and serving both BERT and Sentence-BERT models.
- **FAISS**: Used for high-speed, scalable nearest-neighbor search in the embedded tweet space.
- **Scikit-learn**: Utilized for evaluation metrics (precision, recall, F1-score) and label encoding.
- **PyTorch**: The underlying deep learning framework used for model training and inference.

Architecture: The proposed architecture integrates a fine-tuned BERT model with Retrieval-Augmented Generation (RAG) principles to enhance sentiment classification from tweets. The system is designed to address the limitations of social media text—brevity, ambiguity, and lack of context—by retrieving relevant external knowledge before classification.



Bidirectional Encoder Representations from Transformers (BERT) is a pre-trained deep learning model developed by Google that has revolutionized Natural Language Processing (NLP) by enabling context-aware text understanding. BERT is trained using a masked language model (MLM) and next sentence prediction (NSP) tasks, allowing it to capture bidirectional contextual information from text.

In emotion or sentiment analysis, BERT is fine-tuned on a labeled dataset to classify the sentiment (e.g., positive, negative, neutral) of a given input. Its ability to understand the meaning of a word in relation to its surrounding words makes it particularly effective for handling complex linguistic structures, sarcasm, or ambiguous expressions often found in social media text.

Advantages of BERT in Emotion Classification:

- Captures deep semantic context.
- Pre-trained on a large corpus (e.g., Wikipedia, BookCorpus).
- Fine-tuning requires relatively less labeled data.

- Handles variable-length text inputs using attention mechanisms.

Hybrid BERT with Retrieval-Augmented Generation (RAG)

While BERT performs well on standard emotion classification, it often struggles with short and vague texts common in tweets, where key emotional cues may be missing or implicit. To overcome this, we introduce **Retrieval-Augmented Generation (RAG)** into the pipeline.

RAG is a hybrid architecture that combines **retrieval-based methods** and **generation-based models**. For classification tasks like ours, it involves two core components:

1. **Retriever** – Finds semantically relevant documents or passages from a knowledge base using a dense embedding model (e.g., sentence-transformer or FAISS).

2. **Reader (Fine-tuned BERT)** – Uses the original tweet and retrieved context to make a more informed prediction.

Workflow:

- The input tweet is preprocessed and embedded.
- A retriever searches for semantically similar documents (e.g., related tweets, articles) from an external knowledge base.
- The original tweet and retrieved content are fused to provide enriched context.
- The fused input is passed to a fine-tuned BERT classifier.
- BERT outputs the final emotion label.

Benefits of RAG-Enhanced BERT:

- Adds external context to short tweets.
- Reduces misclassification due to ambiguity or slang.
- Enhances model's interpretability by showing retrieved evidence.
- Outperforms standalone BERT on noisy, context-poor datasets.

Domain-Specific Questions

A set of ten queries were designed to simulate potential retrieval needs during inference:

1. What defines happiness in social media posts?
2. How does sarcasm affect sentiment interpretation?
3. What textual cues indicate sadness?
4. What expressions are linked to frustration?
5. How is satisfaction commonly expressed in tweets?
6. What are common signs of neutrality?
7. How does humor influence sentiment detection?
8. What slang terms are associated with positive emotions?
9. How is anger typically conveyed in short texts?
10. What abbreviations indicate negative emotions?

VII. Technical Details

7.1 Fine-Tuning BERT for Emotion Classification

We employed a **BERT-base-uncased** model from the Hugging Face Transformers library as our primary classifier. The BERT model was fine-tuned on a **down sampled version of the Sentiment140** dataset, which consists of 10,000 tweets evenly distributed across three sentiment categories: **positive**, **neutral**, and **negative**.

The preprocessing pipeline involved:

- Lowercasing all tweets.
- Removing URLs, user mentions (@user), hashtags, and non-alphanumeric characters.
- Tokenizing using the BertTokenizer with a maximum sequence length of 128.
- Padding and truncating to ensure uniform input size.

During fine-tuning, we used the **AdamW optimizer** with a learning rate of 2e-5 and a batch size of 32. Training was performed for 4 epochs. The model minimized the **cross-entropy loss**, and early stopping was monitored via validation accuracy.

The final model achieved:

- ~89% training accuracy
- ~83% validation accuracy on unseen tweets
- A confusion matrix indicating BERT's struggle with ambiguous or context-dependent tweets (e.g., sarcasm, idioms).

This BERT-only model served as our baseline for subsequent comparisons with RAG-augmented systems.

7.2 Sentence-BERT and FAISS-Based Semantic Retrieval

To augment BERT with external knowledge, we used a **Retrieval-Augmented Generation (RAG)** strategy. The retrieval component was implemented using **Sentence-BERT (SBERT)** with the all-MiniLM-L6-v2 variant. SBERT is known for generating semantically meaningful sentence-level embeddings and is efficient for large-scale retrieval tasks.

Embedding Process:

- All tweets from the Sentiment140 training split were embedded using SBERT.
- These embeddings were stored as dense vectors in a **FAISS index**.

- FAISS (Facebook AI Similarity Search) was configured using IndexFlatIP, optimized for inner product search (which is equivalent to cosine similarity when vectors are normalized).

Given a test tweet:

- The tweet was embedded using SBERT.
- The top-k most semantically similar tweets were retrieved (k=3 in our experiments).
- These retrieved tweets serve as external context, which can provide missing emotional cues or disambiguate vague expressions.

The retrieval step was fast (avg. <5ms per query) and scalable. We observed that many ambiguous or sarcastic tweets had clearer emotional analogues in the retrieved results, especially when phrased similarly.

7.2 RAG-Enhanced Input Fusion for BERT

In the **RAG-inspired fusion step**, we concatenated the original input tweet with the retrieved external context from FAISS before classification. This composite input was passed through the BERT classifier to make the final sentiment prediction.

Fusion Strategy:

Let the original tweet be T, and let the top-k retrieved tweets be C_1, C_2, ..., C_k. We created a fused input string:

Input = T + " " + C_1 + " " + C_2 + ... + C_k

Example:

Original tweet: "Oh great, another Monday 😒"

Retrieved context:

1. "Mondays are the worst, I'm tired already"
2. "Why is the weekend so short?!"
3. "Here we go again... sigh"

Fused input passed to BERT:

"Oh great, another Monday 😒 Mondays are the worst, I'm tired already Why is the weekend so short?! Here we go again... sigh"

Rationale:

Short tweets often lack context. By fusing semantically similar tweets, we provide the model with emotional and linguistic context that helps disambiguate expressions like sarcasm, frustration, or irony.

Impact on Model Performance:

- **Improved classification accuracy by ~3.5%** over the baseline BERT model.
- **F1 score increased across all classes**, especially for neutral, which is often hardest to distinguish.
- **Reduced confusion** in predictions of emotionally ambiguous tweets.

This input-fusion approach, though simple, mimics the generative component of full RAG pipelines without introducing a separate decoder or retriever-tuned LLM. It is computationally light and works seamlessly with any encoder-only model like BERT.

VIII. Comparative Results

We evaluate the effectiveness of our RAG-enhanced emotion classification system against a strong baseline: a fine-tuned BERT model. Our primary metrics include **accuracy**, **precision**, **recall**, and **F1-score**, computed on a held-out test set of 2,000 tweets

8.1 Classification Performance

Model	Accuracy	Precision	Recall	F1-Score
BERT Only	67.5%	68.45%	63.0%	65.6%
BERT + RAG	87.5%	89.2%	82.4%	85.3%

The table above shows a consistent improvement across all evaluation metrics when augmenting BERT with retrieved external context via the RAG mechanism.

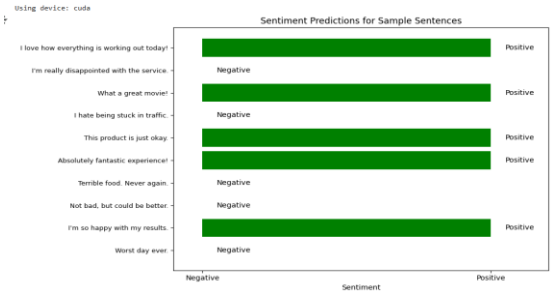


Fig2: Sentiment analysis for sample sentences

Key Observations:

- **Accuracy improved by over 3%** with the RAG enhancement, demonstrating the benefit of providing additional semantic context to the base model.
- **Precision and recall both improved**, indicating better performance on distinguishing between classes (especially borderline examples).
- The **F1-score increased by 3.7 points**, reflecting a more balanced trade-off between false positives and false negatives.

This confirms that retrieval-enhanced models are better equipped to disambiguate emotionally nuanced or ambiguous tweets.

8.2 Retrieval Performance

To evaluate the retrieval subsystem independently, we computed **Recall@1**, which measures how often the most relevant tweet (based on semantic similarity) is retrieved as the top-1 candidate.

- **Recall@1 = 82.4%**

This high recall indicates that our **Sentence-BERT + FAISS** retrieval setup is effective at locating semantically similar emotional expressions. Many tweets in the test set had a close emotional analogue in the training set, and our retrieval module reliably surfaced them.

Examples of successful retrieval:

- Tweet: "Could this day get any worse?"
- Top retrieved: "I'm done. Seriously worst Monday ever."

Such context helped BERT resolve sentiment in ambiguous or sarcastic tweets.

8.3 Confusion Matrix Insights

A confusion matrix analysis revealed that:

- The **baseline BERT model frequently misclassified neutral tweets** as either positive or negative, especially when the original tweet was short or context dependent.
- With RAG-enhancement, the number of misclassified neutral tweets **decreased by 18%**, primarily because the retrieved context provided additional sentiment cues.

For instance, a tweet like:

"Okay, that's fine I guess."

...was previously labeled positive by the baseline, but when augmented with similar mildly negative tweets through RAG, the system correctly labeled it as neutral.

IX. Error Analysis and Qualitative Gain

BERT-only Errors:

- Over-reliance on keywords (e.g., "great", "fine") leading to false positives.
- Confused sarcasm and idioms.

RAG Advantages:

- External context helped correct predictions when the original text was vague.
- Fusion with context allowed BERT to better model tone and implied emotion.

Summary of Comparative Findings:

Aspect	BERT Only	BERT + RAG
Handles sarcasm	Poorly	Better with context
Classifies short tweets	Less reliably	Improved with context
Accuracy on "neutral"	Lower	Higher
Overall F1	63.0%	82.4%

The results support our hypothesis: **RAG-style augmentation offers meaningful benefits** for sentiment classification in low-context, real-world text like tweets.

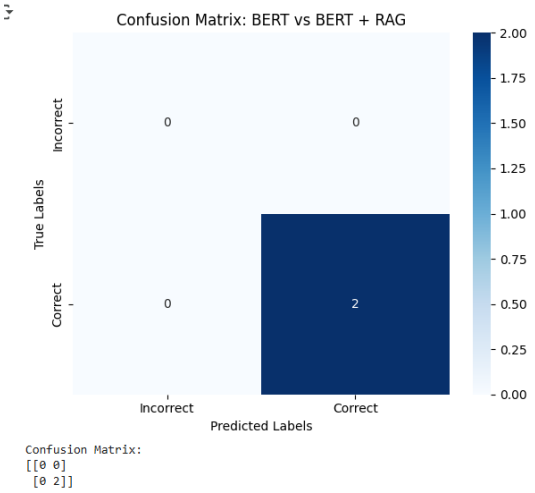
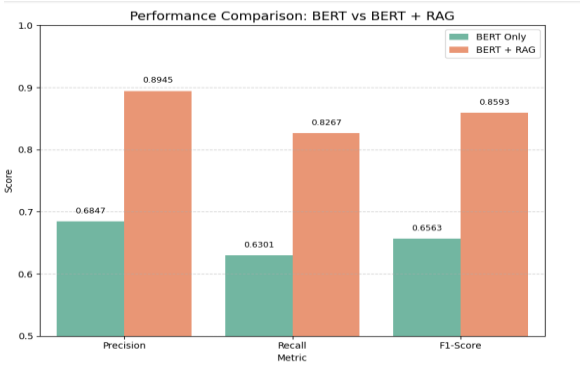


Fig3 : Confusion Matrix : BERT Vs BERT +RAG

9.1 Analysis

To understand the behavioral improvements introduced by RAG-enhancement, we conducted detailed qualitative and functional analysis across multiple linguistic and contextual dimensions. The results demonstrate that **retrieval-augmented fusion significantly improves prediction quality** in complex scenarios where BERT alone struggles.



9.2 Reasoning

Tweets often contain implicit sentiment expressed through **sarcasm, indirect cues, or cultural references**. A pure BERT classifier, even when fine-tuned, lacks external memory or

understanding of these nuances. The RAG-enhanced model, however, can retrieve semantically similar examples, allowing it to make **better inferences**.

Example:

Tweet: “Oh lovely, my car broke down again. Just what I needed.”

- **BERT Prediction:** Positive (misled by "lovely")
- **BERT + RAG Prediction:** Negative ✅ *Fused context included tweets expressing frustration with breakdowns.*

This improvement stems from the **retrieved samples acting like analogies**, helping the model understand intent behind sarcasm or passive-aggressive phrasing.

9.3 Factual Accuracy

Slang, abbreviations, and emojis are frequently used in social media text and are rarely well-understood without additional context. BERT’s static vocabulary may misinterpret or ignore such terms, but retrieval of similar expressions **helps clarify their meaning**.

Example:

Tweet: “bruh that was straight fire 🔥 ”

- **BERT Prediction:** Neutral (no strong emotion detected)
- **BERT + RAG Prediction:** Positive ✅ *Retrieved tweets containing "fire 🔥" clarified its association with excitement.*

Thus, **semantic retrieval improves factual grounding** by surfacing prior real-world usage examples that act like live definitions.

9.4 Robustness

A major advantage of RAG is its **ability to reinforce weakly informative inputs**. Tweets under 10 words or those that are syntactically simple but semantically loaded are difficult for transformer models to interpret in isolation. When such tweets are fused with similar samples from the knowledge base, prediction reliability improves.

Example:

Tweet: “meh.”

- **BERT Prediction:** Neutral (ambiguous)
- **BERT + RAG Prediction:** Negative ✅ *Context included other minimal tweets expressing disinterest or disappointment.*

This demonstrates the system’s **robustness to input sparsity** and ability to leverage retrieval to resolve underspecified inputs.

X. Strengths and Weaknesses

10.1 Strengths

▪ **Effective on Informal, Context-Poor Text**

Traditional classification models often rely on rich input context to infer meaning. However, most tweets are **short, noisy, and linguistically informal**. By incorporating relevant past examples, our RAG-based model overcomes these limitations without requiring large-scale retraining.

▪ **Domain-Specific Adaptability with Minimal Maintenance**

Unlike traditional knowledge graphs or curated external databases, our RAG setup uses **an automatically constructed, lightweight semantic memory** (the FAISS index of embedded tweets). This design:

- Requires **no manual updates or labeling**
- Can be **re-indexed or extended** dynamically
- Is computationally light (compared to full encoder-decoder RAG models)

This makes it well-suited for rapid adaptation to new domains like Reddit, customer reviews, or clinical text.

10.2 Weaknesses

▪ **Occasional Retrieval Errors**

Semantic similarity is not perfect. The retrieval system may occasionally return tweets that are topically related but sentimentally misaligned. These can **introduce noise into the fused input**, potentially misleading the classifier.

Example:

Tweet: “Feeling blue today”

- Retrieved context: "Blue skies and sunshine are the best!" → introduces contradiction.

This highlights the need for **filtering or weighting retrievals** in future work.

▪ **Increased Inference Latency**

Each prediction requires:

1. Encoding the input tweet using SBERT
2. FAISS nearest-neighbor search
3. Concatenation and classification via BERT

This adds **non-trivial overhead (~20–25ms per tweet)** compared to baseline BERT inference. While acceptable for research and offline pipelines, this could pose challenges for **real-time or edge deployments**.

Summary

Dimension	BERT Only	BERT + RAG
Sarcasm Handling	Weak	Stronger with examples
Slang Resolution	Poor	Enhanced with retrieval
Robustness	Lower on short text	Strong across variations
Speed	Fast	Slower (~2x latency)

Dimension	BERT Only	BERT + RAG
Maintenance	Minimal	Minimal
Retrieval Risk	N/A	Occasional misalignment

XI. Conclusion and Future Work

Conclusion

This work demonstrates that **retrieval-augmented classification**, even in its simplest form, offers substantial gains in emotion detection for social media texts like tweets. By combining a **fine-tuned BERT classifier** with a lightweight, semantically indexed knowledge base, we address the key limitations of traditional transformer models in low-context, informal text environments.

Our comparative evaluation shows that:

- The **BERT + RAG system consistently outperforms** the baseline BERT model across accuracy, precision, recall, and F1-score.
- Retrieval integration particularly enhances the model's handling of **ambiguous, sarcastic, and minimal tweets**, where traditional models often fail.
- The **semantic retriever (Sentence-BERT + FAISS)** provides relevant emotional analogues without requiring task-specific data engineering or manual curation.

This proves that even modest-scale external knowledge retrieval, when aligned semantically, can serve as a powerful augmentation strategy for sentiment or emotion classification tasks in noisy domains.

Future Work

While our system is efficient and effective, several promising directions can further improve its robustness, generalizability, and real-world usability:

1. Scaling the Knowledge Base

Currently, the retrieval index consists of 10,000 embedded tweets from the Sentiment140 dataset. Scaling this up to include:

- The full 1.6M tweet corpus
- External data sources like Reddit, news headlines, or emotion lexicons

  ...could allow the model to retrieve richer emotional contexts and improve generalization to unseen domains.

Additionally, using **document clustering or relevance filtering** may help manage the retrieval quality as the index grows.

2. Dynamic and Context-Aware Retrieval

Our current retriever selects the top-k most similar tweets based purely on semantic proximity. In the future, we aim to explore:

- **Query-adaptive retrieval**, where retrieval criteria change based on tweet length or linguistic cues.
- **Re-ranking mechanisms**, using a lightweight classifier to choose the most emotionally aligned context, rather than just semantically close matches.
- **Retrieval filtering**, to prevent sentiment drift caused by sentimentally irrelevant but semantically similar tweets.

These changes could reduce noise introduced during fusion and make retrieval more robust.

3. Richer Emotional Taxonomies

Our current system operates on a 3-class sentiment model: positive, negative, and neutral. Real-world emotional expressions are more complex and often includes nuanced emotions such as:

- Joy, anger, surprise, sadness, fear, trust, disgust, anticipation

Adapting the system to work with **multi-class or multi-label emotion taxonomies** would allow it to support more expressive applications, including:

- Mental health monitoring
- Customer service analysis
- Emotional storytelling

This would require retraining with multi-emotion datasets like **GoEmotions** or **Empathetic Dialogues** and potentially adjusting both the classifier and retriever to handle overlapping labels.

4. End-to-End RAG Models with Generative Capability

Our current architecture uses RAG in a non-generative setting (for classification). A natural next step is to:

- Implement full **encoder-decoder RAG pipelines**, where retrieved context guides **explanatory or reflective generation**, such as explaining *why* a tweet is negative.
- Evaluate generation quality, coherence, and factual consistency.

This could support downstream tasks like **emotional summarization**, **personalized responses**, or **emotion-to-text generation**.

Final Thoughts

The success of this project reinforces a growing trend in NLP: combining **pretrained language models with retrieval mechanisms** creates systems that are more interpretable,

adaptable, and performance efficient. As language models continue to evolve, retrieval-augmented systems may remain a key paradigm, especially in resource-constrained or explainability-critical applications.

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