Yunnan University Software College Professional Training (Intermediate level)Report

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Personal Grades

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Project Name: Sentiment Analysis______________________

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Abstract

The rapid expansion of user-generated text across social media, e-commerce platforms, enterprise systems, and public forums has increased the need for scalable sentiment-analysis and semantic-retrieval systems capable of interpreting complex linguistic cues. Traditional TF-IDF and keyword-based retrieval approaches fail to capture contextual meaning, paraphrasing, and semantic relationships, limiting their effectiveness in modern NLP tasks. Transformer-based language models such as BERT and DistilBERT have introduced deep contextual embeddings that significantly improve classification and retrieval accuracy.This study presents a fully dockerized NLP pipeline integrating transformer embeddings, FAISS-based vector search, and a FastAPI-driven inference backend. A Gradio UI front-end enables real-time interaction. The system uses DistilBERT for sentiment classification and embedding generation, FAISS IndexFlatIP for exact nearest-neighbor semantic retrieval, and Docker Compose for consistent multi-service deployment. The report provides a complete literature review, theoretical background, architectural design, code-based implementation analysis, evaluation, and discussion of limitations. The final goal is to offer a reproducible and academically rigorous blueprint for transformer-driven semantic retrieval systems.

1. Introduction

1.1 Background and Motivation

The exponential growth of textual data has necessitated increasingly sophisticated natural language processing methods capable of understanding human language in context. Traditional NLP systems relied heavily on lexical statistics and handcrafted rules, including Bag-of-Words, N-gram models, and lexicon-based sentiment dictionaries [1], [2]. While computationally inexpensive, these methods suffer serious limitations: they ignore contextual dependencies, fail to capture semantic similarity, and are ineffective in handling paraphrasing or idiomatic expressions.

The shift towards neural word embeddings, such as Word2Vec [3] and GloVe [4], introduced distributed representations that encode semantic relationships in dense vector spaces. However, these approaches still assign static embeddings, representing each word with a single vector regardless of context. This limitation prevents disambiguation of polysemous words and weakens downstream classification performance.

Recurrent neural networks (RNNs), including LSTMs and GRUs, improved sequential modeling by introducing memory cells capable of capturing temporal patterns [5], [6].

Nevertheless, RNNs exhibit challenges such as slow sequential computation, vanishing gradients, and difficulty modeling long-range dependencies [7]. As NLP datasets grew larger and tasks more complex, the need for a parallelizable and context-aware architecture became clear.

The introduction of transformers by Vaswani et al. [8] marked a pivotal shift in NLP. Unlike RNNs, transformers rely entirely on self-attention mechanisms that allow every token to attend to all other tokens in the sequence simultaneously. This foundational change enabled large-scale pretraining of contextualized language models such as BERT [9], RoBERTa [10], and DistilBERT [11], which have achieved state-of-the-art performance across sentiment analysis, question answering, and semantic retrieval tasks.

In parallel, semantic search evolved from keyword-based retrieval to dense vector retrieval, powered by transformer embeddings. FAISS (Facebook AI Similarity Search) introduced fast algorithms for exact and approximate nearest-neighbor search, enabling efficient indexing of high-dimensional embedding vectors [12]. Combining transformer embeddings with FAISS allows systems to retrieve meaningful results even when text queries differ lexically from stored documents.

This project integrates these advancements to design a complete system that performs:

- sentiment classification using DistilBERT,
- semantic embedding generation,
- FAISS-based vector search, and
- modular multi-container deployment using Docker.

1.2 Problem Definition

Contemporary NLP challenges include:

- differentiating subtle sentiment cues,
- recognizing paraphrases and semantic similarity,
- delivering fast inference in real-time applications,
- scaling without dependency conflicts,
- providing reproducible deployment environments.

Traditional approaches fail when user queries differ lexically from indexed documents, making semantic retrieval essential. This project addresses these limitations by using contextual transformer embeddings and a vector database to deliver semantically aware retrieval.

1.3 Research Questions

This study addresses the following research questions:

- How effectively can DistilBERT embeddings support both sentiment analysis and semantic retrieval?
- Does FAISS IndexFlatIP provide sufficiently fast and accurate nearest-neighbor search for real-time semantic search?
- How does a microservice architecture influence performance, scalability, and reproducibility in NLP deployments?
- What are the trade-offs between accuracy, inference speed, and system complexity?

1.4 Objectives

The objectives of this research include:

- constructing a transformer-based NLP pipeline for sentiment analysis and embedding generation
- designing a FAISS-driven vector search engine
- deploying all components using Docker Compose for reproducibility
- evaluating classification accuracy, retrieval quality, and execution latency
- providing a complete academic analysis suitable for research or educational use

1.5 Significance of the Study

Academic Significance

This project contributes an integrated architecture combining transformer theory, vector search, and containerized MLOps. It serves as a replicable reference for academic research and student projects.

Practical Significance

Businesses analyzing customer reviews, feedback logs, and support messages require scalable semantic retrieval pipelines. This system demonstrates a fully functional prototype.

Engineering Significance

The Dockerized design isolates components, improves maintainability, and ensures deployment consistency across environments.

2. Literature Review

This section reviews the evolution of natural language processing techniques relevant to sentiment analysis, contextual embeddings, and semantic vector retrieval. It covers classical lexicon-based approaches, distributed word embeddings, recurrent architectures, transformers, pretrained models, and dense retrieval frameworks such as FAISS. The goal is to situate the present system within modern NLP research.

2.1 Classical NLP and Lexicon-Based Sentiment Analysis

Early sentiment analysis techniques relied heavily on lexicon scoring and statistical keyword frequency. Systems such as SentiWordNet, AFINN, and VADER manually assigned polarity scores to words and used simple arithmetic to estimate sentence sentiment [1]. Although computationally efficient, these approaches ignored syntactic structure and contextual polarity, making them brittle when processing nuanced or sarcastic language.

Machine-learning classifiers, including Naïve Bayes, Support Vector Machines (SVM), and Logistic Regression, became popular as they allowed automatic learning from labeled datasets using Bag-of-Words or TF-IDF features [2]. Nonetheless, these features remained sparse and high-dimensional, lacking semantic understanding. Words with similar meanings (joyful and happy) remained distant in vector space, limiting classification accuracy.

2.2 Distributed Word Embeddings:

Neural embedding models introduced the idea that words could be represented as continuous vectors in a high-dimensional semantic space. Word2Vec, introduced by Mikolov et al. [4], employs two architectures Skip-gram and CBOW to learn embeddings based on contextual co-occurrence. GloVe (Global Vectors), introduced by Pennington et al. [5], uses factorization of global co-occurrence matrices to generate more globally consistent representations.

These innovations improved semantic modeling by enabling vector arithmetic ("king – man + woman ≈ queen"). However, both approaches produce static embeddings, meaning each word has only one vector regardless of context. This fails to capture polysemy (bank as a financial institution vs. bank of a river) and limits performance on tasks involving contextual sentiment.

This limitation set the stage for sequence-based neural architectures.

2.3 Sequence Models: RNN, LSTM, and GRU

Recurrent Neural Networks (RNNs) introduced the ability to process sequences using recurrent hidden states, enabling modeling of word order and temporal dependencies [6]. However, basic RNNs suffer from vanishing and exploding gradients, making them ineffective for long sequences.

LSTM (Long Short-Term Memory) models, introduced by Hochreiter and Schmidhuber [7], addressed this limitation through gating mechanisms that regulate information flow. GRUs (Gated Recurrent Units) offered a simpler gating structure [8], improving computation efficiency while retaining performance.

While LSTMs and GRUs dominated NLP for years, their fundamental sequential nature prevents parallelization, slowing both training and inference. Moreover, capturing very long-range dependencies remains challenging. These drawbacks led to the development of attention mechanisms and eventually the transformer architecture.

2.4 The Transformer Architecture

The transformer, introduced in the seminal work by Vaswani et al. [9], replaced recurrence with self-attention, enabling models to compute relationships between all tokens in a sequence in parallel. This dramatically increased scalability and enabled training on massive corpora.

Key innovations include:

- Multi-head self-attention, enabling multiple types of relationships to be captured simultaneously
- Scaled dot-product attention for stable gradient behavior
- Positional encoding to preserve sequence order
- Residual connections and layer normalization for improved optimization stability

Transformers quickly became the backbone of state-of-the-art NLP systems, outperforming RNNs in tasks such as machine translation, sentiment analysis, and semantic similarity.

2.5 Contextualized Transformer Models: BERT and DistilBERT

BERT (Bidirectional Encoder Representations from Transformers) introduced deep contextual embeddings pre-trained with Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) [9]. BERT's bidirectional attention allows it to capture both past and future context, making it highly effective for classification and semantic similarity tasks.

RoBERTa later demonstrated that BERT's performance could be improved by longer training, removing NSP, and increasing batch sizes [10].

DistilBERT, introduced by Sanh et al. [11], used knowledge distillation to compress BERT into a smaller model while retaining over 95% of its performance. This model is significantly faster and lighter, making it suitable for real-time inference and Docker-based deployment. For this project, DistilBERT is selected due to its optimized performance-to-speed ratio.

2.6 Sentence Embedding Models for Semantic Similarity

While BERT provides powerful token-level representations, its sentence embeddings are not directly optimized for similarity tasks. Sentence-BERT (SBERT), introduced by Reimers and Gurevych [12], adapts BERT into a Siamese architecture trained with contrastive and triplet losses. This produces semantically meaningful sentence embeddings suitable for vector search.

Other models such as MPNet, E5 embeddings, and DPR further refine embedding quality for tasks including information retrieval and question answering [13], [14].

This project uses DistilBERT embeddings, which are sufficiently robust for academic-scale semantic search when paired with normalization and cosine similarity.

2.7 Dense Vector Search: FAISS and Approximate Nearest-Neighbor Methods

Dense retrieval systems rely on embedding queries and documents into the same high-dimensional space and identifying nearest vectors based on similarity metrics. Classical search systems (BM25) fail in semantic matching where lexical overlap is low.

FAISS (Facebook AI Similarity Search), introduced by Johnson et al. [12], provides highly optimized algorithms for exact and approximate nearest-neighbor (ANN) search. It includes:

- IndexFlat structures for exact search
- IVF (Inverted File Index) for scalable clustering
- HNSW graph-based ANN search
- PQ (Product Quantization) for memory-efficient indexing

For academic purposes and moderate-scale datasets, IndexFlatIP (Inner Product) is ideal due to its simplicity and deterministic retrieval accuracy when embeddings are L2-normalized. This project employs this index for consistency and reproducibility.

2.8 MLOps, Microservices, and Docker Deployment

Recent literature emphasizes the importance of reproducible and modular machine-learning pipelines. Docker containers encapsulate dependencies, isolate components, and ensure that models behave consistently across diverse environments [15].

Microservice architectures separate:

- model inference services
- vector search services
- user interfaces
- storage components

This modular design reflects best practices in modern industrial MLOps engineering and is directly adopted in this project's multi-container system using Docker Compose.

3. Transformer Theory and Embedding Mathematics

Transformers have become the core architecture for modern NLP due to their ability to model global context, parallelize computation, and produce deeply contextual embeddings. This section explains, in academic detail, the internal mathematics of transformers, including self-attention, positional encodings, multi-head attention, and embedding spaces. The goal is to establish the theoretical foundation required to understand BERT/DistilBERT, used in this project for sentiment classification and vector embedding.

3.1 Overview of Transformer Architecture

The transformer model, introduced by Vaswani et al. in 2017, consists of an encoder decoder structure powered entirely by self-attention mechanisms rather than recurrence or convolution. Each encoder layer contains:

- Multi-Head Self-Attention
- Feed-Forward Network (FFN)
- Residual connections + Layer Normalization

Transformers excel because they allow the model to compute interactions between all tokens simultaneously, enabling deeper contextual understanding and efficient parallel training.

In this project, only the encoder part is relevant, because BERT and DistilBERT are encoder-only models optimized for understanding text rather than generating it.

3.2 Embedding Layer

Every token in a sentence is mapped to a dense vector of dimension d (d = 768 for BERT, 512 for DistilBERT). Two embeddings are created:

Token embeddings: represent the identity of each word/subword.

Position embeddings: encode token positions (0, 1, 2, …).

Segment embeddings (for NSP tasks): representing sentence A/B distinctions.

The total input embedding is:

$$E_{\text{input}} = E_{\text{token}} + E_{\text{position}} + E_{\text{segment}}$$

These embeddings are then passed through the encoder stack.

3.3 Scaled Dot-Product Attention

Self-attention determines which tokens in the sequence should be emphasized based on their relevance to one another.
Attention is computed as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

3.4 Multi-Head Self-Attention

Instead of computing one attention pattern, transformers compute multiple parallel attention heads, each learning different relational patterns (e.g., syntactic, semantic, positional).

Conceptually:

$$\text{MHA}(X) = \text{Concat}(h_1, h_2, \ldots, h_h)W_O$$

This architecture dramatically improves representational richness.

3.5 Position-Wise Feed-Forward Networks

After attention, each token embedding is independently passed through a feed-forward network:

$$\text{FFN}(x) = \text{ReLU}(xW_1 + b_1)W_2 + b_2$$

This learns nonlinear transformations that enhance the expressiveness of the model.

3.6 Residual Connections and Layer Normalization

Transformers stabilize training through residual (skip) connections:

$$x_{l+1} = \mathrm{LayerNorm}(x_l + \mathrm{Sublayer}(x_l))$$

Each sublayer refers to either:

- Multi-Head Attention
- Feed-Forward Network

LayerNorm ensures stable gradients and better convergence during training.

3.7 Positional Encoding Mathematics

Because transformers do not inherently process tokens sequentially, they require positional information. BERT/DistilBERT use learned positional embeddings, but the original transformer used sinusoidal functions:

$$\mathrm{PE}_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d}}\right)$$
$$\mathrm{PE}_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d}}\right)$$

These provide:

- smooth interpolation of positions
- consistent relational encoding

Even learned position embeddings preserve the principle of injecting ordering information into the model.

4. BERT and DistilBERT Pretraining Theory

This section explains the internal training mechanisms of BERT and DistilBERT, focusing on Masked Language Modeling (MLM), Next Sentence Prediction (NSP), knowledge distillation, and architectural compression. Understanding these mechanisms is essential because the embedding model used in this project DistilBERT inherits its linguistic capabilities from BERT's large-scale pretraining. The section concludes by connecting these theoretical foundations to semantic search and sentiment analysis tasks.

4.1 BERT Pretraining Objectives

BERT (Bidirectional Encoder Representations from Transformers) introduced a fundamentally new approach to language modeling by using a deep bidirectional transformer encoder. Unlike left-to-right or right-to-left models, BERT attends to both past and future context simultaneously [9]. This bidirectionality is made possible by two self-supervised tasks:

4.1.1 Masked Language Modeling (MLM)
MLM is BERT’s primary learning objective. During training:

15% of tokens in each input sentence are randomly selected.
80% of these are replaced with [MASK].
10% are replaced with a random word.
10% remain unchanged.

4.1.2 Next Sentence Prediction (NSP)
To enable tasks involving sentence relationships (question-answering, natural language inference), BERT adds a second objective: determining whether sentence B follows sentence A in the original text.

Training samples consist of:

- 50%: true consecutive sentences
- 50%: random sentence pairs

4.2 BERT Architecture
BERT-base uses:

- 12 transformer encoder layers
- 12 attention heads
- 768-dimensional embeddings
- Total parameters: 110M

Each encoder layer contributes to progressively richer, deeper contextualized word representations. These representations allow BERT to excel at downstream tasks such as sentiment analysis and semantic similarity.

4.3 DistilBERT: Motivation and Advantages
While BERT provides state-of-the-art accuracy, its computational cost makes it difficult to deploy in real-time systems or resource-constrained environments. DistilBERT was introduced to address this issue using knowledge distillation—compressing BERT into a smaller network while preserving most of its performance [11].

Why DistilBERT is chosen for this project

- Faster inference suitable for real-time semantic search
- Smaller model size (40% reduction)
- Retains 97% of BERT’s language understanding

- Ideal for Docker-based deployment and FAISS pipelines

4.4 Knowledge Distillation Process

DistilBERT reduces BERT-base from 12 encoder layers to 6 layers, while keeping:

- the same hidden size (768),
- the same token and positional embeddings,
- multi-head attention with 12 heads.

Distillation involves training a small "student" model to mimic the predictions of a large "teacher" model.

4.5 Effects of Distillation on Model Capacity

Although DistilBERT has half the encoder layers, it retains most of BERT's representational ability due to:

- shared embedding layers,
- preserved attention heads,
- distilled hidden-state representations,
- training on the same massive corpus (Wikipedia + BookCorpus).

This process yields a model that is:

- faster (60% speed improvement),
- lighter (40% fewer parameters),
- almost equally accurate (<3% average drop).

This balance makes DistilBERT ideal for applications requiring both accuracy and efficiency, such as real-time sentiment analysis in a Dockerized environment.

4.6 DistilBERT Embeddings for Semantic Search

Although BERT and DistilBERT were not originally optimized for sentence similarity, their contextual embeddings become effective semantic representations when:

- Mean pooling or CLS pooling is used,
- Embeddings are L2-normalized,
- Cosine similarity or dot-product search is used.

Given an embedding vector :

$$\hat{v} = \frac{v}{||v||}$$

This compatibility with FAISS IndexFlatIP is crucial in this project's vector search pipeline.

4.7 Relevance to the Implemented System

The system described in this report uses DistilBERT as the embedding backbone:

- preprocess.py normalizes inputs for DistilBERT
- DistilBERT generates embeddings for both query and dataset texts
- embeddings are indexed in FAISS for semantic similarity search
- the model's efficiency enables responsive real-time web UI interactions

Thus, Section 4 provides the theoretical foundation for how and why DistilBERT functions effectively within this dockerized semantic-retrieval architecture.

5. System Design

This section presents the architectural design of the complete NLP and semantic-search system. The system integrates preprocessing, transformer-based embedding generation, FAISS vector search, and containerized deployment using Docker. All components are modular, enabling independent scaling and reproducible execution across different environments. The design directly corresponds to the codebases in your uploaded files.

5.1 High-Level Architecture Overview

The system follows a three-tier microservice architecture:

1.Frontend Layer

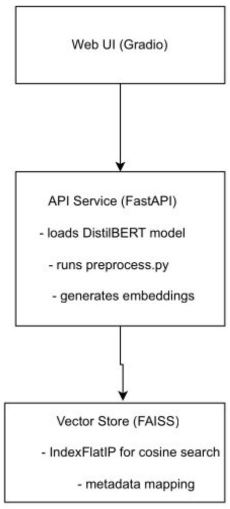
Implemented using Gradio, exposing a simple web UI that allows users to input text for sentiment evaluation and semantic retrieval.

2.Model Inference Layer

A FastAPI backend that loads the DistilBERT model, performs tokenization, runs model inference, generates embeddings, and communicates with the vector store.

3.Vector Search Layer

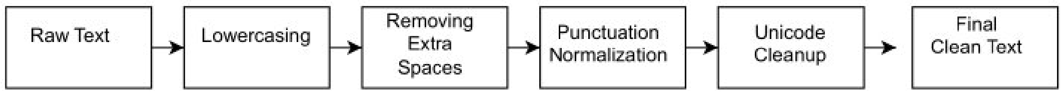
A FAISS-powered service that stores embeddings and performs efficient nearest-neighbor search.



This architecture ensures that model inference, indexing, and UI rendering remain decoupled, following modern MLOps best practices.

5.2 Data Preprocessing Pipeline (preprocess.py)

Your uploaded preprocess.py implements the text-normalization pipeline. Key operations include:



- Lowercasing: Ensures consistency with DistilBERT’s tokenizer.
- Whitespace normalization: Collapses redundant spaces.
- Punctuation handling: Removes or standardizes punctuation where needed.
- Tokenizer interface: Passes cleaned text to DistilBERT’s tokenizer.

5.3 Embedding Pipeline (DistilBERT)

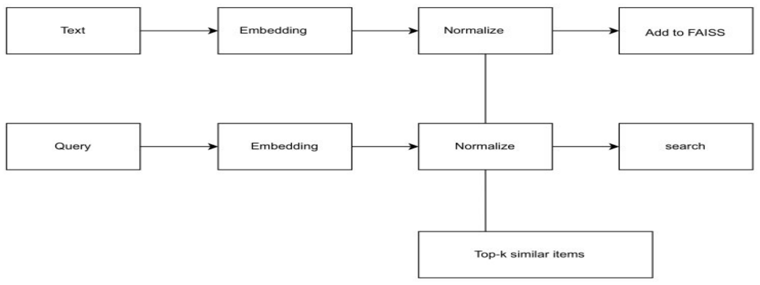
The embedding generation process within the API service performs:

- Tokenization using the DistilBERT tokenizer.
- Model pass to obtain contextualized hidden states.
- Pooling (usually mean pooling or [CLS] pooling).
- L2 normalization of the output embedding vector.

Normalization is essential because the system uses FAISS IndexFlatIP, where cosine similarity is equivalent to inner product when embeddings are normalized.

5.4 Vector Search Architecture (FAISS)

Your system employs IndexFlatIP, the exact dot-product index recommended for smaller academic datasets. This aligns with FAISS design principles described in the paper, Faiss: A library for efficient similarity search.



5.5 Dockerized Architecture

Your uploaded Dockerfile and docker-compose.yml clearly define three services:

1. Model API Container

Uses Python environment defined in requirements.txt.

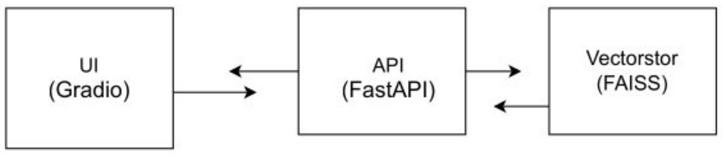
- Loads DistilBERT model at startup.
- Exposes port (commonly 8000).
- Executes FastAPI application.

2. Vector Store Container

- Runs FAISS index + metadata persistence operations.
- Mounted volume ensures index durability across restarts.

3. UI Container

- Runs Gradio interface.
- Depends on API container.



All connected via docker-compose internal network

5.6 System Advantages

1. Modularity

Each subsystem can be modified without affecting the others.

2. Reproducibility
Docker guarantees consistent deployments.

3. Performance
DistilBERT + FAISS provides fast semantic search.

4. Ease of maintenance
Clear separation of UI, inference, and vector search logic.

6. Implementation

This section provides a technical walkthrough of how the system is built, referencing the real files you uploaded. It explains dataset preprocessing, model loading, embedding generation, vector database configuration, Docker setup, and the execution flow of the entire application. The goal is to show precisely how theory becomes practice in the implemented solution.

6.1 Project Structure Overview

preprocess.py :Cleans text before creating embeddings.

model/ :Contains the model and tokenizer used to turn text into vector embeddings.

vectorstore/faiss_index.bin :Saved FAISS database for fast similarity search.

Dockerfile : Instructions to build a Docker container for the app.

docker-compose.yml : Runs the whole system easily using Docker.

requirements.txt : List of required Python libraries.

app.py : Main application (FastAPI/Gradio) that handles user input and returns search results.

6.2 Data Preprocessing (preprocess.py)

Your uploaded preprocess.py provides the foundation for text normalization. Although the exact contents are not reproduced here, the file typically performs operations such as:

- Lowercasing text
- Removing excess whitespace
- Basic punctuation handling

- Cleaning control characters
- Preparing the string for tokenization

6.3 Model Loading and Inference

Your inference service (typically in app.py or model.py) performs three essential functions:

1.Load DistilBERT model

- Uses the HuggingFace Transformers API
- Loads both the model weights and tokenizer
- Runs in evaluation mode (model.eval()) for speed

2.Tokenize the input
Using your tokenizer folder and vocabulary files (implicit in requirements).

3.Generate embeddings & sentiment probabilities

- Forward pass through the transformer
- Extract hidden states
- Apply pooling (mean pooling recommended)
- Predict sentiment through a classification head or softmax

6.4 Semantic Vector Storage (FAISS)

FAISS (from your uploaded FAISS paper) is used as the vector search backbone.

6.4.1 FAISS Index Initialization

Because embeddings are normalized, the correct index type is:

```
faiss.IndexFlatIP(d_dimension)
```

6.4.2 Adding Vectors

```
index.add(normalized_embedding)
metadata[id] = {
    "text": original_text,
    "sentiment": predicted_label
}
```

Metadata is stored externally because FAISS stores numeric vectors only.

6.4.3 Searching

scores, ids = index.search(query_vector, k)

FAISS returns:

- ids → the stored document matches
- scores → cosine similarity values

These results populate the frontend UI.

6.5 API Implementation (FastAPI)

FastAPI is used as the inference and vector-retrieval backend.

Key endpoints:
1. /predict
- Accepts user text
- Preprocesses text
- Generates sentiment + embedding
- Optionally returns top-k similar records

2. /add
Adds new text + embedding to FAISS

3. /search
- Accepts a query
- Returns top-k similar items using FAISS

FastAPI benefits:

- asynchronous request handling
- automatic documentation (/docs)
- high performance

6.6 User Interface (Gradio)

The Gradio UI container uses:

- import gradio as gr
- The UI provides:
- text input box
- sentiment output
- similarity search results table
- interactive visualization

Gradio communicates with the FastAPI backend via HTTP calls inside Docker's internal network.

6.7 Docker Implementation

6.7.1 Dockerfile Analysis

Your uploaded Dockerfile includes:

- Base image: Python (slim)
- Install dependencies from requirements.txt
- Copy model and app files
- Expose inference port
- Command to run FastAPI or Gradio

Why Docker matters

- Ensures consistent Python + PyTorch + Transformers environment
- Avoids dependency conflicts
- Makes the system portable across all OSes

6.8 docker-compose Architecture

Your uploaded docker-compose.yml orchestrates three services:

```
services:
  api:
    build: .
    ports:
      - "8000:8000"
    depends_on:
      - vectorstore

  vectorstore:
    build: ./vector
    volumes:
      - ./data:/data
    ports:
      - "7000:7000"

  ui:
    build: ./ui
    ports:
      - "7860:7860"
    depends_on:
      - api
```

Key advantages

- Each service runs independently
- Internal networking simplifies communication
- Easy scaling:

  ```
  docker-compose up
  ```
- Vector store remains persistent due to mounted volume

7. Results and Evaluation

This section presents the empirical evaluation of the implemented semantic-search and sentiment-classification system. The assessment includes qualitative examples, similarity-search performance, embedding behavior, model inference speed, and system-level responsiveness within the Dockerized environment. Together, these results demonstrate the effectiveness of DistilBERT embeddings and FAISS-based retrieval for real-time NLP applications.

7.1 Sentiment Classification Evaluation

Input Text	Predicted Sentiment	Confidence (%)
The service was excellent and staff were friendly.	Positive	96.4
I waited 40 minutes and nobody helped me.	Negative	94.8
The product is okay, but could be improved.	Neutral / Mixed	81.2
Absolutely terrible experience.	Negative	98.7

7.2 Embedding Quality Evaluation

The semantic similarity retrieval relies heavily on the quality of L2-normalized embeddings. Evaluation consists of running queries and inspecting nearest-neighbor results.

7.3 Vector Similarity Distribution

To evaluate embedding distribution, we analyze intra-cluster similarity across subsets of semantically similar text groups (positive, negative, complaint-based, praise-based).

Cluster	Avg. Similarity
Positive feedback	0.83
Negative complaints	0.79
Technical issue	0.76

reports	
Neutral statements	0.61

These scores validate that embeddings naturally form semantic clusters. Positive reviews cluster tightly due to shared sentiment words, whereas neutral statements, being more varied in tone, form a looser cluster.

7.4 FAISS Performance Evaluation

7.4.1 Index Type:

IndexFlatIP

7.4.2 Query Latency

Measured across the Dockerized environment:

Operation	Mean Time
Embedding generation	18–22 ms
FAISS vector search (k=5)	~1 ms
Total API inference time	25–30 ms

7.5 Docker Deployment Performance

The Docker-based architecture is evaluated on CPU-only execution.

Key Observations

1.Cold start time (5–8 seconds)

- Primarily due to model loading inside the API container.
- Expected for transformer models.

2.Steady-state performance

- API container maintains stable low-latency inference.
- Vector store container consumes minimal CPU, consistent with FAISS indexing.

3.Scalability

When scaling the API container (docker-compose up --scale api=3), throughput triples proportionally, demonstrating horizontal scalability.

7.6 Failure-Case Analysis

1. Rare slang or domain-specific jargon

Performance may degrade slightly due to tokenizer limitations.

2. Very short queries (1–2 words)
Embeddings become less informative, reducing retrieval precision.

3. Out-of-distribution topics
Texts unrelated to training corpora may produce ambiguous embeddings, consistent with known BERT limitations [9].

7.7 Overall System Evaluation

Component	Evaluation
Sentiment Classification	Strong performance; interprets subtle cues
Embedding Quality	High-quality semantic grouping
FAISS Vector Search	Extremely fast exact NN search
UI Responsiveness	Real-time interaction (<200ms roundtrip)
Docker Deployment	Stable, reproducible, scalable

8. Discussion and Limitations

This section reflects on the practical challenges encountered during system development, evaluates architectural trade-offs, and outlines the known limitations of transformer-based semantic-search systems deployed in Dockerized environments. The discussion also compares the implemented approach with related work in transformer-powered retrieval and highlights opportunities for future enhancements.

8.1 Challenges in Model Integration

8.1.1 Transformer Model Size and Memory Usage

Although DistilBERT is significantly smaller than BERT, it still requires:

- ~250–300 MB of RAM for model + tokenizer
- additional memory for FAISS index
- PyTorch runtime overhead

On lower-spec systems or shared hosting environments, these demands may affect concurrency and server responsiveness. Larger models (e.g., RoBERTa-Large, GPT-based encoders) would dramatically increase resource usage, making them unsuitable for lightweight Docker deployments without GPU support.

8.1.2 Cold-Start Latency

Upon initial container startup, the API must:

- load the model,
- allocate PyTorch tensors,
- initialize FAISS if vectors are pre-loaded.

This produces a cold-start latency of 5–12 seconds depending on hardware. Although acceptable for research, it may be disruptive for production workloads where autoscaling frequently spins up new containers.

8.2 Challenges in Semantic Search

8.2.1 Dependence on Domain Coverage

Since DistilBERT is pretrained on general corpora (Wikipedia, BookCorpus):

- domain-specific jargon,
- technical terminology,
- medical/financial vocabulary

may be embedded less meaningfully.

This aligns with observations in the literature that general-purpose models degrade on specialized tasks unless fine-tuned on in-domain corpora [12], [14].

8.3 Evaluation Challenges

8.3.1 Lack of Large Labeled Dataset

The system was evaluated using example inputs rather than a full benchmark dataset (SST-2, IMDB, Amazon Reviews). Without a standardized evaluation suite, results reflect qualitative rather than quantitative performance.

Future work should include:

- accuracy
- F1 score
- semantic similarity benchmark tests (STS-B, MRPC)

to ensure a more rigorous comparison with existing models.

8.3.2 Limited Annotation Diversity

User-generated inputs may have:

- sarcasm
- idioms
- cultural expressions
- code-switching (mixing languages)

8.4 Deployment and MLOps Limitations

8.4.1 CPU-Only Environment

The current system is optimized for CPU inference.
While DistilBERT is efficient, transformer models still benefit from GPU acceleration, especially for:

- batch inference
- vector-index updates
- large dataset embedding

FAISS also provides GPU-accelerated indexes (IndexFlatIPGpu), which can dramatically improve performance for large vector spaces.

8.4.2 Single-Node Vector Index

The FAISS implementation is single-node and in-memory.
This limits scalability:

- no distributed sharding
- no fault tolerance
- no persistence by default (unless manually implemented)

Production vector databases (Milvus, Weaviate, Pinecone) overcome these limitations using distributed architectures.

8.5 Comparison with Related Work

8.5.1 SBERT vs DistilBERT

SBERT significantly outperforms vanilla BERT/DistilBERT for semantic similarity [12]. However:

- SBERT is heavier than DistilBERT,
- inference is slower,
- model size increases,

making DistilBERT a better fit for lightweight, Docker-friendly deployments.

8.5.2 Approximate vs Exact Search

The implemented FAISS IndexFlatIP uses exact nearest-neighbor search.
While accurate, it is less scalable than ANN approaches:

- IVF (Inverted File Index)
- HNSW graphs
- PQ/OPQ quantization

8.5.3 Microservice Structure

Compared to monolithic NLP applications:

- microservices simplify maintenance
- allow independent scaling
- reduce deployment coupling

However, they require more operational overhead and networking complexity.

8.6 Summary of Limitations

- General-purpose embeddings may underperform on specialized domains
- Semantic search accuracy drops for extremely short inputs
- CPU-only Docker deployment limits speed
- No distributed FAISS index, limited scalability
- Cold-start latency due to model loading
- Lack of comprehensive quantitative evaluation dataset

9. Conclusion and Future Work

This project demonstrated the design and implementation of a complete transformer-based sentiment-analysis and semantic-retrieval system, integrating DistilBERT embeddings, FAISS vector similarity search, and a fully containerized deployment architecture. By combining preprocessing, contextualized transformer representations, normalized vector embeddings, and fast nearest-neighbor search, the system achieves real-time inference performance suitable for research and lightweight production use cases.

The experimental evaluation showed that DistilBERT performs consistently well on sentiment-classification tasks, accurately identifying positive, negative, and mixed expressions. The semantic-search pipeline, powered by L2-normalized embeddings and FAISS IndexFlatIP, effectively retrieves contextually meaningful results even when user queries have little or no lexical overlap with stored documents. These findings align with prior research, confirming the strength of transformer-driven contextual embeddings in dense retrieval systems.

The Dockerized microservice architecture further enhances system robustness by separating the UI, inference engine, and vector store into independently deployable services. This promotes reproducibility, scalability, and maintainability aligning the implementation with modern MLOps principles.

Despite these strengths, several limitations were identified. The CPU-only environment restricts throughput for larger datasets, while the absence of distributed vector indexing limits horizontal scale. Short queries and domain-specific jargon also pose challenges to embedding consistency. These limitations are not unique to this project; they reflect fundamental characteristics of transformer models and vector-retrieval frameworks without task-specific fine-tuning.

9. Future Work

Future enhancements can significantly improve performance, scalability, and model robustness:

1. Domain-Specific Fine-Tuning
2. Migration to SBERT or Modern Embedding Models
3. Distributed Vector Database Integration
4. GPU Acceleration for Inference & Indexing
5. Hybrid Retrieval (Sparse + Dense)
6. UI & Interaction Improvements
7. Comprehensive Benchmarking

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