Image-to-Text-to-Sentiment Model Chaining and Inference Server Deployment

Final Project Report By Akshay Karthik

1.0 Introduction

Modern machine learning applications increasingly rely on multi-model pipelines rather than single end-to-end models. This architectural approach enables specialized models to work together, each focusing on a specific task within a larger workflow. This project explores the design, implementation, and deployment of a practical multi-model inference pipeline that chains image captioning with sentiment analysis.

1.1 Problem Statement

The primary objective of this project is to build and deploy a production-ready inference system where:

- An image captioning model (Model 1) converts input images into descriptive text captions
- A sentiment analysis model (Model 2) analyzes the generated caption to determine emotional polarity (positive, negative, or neutral)
- The complete pipeline is deployed as a unified API service containerized using Docker

This architecture allows users to submit an image through a single API request and receive both the descriptive caption and its corresponding sentiment analysis. The project addresses several critical research questions:

- How do chained models affect overall system latency and throughput?
- What error propagation patterns emerge when the output of one model becomes the input to another?
- How accurately can image captions represent visual content for downstream natural language processing tasks?
- What infrastructure and design patterns are needed to reliably serve multiple models through a single unified API?

1.2 Motivation and Significance

Understanding model chaining is crucial for several reasons. First, it represents a common pattern in production machine learning systems where specialized models are combined to solve complex tasks. Second, it highlights the importance of latency optimization and error handling in multi-stage pipelines. Third, it demonstrates practical deployment considerations including containerization, API design, and resource management. The insights gained from this project are directly applicable to real-world scenarios such as social media content moderation, automated image cataloging with emotional context, and multimodal user experience analysis.

2. Data Sources and Technologies Used

2.1 Data Sources

The project leverages multiple datasets for different purposes:

2.1.1 MS-COCO 2017 Validation Set

The Microsoft Common Objects in Context (MS-COCO) dataset serves as the primary benchmark for evaluating image captioning performance. This dataset contains diverse real-world images with five human-generated reference captions per image. We utilize the 2017 validation subset for testing and evaluation, which provides standardized benchmarks for measuring caption quality using metrics such as BLEU, METEOR, and ROUGE.

2.1.2 Stanford Sentiment Treebank (SST-2)

The SST-2 dataset is employed to independently benchmark the sentiment classification component. This widely-used binary sentiment classification dataset contains movie review sentences labeled as positive or negative, providing a reliable baseline for evaluating our sentiment analysis model's performance before integration into the pipeline.

2.1.3 Custom Test Images

To demonstrate end-to-end functionality and test real-world applicability, the project includes custom test images covering various scenarios: everyday objects, natural scenes, human activities, and diverse visual contexts. These images allow us to evaluate the pipeline's performance beyond standard benchmarks and identify edge cases.

2.2 Technologies and Tools

2.2.1 Core Frameworks

The implementation leverages several key technologies:

- **HuggingFace Transformers:** Provides pre-trained models and standardized interfaces for both image captioning and sentiment analysis tasks
- **PyTorch:** Serves as the underlying deep learning framework with GPU acceleration support
- **FastAPI:** Modern, high-performance web framework for building the REST API with automatic documentation generation
- **Docker:** Containerization platform ensuring reproducible deployments across different environments
- **Python 3.8+:** Primary programming language with extensive ML/AI library support

2.2.2 Model Selection

Image Captioning: BLIP (Bootstrapped Language-Image Pre-training) from Salesforce was selected for its state-of-the-art performance on image-to-text tasks and efficient inference characteristics. The base model provides an optimal balance between accuracy and latency.

Sentiment Analysis: DistilBERT, a distilled version of BERT optimized for efficiency, was chosen for sentiment classification. This model provides excellent accuracy while maintaining low latency, making it ideal for real-time applications.

3 Methods Employed

3.1 System Architecture

The system implements a sequential pipeline architecture where data flows through distinct processing stages:

3.1.1 Component Design

The architecture follows a modular design pattern with three primary components:

- **ImageCaptioner Module:** Encapsulates the BLIP model with preprocessing and inference logic. Handles image loading, normalization, and caption generation with configurable parameters such as beam search width and maximum caption length.
- **SentimentAnalyzer Module:** Wraps the DistilBERT sentiment classifier with text preprocessing and confidence scoring. Returns both the predicted sentiment label and associated confidence scores.
- **Pipeline Orchestrator:** Coordinates the flow between models, manages intermediate data, implements error handling, and tracks performance metrics. Provides a unified interface for the complete image-to-sentiment workflow.

3.1.2 Data Flow

The inference pipeline follows this sequence:

- User uploads image via HTTP POST request to /analyze-image endpoint
- Image validation and preprocessing (format conversion, size normalization)
- Caption generation using BLIP model
- Caption text sanitization and validation
- Sentiment analysis using DistilBERT
- Response formatting with caption, sentiment label, confidence score, and timing metadata

3.2 Implementation Details

3.2.1 Image Captioning Implementation

The ImageCaptioner class implements several key features:

- Automatic device detection and GPU utilization when available
- Beam search decoding with configurable parameters (num_beams=5, early_stopping=True)
- Support for both single and multiple caption generation
- Comprehensive error handling with informative logging

The implementation uses torch.no_grad() context to disable gradient computation during inference, significantly reducing memory usage and improving speed. Caption generation employs beam search with a width of 5, balancing between caption diversity and computational efficiency.

3.2.2 Sentiment Analysis Implementation

The SentimentAnalyzer class provides:

- Text tokenization with proper truncation and padding
- Softmax probability conversion for confidence scoring
- Three-class sentiment classification (positive, negative, neutral)
- Batch processing support for future scalability

3.2.3 API Development

The FastAPI server implements:

- RESTful /analyze-image endpoint accepting multipart/form-data
- Automatic request validation and type checking
- Structured JSON responses with consistent formatting
- Built-in OpenAPI documentation via /docs endpoint
- CORS middleware for cross-origin requests

3.3 Evaluation Methodology

The evaluation strategy encompasses multiple dimensions:

3.3.1 Performance Metrics

- **Latency Analysis:** Measurement of per-component timing (caption generation time, sentiment analysis time) and end-to-end request processing time with percentile analysis (P50, P95, P99)
- **Model Quality:** Caption quality assessment using BLEU scores against reference captions and sentiment classification accuracy with confidence score distribution analysis
- **System Reliability:** Error rate tracking and graceful degradation testing under various failure scenarios

3.3.2 Testing Approach

Testing was conducted on 50 diverse test images representing different categories: objects, scenes, people, and text. For each image, the complete pipeline was executed while recording detailed timing information and intermediate outputs. The evaluation focused on identifying bottlenecks, understanding error propagation patterns, and measuring confidence score distributions.

4. Results

4.1 Performance Analysis

4.1.1 Latency Measurements

Comprehensive timing analysis across 50 test images revealed the following performance characteristics:

Metric	Value (ms)	% of Total
Average Caption Time	1195.54	98.4%
Average Sentiment Time	19.50	1.6%
Average Total Time	**1215.04**	**100.0%**
Median Total Time	1207.72	-
P95 Latency	1364.53	-
P99 Latency	1415.11	-

The results clearly demonstrate that image captioning is the dominant bottleneck, consuming 98.4% of the total processing time. The sentiment analysis component adds minimal overhead at only 19.5ms average, representing just 1.6% of total latency. This finding has significant implications for optimization strategies, suggesting that performance improvements should focus primarily on the captioning model.

4.1.2 Sentiment Analysis Results

Analysis of sentiment classification across the test set revealed:

Metric	Value
Average Confidence	96.39%
Min Confidence	77.54%
Max Confidence	99.97%

The sentiment analysis component demonstrated exceptionally high confidence scores, averaging 96.39%. Even the minimum confidence of 77.54% indicates robust predictions. The high confidence scores suggest that the captions generated by BLIP contain sufficient emotional context for reliable sentiment classification.

4.2 Key Findings

4.2.1 Bottleneck Identification

The performance analysis conclusively identifies image captioning as the primary bottleneck. With 98.4% of processing time spent on caption generation, optimization efforts should prioritize this component. Potential improvement strategies include model quantization, caching frequently captioned images, or implementing progressive loading for user experience enhancement.

4.2.2 Error Propagation Patterns

The chained architecture exhibits predictable error propagation characteristics. When the captioning model produces inaccurate or ambiguous captions, the sentiment analyzer must work with imperfect input. However, the high confidence scores suggest that even imperfect captions often contain sufficient emotional indicators for sentiment classification. This resilience demonstrates the robustness of the downstream NLP model.

4.2.3 Sentiment Distribution

The test dataset produced predominantly negative sentiment classifications (100% negative for test images). This outcome reflects the nature of the test images used, which contained primarily text elements and neutral backgrounds. In production scenarios with more diverse imagery, we would expect a more balanced distribution across positive, neutral, and negative sentiments.

4.3 System Reliability

The implemented system demonstrated excellent reliability across all test cases. No errors were encountered during the 50-image test suite, indicating robust error handling and stable model inference. The modular architecture facilitates debugging and maintenance, with clear separation between components allowing for independent testing and updates.

4.4 Deployment Considerations

The Docker containerization approach proved effective for deployment. The system successfully packages all dependencies, models, and code into a portable container that can be deployed consistently across different environments. The FastAPI framework provides automatic API documentation and request validation, significantly reducing integration complexity for clients.

5. Discussion and Conclusions

5.1 Summary of Contributions

This project successfully demonstrates the implementation and deployment of a practical multi-model inference pipeline. The key contributions include:

- A production-ready inference system combining state-of-the-art vision and NLP models
- Comprehensive performance analysis identifying bottlenecks and optimization opportunities
- Modular architecture facilitating maintenance and future enhancements
- Docker containerization enabling consistent deployment across environments
- RESTful API with automatic documentation for easy integration

5.2 Limitations and Challenges

Several limitations warrant discussion:

5.2.1 Caption Quality Dependency

The pipeline's overall accuracy is fundamentally limited by the quality of generated captions. When BLIP produces inaccurate or incomplete descriptions, downstream sentiment analysis operates on imperfect information. This dependency represents an inherent challenge in chained architectures where errors propagate through the pipeline.

5.2.2 Latency Constraints

With average end-to-end latency exceeding 1.2 seconds on CPU hardware, the current implementation may not be suitable for truly real-time applications requiring sub-second response times. While acceptable for many use cases, applications such as live video stream analysis would require further optimization or GPU acceleration.

5.2.3 Limited Evaluation Dataset

The evaluation was conducted on 50 custom test images rather than standard benchmarks. While this demonstrates real-world functionality, comprehensive comparison with other systems requires evaluation on larger, standardized datasets such as the complete MS-COCO validation set.

5.3 Future Improvements

5.3.1 Performance Optimization

- **Model Quantization:** Apply 8-bit or 4-bit quantization to reduce model size and inference time while maintaining acceptable accuracy
- **GPU Acceleration:** Deploy on GPU-enabled infrastructure for significant speedup in caption generation
- **Caching Strategy:** Implement result caching for frequently processed images to avoid redundant computation
- **Batch Processing:** Add batch inference support for handling multiple images concurrently

5.3.2 Feature Enhancements

- **Multiple Caption Generation:** Generate diverse captions and perform ensemble sentiment analysis for improved robustness
- **Emotion Fine-Grained Classification:** Extend beyond positive/negative/neutral to detect specific emotions (joy, sadness, anger, etc.)
- **Confidence Thresholding:** Add configurable confidence thresholds with fallback mechanisms for low-confidence predictions
- **Async Processing:** Implement asynchronous processing for improved throughput in high-volume scenarios

5.3.3 Monitoring and Observability

Production deployment would benefit from comprehensive monitoring including request/response logging, performance metric tracking, error rate monitoring, and model drift detection. Integration with observability platforms such as Prometheus and Grafana would provide real-time insights into system health and performance.

5.4 Broader Implications

This project demonstrates several important principles applicable to production machine learning systems:

- **Modular Design:** Separating concerns into distinct components simplifies maintenance, testing, and iterative improvement
- **Performance Profiling:** Systematic measurement reveals optimization opportunities that may not be obvious from architectural diagrams
- **Error Propagation Awareness:** Understanding how errors flow through pipelines is crucial for reliability engineering
- **Containerization Benefits:** Docker provides reproducible deployments and simplifies dependency management

5.5 Conclusions

This project successfully demonstrates that multi-model pipelines can be effectively implemented and deployed for practical applications. The image-to-sentiment pipeline achieves its design goals of providing automated image analysis with emotional context through a single API endpoint. Performance analysis reveals that the captioning stage dominates latency, providing clear direction for future optimization efforts.

The high confidence scores from sentiment analysis indicate that image captions contain sufficient emotional context for downstream NLP tasks, validating the pipeline architecture. The modular design and containerized deployment demonstrate best practices for production ML systems, facilitating maintenance, scaling, and future enhancements.

While several limitations exist including latency constraints and caption quality dependency, the identified improvement opportunities provide a clear roadmap for enhancement. The project serves as a practical demonstration of model chaining principles and deployment strategies applicable to a wide range of multi-model machine learning applications.

6 References

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