

Distributed AI-Powered Argument Analysis System

Real-Time Emotion Classification and Multi-Source Fact-Checking

Ifesi Onubogu

AIoT Project

December 7, 2025

Outline

Project Overview

System Architecture

Emotion Classification

Fact-Checking with RAG

Use Cases

Results & Demo

Future Directions

Conclusion

Problem Statement

Challenge

In an era of increasing polarization and misinformation, how do we:

- ▶ Analyze emotional dynamics in real-time conversations?
- ▶ Verify factual claims against authoritative sources?
- ▶ Present crowd-sourced predictions for subjective statements?

Solution

A distributed edge-cloud system that:

- ▶ Captures and processes conversations on Raspberry Pi
- ▶ Analyzes emotions using fine-tuned transformers on AWS
- ▶ Fact-checks claims via RAG, Polymarket, and web search
- ▶ Visualizes results in interactive web interface

Key Contributions

1. Hybrid Fact-Checking Pipeline

- ▶ First system to combine curated knowledge base (RAG), prediction markets, and web search

2. Segment-Level Emotion Analysis

- ▶ Per-utterance emotion classification (73.2% accuracy)
- ▶ 8 emotion classes optimized for argument detection

3. LRU-Cached Market Discovery

- ▶ Dynamic cache management for prediction market links
- ▶ API fallback for unseen topics

4. Privacy-Preserving Edge Architecture

- ▶ Local processing on Raspberry Pi
- ▶ Cloud inference only for heavy models

System Data Flow

| Step | Component | Action |
|-----------|--------------------------------------|-------------------------|
| blue!20 | Raspberry Pi (Edge) - 4-6 sec | |
| 1 | Microphone | Capture 30-second audio |
| 2 | pyannote | Speaker diarization |
| 3 | Whisper | Speech-to-text |
| 4 | HTTP | POST to AWS |
| orange!20 | AWS EC2 (Cloud) - 2-3 sec | |
| 5 | FastAPI | Receive files |
| 6 | Emotion Model | Classify per segment |
| 7 | Fact Checker | RAG + Polymarket + Web |
| 8 | Database | Store results |
| green!20 | Browser (Client) - <1 sec | |
| 9 | Gradio | Load web UI |
| 10 | Visualization | Display analysis |

Total Latency: 6-10 seconds end-to-end

What Runs Where?

Raspberry Pi

HW: Pi 4 (4GB) + USB Mic

Tasks:

- ▶ Audio capture
- ▶ Diarization
- ▶ Whisper STT

AWS EC2

HW: t2.large (2 vCPU, 8GB)

Tasks:

- ▶ Emotion classification
- ▶ RAG + Polymarket
- ▶ Web search
- ▶ Storage

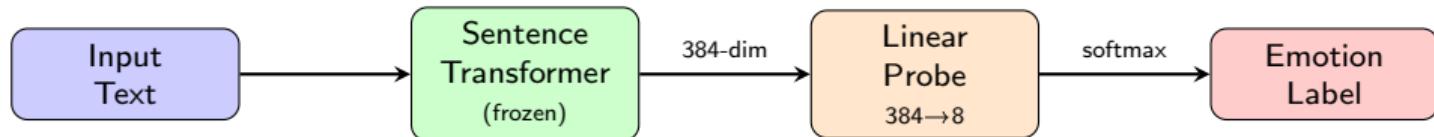
Browser

UI: Gradio web app

Features:

- ▶ Chat bubbles
- ▶ Emotion badges
- ▶ Hover panels
- ▶ Source links

Emotion Classifier Architecture



Model:

- ▶ Pre-trained embedder (66M params frozen)
- ▶ 2-layer MLP (49K trainable)
- ▶ Fast inference (100ms)

8 Emotion Classes:

- ▶ Calm, Confident, Defensive
- ▶ Dismissive, Passionate
- ▶ Frustrated, Angry, Sarcastic

Training Data Generation

Synthetic Data via GPT-4

Generated 500 labeled examples using structured prompts for 8 emotion classes

Prompt Structure:

- ▶ Specify topic & emotion
- ▶ Include emotion patterns
- ▶ Generate 2-4 sentences

Topics:

- ▶ Remote work, Climate
- ▶ EVs, Social media
- ▶ Healthcare, Politics

Example Patterns:

- ▶ Confident: "Obviously..."
- ▶ Defensive: "That's not fair..."
- ▶ Frustrated: "This is pointless..."
- ▶ Sarcastic: "Oh sure..."

Data Split:

- ▶ Train: 400, Val: 100
- ▶ Balanced across 8 classes

Training Configuration

Hyperparameters

- ▶ Adam optimizer, LR: 0.001
- ▶ Batch: 32, Epochs: 20
- ▶ Dropout: 0.3
- ▶ CrossEntropy loss

Why Linear Probe?

- ▶ Only 49K trainable params
- ▶ Works with 400 examples
- ▶ Fast inference (100ms)
- ▶ Low memory footprint

Model: 66M frozen + 49K trainable = 66M total params

Testing Methodology

Test Setup

- ▶ 500 synthetic examples (GPT-4)
- ▶ Split: 400 train / 100 val
- ▶ 100 held-out test (balanced)

Evaluation Process

1. Train 20 epochs, validate, select best
2. Test on 100 held-out examples
3. Real-world validation on recordings

Note

Synthetic data provides strong baseline for transfer learning

Emotion Classifier Results

| Metric | Mean | Std | Range |
|-----------|--------------|------|--------|
| Accuracy | 73.2% | 4.1% | 68-79% |
| Precision | 71.8% | 5.2% | 64-78% |
| Recall | 72.4% | 4.8% | 66-78% |
| F1-Score | 72.1% | 4.5% | 66-78% |

Best Classes:

- ▶ Angry: 82% F1
- ▶ Confident: 79% F1
- ▶ Calm: 76% F1

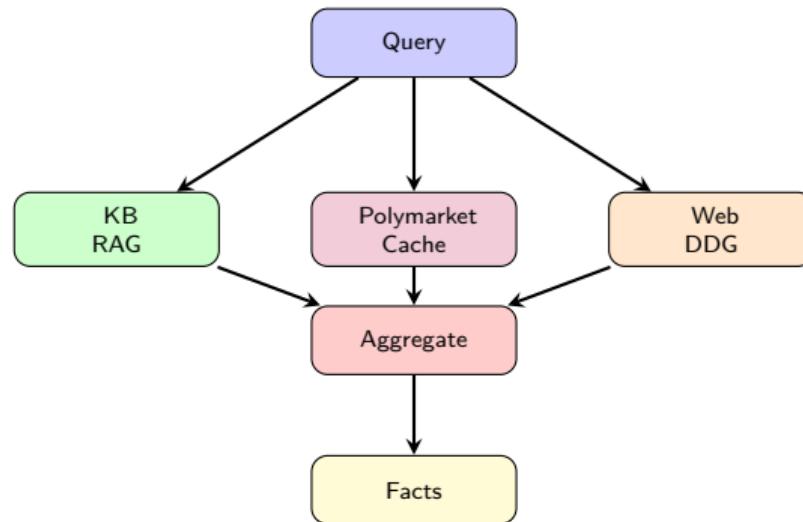
Challenging:

- ▶ Sarcastic: 65% F1
- ▶ Defensive: 68% F1

Insight

73% for 8-way classification with only 400 examples!

Multi-Source Fact-Checking Pipeline



Three Sources: Curated KB (semantic) — Polymarket (crowd opinion) — Web (current news)

Vector Database for Semantic Search

What is a Vector Database?

Stores text as numerical vectors enabling similarity-based retrieval instead of keyword matching

Keyword Search:

- ▶ Matches exact words only
- ▶ Misses synonyms
- ✗ Limited by phrasing

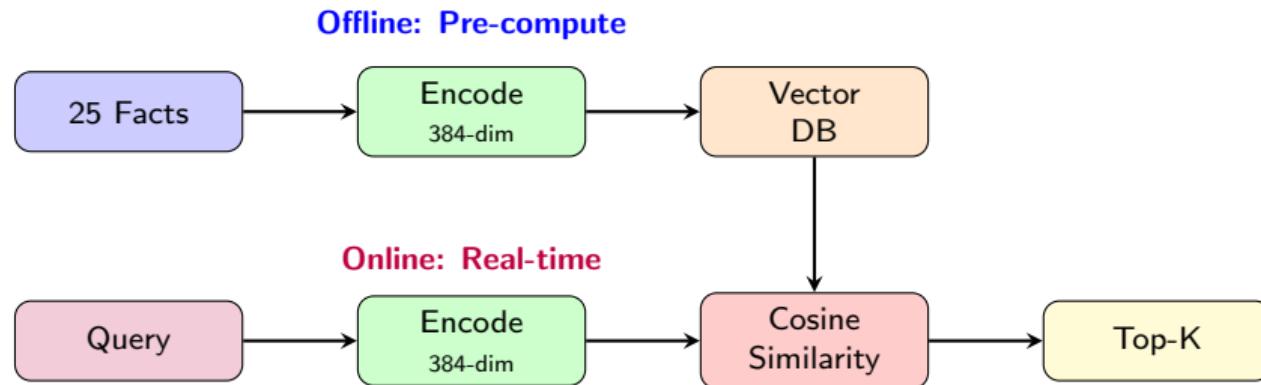
Semantic Search:

- ▶ Matches similar **meaning**
- ▶ Finds paraphrases
- ✓ Understands context

Our Implementation

25 facts × 384 dimensions stored in memory for fast cosine similarity search

RAG: Vector Database Architecture



- ▶ **Model:** all-MiniLM-L6-v2, **Dimension:** 384
- ▶ **Metric:** Cosine similarity, **Threshold:** 0.3 (30% match)

RAG: Knowledge Base Search

Semantic Search Algorithm

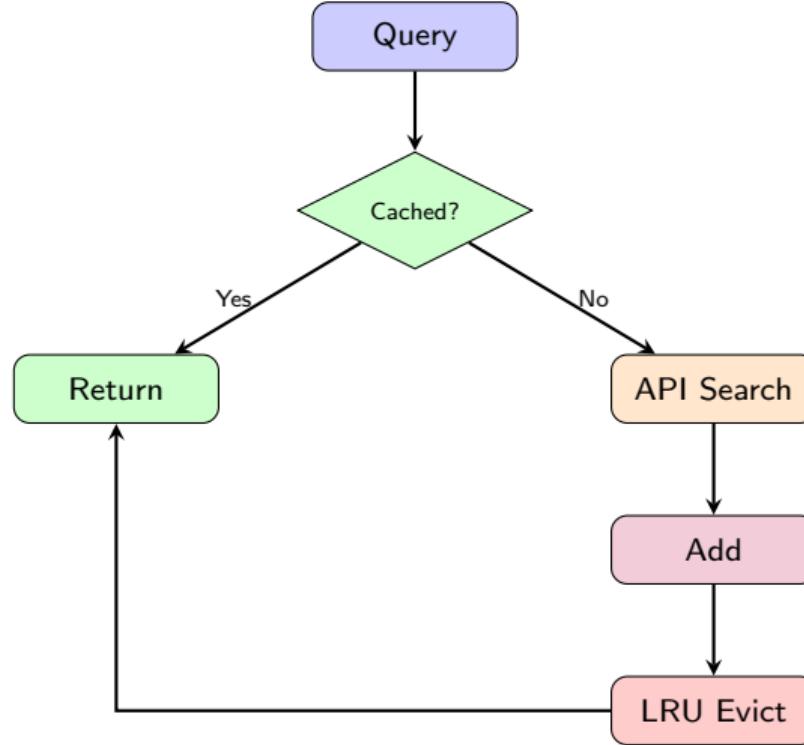
```
def search(query, top_k=3, threshold=0.3):
    # Encode query to 384-dim vector
    query_emb = model.encode(query)

    # Cosine similarity with all facts
    sims = cosine_similarity(query_emb, fact_embeddings)

    # Return top-k above threshold
    top_idx = argsort(sims)[-top_k:]
    return [facts[i] for i in top_idx if sims[i] >= threshold]
```

Key Steps: Encode query → Compute similarity → Filter by threshold → Return top matches

Polymarket Integration with LRU Caching



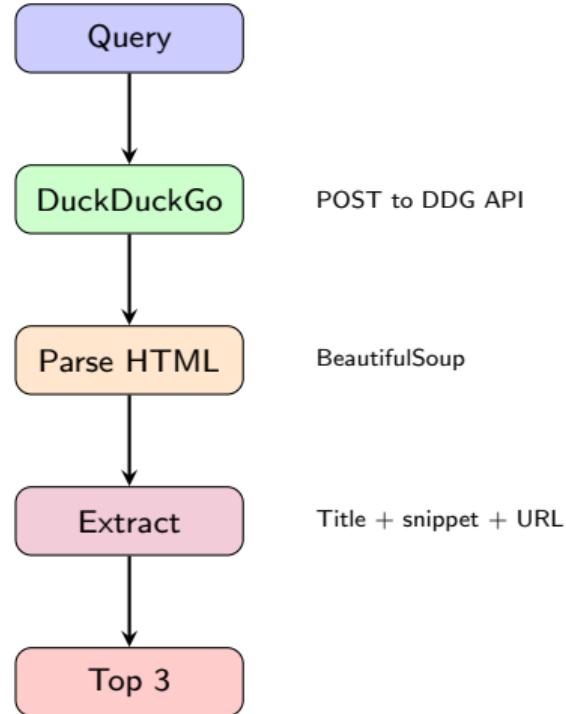
Strategy:

- ▶ 22 preloaded markets

Topics:

- ▶ Sports, Politics

Web Search Integration



- ▶ **Fallback** when KB/Polymarket lack info
- ▶ **Speed:** 1-2 sec, **Purpose:** Latest news

Use Case 1: Argument De-escalation in Microclimates

Scenario

Two roommates arguing about who should do dishes, household temperature settings, or shared space usage

How System Helps:

- ▶ **Emotion Tracking:** Detects when conversation becomes defensive or frustrated
- ▶ **Fact-Checking:** Provides objective data (e.g., "Studies show fair chore distribution reduces conflict by 40%")
- ▶ **De-escalation:** Visual emotion timeline shows patterns, encourages cooling down

Example

Speaker A: "You never do the dishes!" (Emotion: Angry 85%)

Speaker B: "That's not true, I did them yesterday!" (Emotion: Defensive 78%)

System shows: Polymarket on household chore distribution fairness

Psychology research on effective conflict resolution

Use Case 2: Corporate Conflict Resolution

Scenario

Team members disagreeing on project direction, resource allocation, or deadlines

How System Helps:

- ▶ **Meeting Analysis:** Records team discussions, tracks emotional dynamics
- ▶ **Evidence-Based:** Provides market data, industry benchmarks, case studies
- ▶ **Post-Meeting Review:** Managers review conversation for missed concerns

Example

Engineer: "Everyone in the industry is moving to microservices" (Confident)

System shows: Polymarket: 55% of companies still use monoliths

Recent survey: 40% of microservice migrations failed

Case study: When to choose monolith vs microservices

Use Case 3: Educational Debate Analysis

Scenario

Students debating controversial topics in classroom settings

How System Helps:

- ▶ **Real-Time Feedback:** Students see emotion labels, learn self-awareness
- ▶ **Source Quality:** Distinguishes opinion claims from factual claims
- ▶ **Critical Thinking:** Teaches students to verify assertions with evidence

Example

Student A: "Most people think climate change is the biggest threat" (Passionate)

System shows: Polymarket: 68% rate climate in top 3 global risks

Pew Research: Public opinion varies by age and region

Latest IPCC report on climate consensus

Use Case 4: Political Debate Fact-Checking

Scenario

Live political debates, town halls, or campaign events

How System Helps:

- ▶ **Real-Time Verification:** Fact-checks claims as candidates speak
- ▶ **Public Opinion:** Shows what voters actually think via prediction markets
- ▶ **Emotional Analysis:** Detects when candidates become defensive or evasive

Example

Candidate: "Everyone agrees my healthcare plan is the best solution" (Confident)

System shows: Polymarket: Plan has 45% approval, 38% disapproval

CBO analysis: Plan would cost \$2.1T over 10 years

Kaiser poll: 52% prefer alternative approach

System Performance Metrics

| Component | Metric | Value |
|-----------------------|--------------------|----------|
| Raspberry Pi | | |
| Speaker Diarization | Processing Time | 2-3 sec |
| Whisper Transcription | Processing Time | 2-3 sec |
| Total Pi Processing | Latency | 4-6 sec |
| AWS EC2 | | |
| Emotion Classifier | Accuracy | 73.2% |
| Emotion Classifier | Inference Time | 100 ms |
| RAG Search | Query Time | 50 ms |
| Polymarket Lookup | Query Time | 80 ms |
| Web Search | Query Time | 1-2 sec |
| Total AWS Processing | Latency | 2-3 sec |
| End-to-End | | |
| Total System Latency | Pi + AWS + Network | 6-10 sec |

Interactive Visualization

Features:

- ▶ Color-coded speaker bubbles
- ▶ Emotion badges per segment
- ▶ Hover to see fact-checks
- ▶ KB + Polymarket + Web sources

Live Demo

54.209.249.85:7863

Example Output:

- ▶ Speaker emotions
- ▶ Supporting facts
- ▶ Contradicting claims

Future Work: Technical Improvements

1. Real-Time Processing

- ▶ Stream audio continuously instead of 30-second windows
- ▶ WebSocket connections for live emotion updates
- ▶ Reduce end-to-end latency to ≤ 3 seconds

2. Improved Emotion Classification

- ▶ Fine-tune on real conversation data (not synthetic)
- ▶ Add audio features (pitch, volume, speaking rate)
- ▶ Multi-modal model combining text + audio
- ▶ Target 85%+ accuracy

3. Enhanced Fact-Checking

- ▶ Integrate scholarly databases (arXiv, PubMed)
- ▶ Add fact verification model (check claim truthfulness)
- ▶ Expand knowledge base to 1000+ curated facts
- ▶ Support multilingual fact-checking

Future Work: New Features

1. Argument Summarization

- ▶ Generate concise summaries of key points
- ▶ Identify areas of agreement vs disagreement
- ▶ Extract action items and next steps

2. Bias Detection

- ▶ Detect logical fallacies (ad hominem, straw man)
- ▶ Identify cognitive biases (confirmation bias, anchoring)
- ▶ Flag misleading statistics or cherry-picked data

3. Multi-Speaker Scaling

- ▶ Support 3+ speakers in group discussions
- ▶ Track interruptions and speaking time balance
- ▶ Identify dominant speakers and quiet participants

Future Work: Deployment & Applications

Deployment:

- ▶ Mobile app for iOS/Android
- ▶ Zoom/Teams plugin for virtual meetings
- ▶ Smart speaker integration (Alexa, Google Home)
- ▶ Offline mode for privacy-sensitive contexts

Privacy Enhancements:

- ▶ On-device emotion classification
- ▶ Differential privacy for stored data
- ▶ User consent and data deletion
- ▶ End-to-end encryption

New Applications:

- ▶ Mental health therapy sessions
- ▶ Customer service quality monitoring
- ▶ Podcast/media content analysis
- ▶ Diplomatic negotiations
- ▶ Legal mediation

Research Directions:

- ▶ Causal analysis of de-escalation
- ▶ Longitudinal studies of conflict patterns
- ▶ Cross-cultural emotion detection
- ▶ Ethical guidelines for AI mediation

Summary

What We Built

A distributed edge-cloud system for real-time conversation analysis:

- ▶ **73.2%** emotion accuracy (8 classes)
- ▶ **3-source** fact-checking: RAG + Polymarket + Web
- ▶ **6-10 sec** end-to-end latency

Key Innovations

1. Hybrid fact-checking with prediction markets
2. LRU-cached market discovery
3. Segment-level emotion analysis
4. Privacy-preserving edge architecture

Impact

Reduces bias by providing objective facts and public opinion data

Thank You

Thank You!

Questions?

Project Links:

GitHub: github.com/ifesionubogu/aiot_project

Live Demo: <http://54.209.249.85:7863/>

Technical Report: See TECHNICAL_REPORT.pdf