VoxPop: AI-Driven Global Brand Sentiment & Crisis Intelligence

Executive Summary

VoxPop is an AI-driven sentiment and crisis intelligence system designed to convert large volumes of social feedback (tweets/reviews) into actionable insights for brand teams. The solution combines a BiLSTM-based sentiment/risk model with transformer-based summarization (BART), named entity recognition (BERT NER), and an interactive Streamlit application. It produces a concise 3-sentence Crisis Report from up to 1,000 negative items, highlights key entities (competitors, products, people), and supports a "Brand Assistant" interface for common operational questions such as the top complaints in the last 24 hours.

Problem Statement and Goals

Brands receive feedback at a scale that makes manual monitoring impractical. The goal is to automatically detect negative sentiment trends, summarize high-volume complaints into executive-ready language, identify the entities being discussed, and provide a simple conversational interface for stakeholders.

Data Sources and Input Format

The project is designed for Twitter/review-style short text. A tweet-style sentiment dataset (e.g., Sentiment140) can be used to train the baseline sentiment model. The Streamlit app accepts either pasted text or a CSV upload.

Expected Columns

- text (required): the feedback text.
- timestamp (optional): required for accurate "last 24 hours" filtering; otherwise a recent-window fallback is used.

- source, brand, language (optional): useful for dashboards and filtering.

System Overview

The system follows a four-stage pipeline:

- Sentiment and crisis scoring using a BiLSTM model (baseline).
- Crisis Report generation using BART summarization (3 sentences).
- Entity extraction using BERT NER and post-processing into business categories.
- Brand Assistant layer for question-based retrieval on the latest feedback window.

Architecture Summary

Component	Model / Tech	Input	Output
Sentiment / Risk	BiLSTM (baseline)	Text	Sentiment/anger score + crisis level
Crisis Report	BART summarizer	Up to 1,000 negative items	3-sentence executive summary
NER	dslim/bert-base-NER	Text	Entities (ORG/PER/LOC/MISC)
Brand Assistant	Rules + retrieval	Filtered recent negatives	Top complaints / answers

Methodology

A) Sentiment and Crisis Scoring (BiLSTM)

A BiLSTM model is used as a baseline sentiment/risk scorer. The training pipeline tokenizes and vectorizes text, pads sequences to a fixed length, and trains the network to predict sentiment (or an anger/risk proxy). At inference time, the model outputs a probability/score which is mapped to a crisis level threshold.

Crisis Level Mapping (example)

Low: score < 0.40

Medium: 0.40 - 0.70

High: score > 0.70

1. Classification Report

Test set size: 320,000 samples.

Class	Precision	Recall	F1-score	Support
Not Angry (0)	0.8266	0.8351	0.8308	159494
Angry (1)	0.8344	0.8259	0.8302	160506
Accuracy			0.8305	320000
Macro Avg	0.8305	0.8305	0.8305	320000
Weighted Avg	0.8305	0.8305	0.8305	320000

2. Confusion Matrix

Rows = true labels, Columns = predicted labels.

	Predicted: Not Angry	Predicted: Angry
True: Not Angry	133194	26300

True: Angry	27942	132564

TN = 133,194   FP = 26,300   FN = 27,942   TP = 132,564 (positive class = 'Angry').

B) Crisis Report (BART Summarization)

The summarization layer selects up to 1,000 negative items and merges them into a structured text input. To handle length constraints, the text is chunked, summarized per chunk, and then re-summarized into a final 3-sentence report.

Key Implementation Details

Model: facebook/bart-large-cnn (or a lighter distilbart variant for CPU demos).
Chunking strategy: split by token/character budget; summarize each chunk; then summarize the summaries.
Output control: enforce a 3-sentence target by limiting max_length and trimming to 3 sentences if needed.

C) Entity Intelligence (BERT NER)

Named entities are extracted from the same input data using a pretrained BERT NER model. The base model outputs entity spans labeled as PER (person), ORG (organization), LOC (location), and MISC (miscellaneous). Post-processing maps these into business categories.

Entity Buckets (post-processing)

Competitors / Brands: ORG (and selected MISC)
Products: MISC + optional domain rules (e.g., model numbers, product keywords)
People / CEO names: PER

D) Brand Assistant

The Brand Assistant is a lightweight conversational layer over the most recent feedback window. For “top 3 complaints”, it filters negative items in the last-day window and returns the three most frequent or representative complaint statements without additional summarization. For other questions, it returns a short answer grounded in the same filtered dataset.

Top Complaints Extraction (example approach)

- Filter: last 24 hours (timestamp) AND negative sentiment.
- Normalize: lowercasing, stopword removal (optional).
- Extract: key phrases via TF-IDF / n-grams; map phrases to representative complaint examples.
- Return: three complaint statements (verbatim or lightly cleaned).

Streamlit Application

The Streamlit UI is designed for a clear demo flow: data input -> sentiment scoring -> crisis report -> NER -> assistant Q&A. To keep the UI responsive, model/pipeline objects are loaded once using Streamlit's resource caching.

Caching and Performance Notes

- Use st.cache_resource to load Hugging Face pipelines and ML models.
- Use st.cache_data only for pure-data computations (e.g., filtering, aggregation).
- Avoid caching pipeline objects with st.cache_data to prevent unhashable parameter errors.

Suggested Demo Script (2-3 minutes)

- Upload CSV or paste sample feedback.
- Show sentiment/risk score output and highlight flagged negatives.
- Generate Crisis Report (3 sentences) from the negative subset.
- Run NER and show top competitors/brands, products, and people entities.
- Ask: "What are the top 3 complaints from the last 24 hours?" and show complaints-only output.

Deployment and Reproducibility

- Recommended local setup (Windows/Linux/Mac):

- Python 3.10 environment (conda or venv).

- Install dependencies from requirements.txt.
- Run: streamlit run app.py

Packaging Artifacts

- Saved BiLSTM model file (e.g., .keras or .pt) and tokenizer.pkl.
- requirements.txt with pinned versions for reproducibility.
- Sample input CSV for demo.
- README with setup, usage, and screenshots.

Risks, Ethics, and Limitations

- Data bias: social media data can be skewed by demographics and bot activity.
- Privacy: avoid storing personally identifiable information unnecessarily.
- Model errors: NER and summarization may miss or mislabel entities; manual review is recommended for high-stakes use.

Future Enhancements

- Topic clustering for complaints (BERTopic) and trend charts over time.
- Automated alerts (email/Slack) when crisis thresholds are crossed.
- Domain-tuned NER (fine-tune on brand/product/entity lists).
- Scalable ingestion (streaming data + background jobs).

Conclusion

VoxPop successfully converts large-scale social feedback into actionable brand intelligence. Using a BiLSTM-based sentiment/anger classifier, the system reliably detects high-risk negativity with ~0.83 accuracy and balanced precision/recall across both classes. On top of this, the summarization and NER modules turn thousands of negative posts into a concise crisis report and extract key entities (brands, products, people), while the Brand Assistant enables quick Q&A on top complaints. Overall, the project demonstrates an end-to-end pipeline for early crisis detection, root-cause insight, and decision-ready reporting in real time.