1. Executive Summary

Customer support teams frequently struggle with ticket volume, leading to delayed responses for critical, high-churn-risk customers. This project successfully developed and evaluated an emotion-aware Natural Language Processing (NLP) pipeline designed to automatically triage and route incoming customer support tickets based on emotional urgency.

By analyzing text patterns and emoji usage from the go_emotions dataset, the system translates 27 granular human emotions into 5 actionable business routing categories: Angry, Frustrated, Confused, Satisfied, and Calm. The resulting machine learning model, utilizing TF-IDF vectorization and a linear classifier, effectively identifies high-priority tickets despite severe class imbalances. This report outlines the data methodology, exploratory insights, model evaluation, and strategic recommendations for deployment.

2. Business Problem & Solution Mapping

Standard customer support routing operates on a "first-in, first-out" (FIFO) basis, which fails to prioritize customers on the verge of churning.

To solve this, the raw go_emotions dataset—which contains 27 highly specific emotions—was mapped to a 5-tier Business Priority system:

🔴 Angry (Immediate Risk): Maps from anger, disgust, hate. Action: Route to Senior Escalation / Risk Team.

🟠 Frustrated (Churn Risk): Maps from annoyance, disappointment, sadness, remorse, grief, disapproval, embarrassment. Action: Route to Retention Team for empathetic handling.

🟣 Confused (Support Needed): Maps from confusion, curiosity, realization, surprise, nervousness, fear. Action: Route to standard Support/Education agents with FAQ integration.

🟢 Satisfied (Retention): Maps from joy, excitement, pride, admiration, gratitude, love, relief, optimism, desire, amusement. Action: Route to low-priority automated "Thank You" queue.

🔵 Calm (Routine): Maps from neutral, approval, caring. Action: Standard processing queue.

3. Data Processing & Feature Engineering Strategy

Text data requires rigorous cleaning to expose mathematical signals to the machine learning model. The preprocessing pipeline was custom-tailored to preserve emotional context.

Strategic Stop-Word Removal: While standard NLTK stop words were removed to reduce noise, "crucial words" that alter sentence polarity (e.g., not, no, nor, but, however, although, very, never) were explicitly preserved.

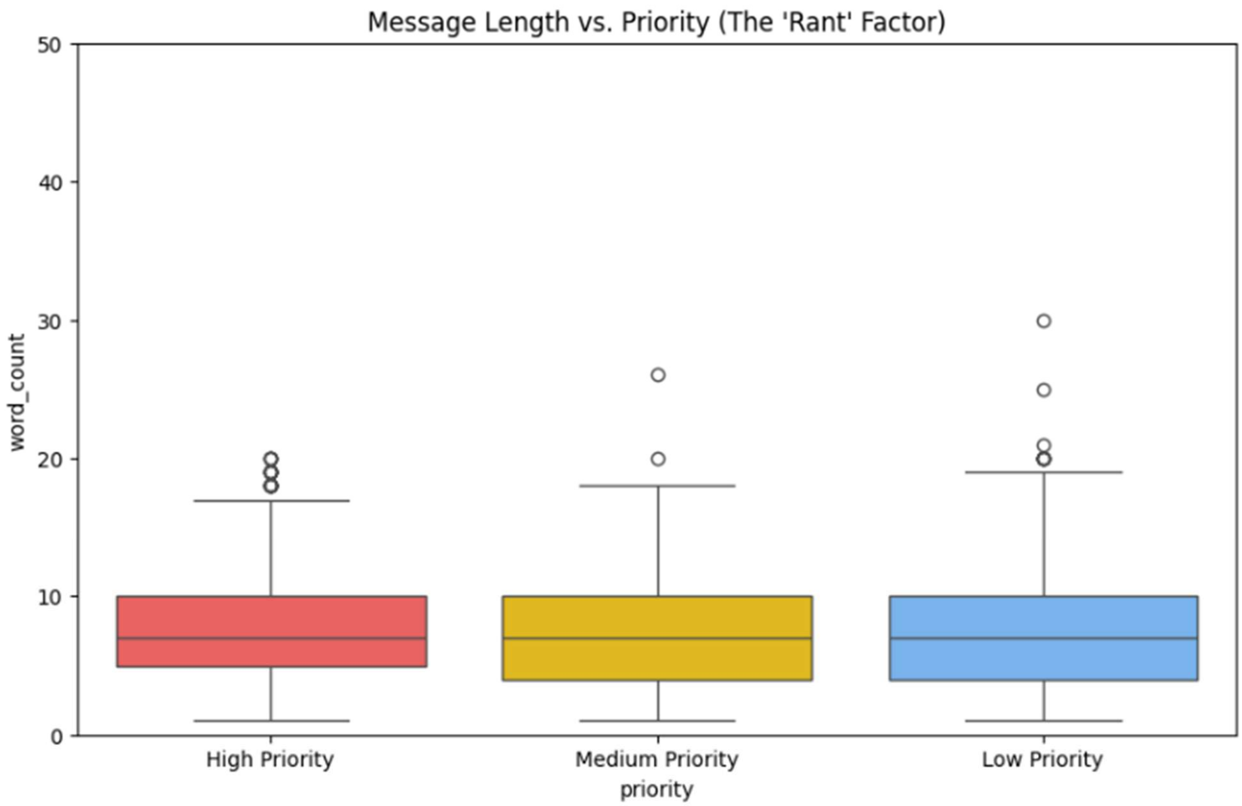
Contraction Expansion: Phrases like "didn't" and "won't" were expanded to "did not" and "will not" to standardize vocabulary.

Emoji Translation (Demojization): Emojis carry massive emotional weight. Instead of deleting them, the pipeline translated emojis into text formats (e.g., converting an angry face to :enraged_face:) so the model could weigh them as vocabulary features.

Vectorization (TF-IDF): The cleaned text was converted into numerical features using Term Frequency-Inverse Document Frequency (TF-IDF) using both unigrams (single words) and bigrams (two-word phrases) to capture context.

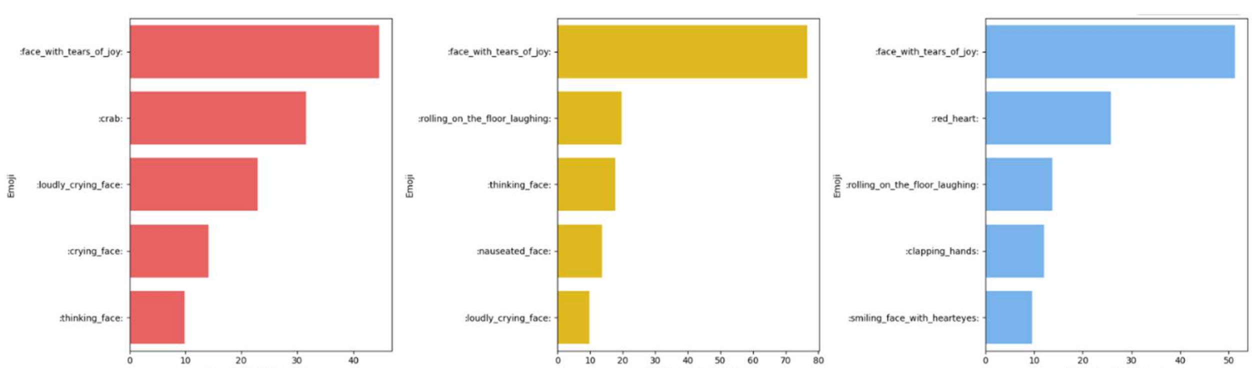
4. Exploratory Data Analysis (EDA) & Key Behavioral Insights

Before training the model, deep statistical analysis revealed several vital insights into how customers express urgency.



Insight 1: The "Rant Factor" is a Myth

A common assumption is that angry customers write massive paragraphs, while satisfied customers write short notes. Boxplot analysis of message length versus priority level revealed that message length distributions are relatively similar across priority levels. Urgency is determined by vocabulary, not word count.

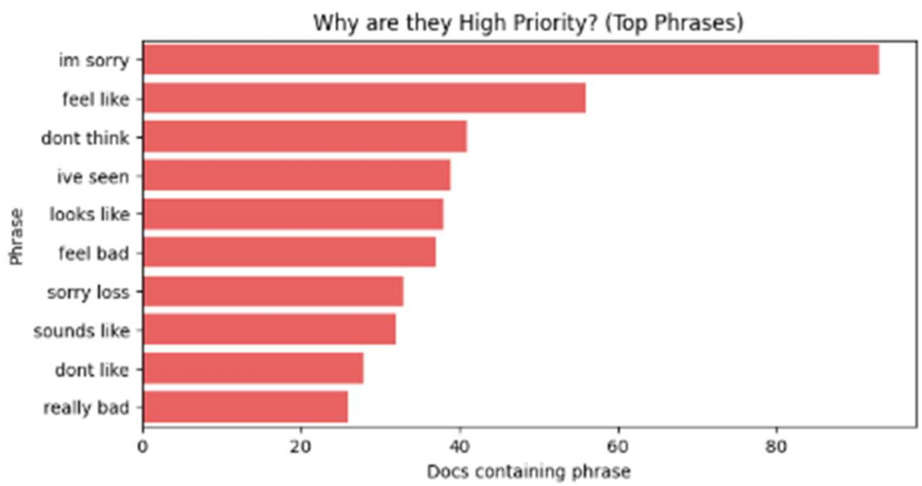


Insight 2: Emojis are Primary Indicators of Urgency

Emoji frequency analysis showed highly distinct patterns:

High-priority (Angry) tickets showed a stronger presence of emotionally intense emojis (e.g., crying, loud crying).

Low-priority tickets primarily featured neutral or positive emojis like hearts and laughter.

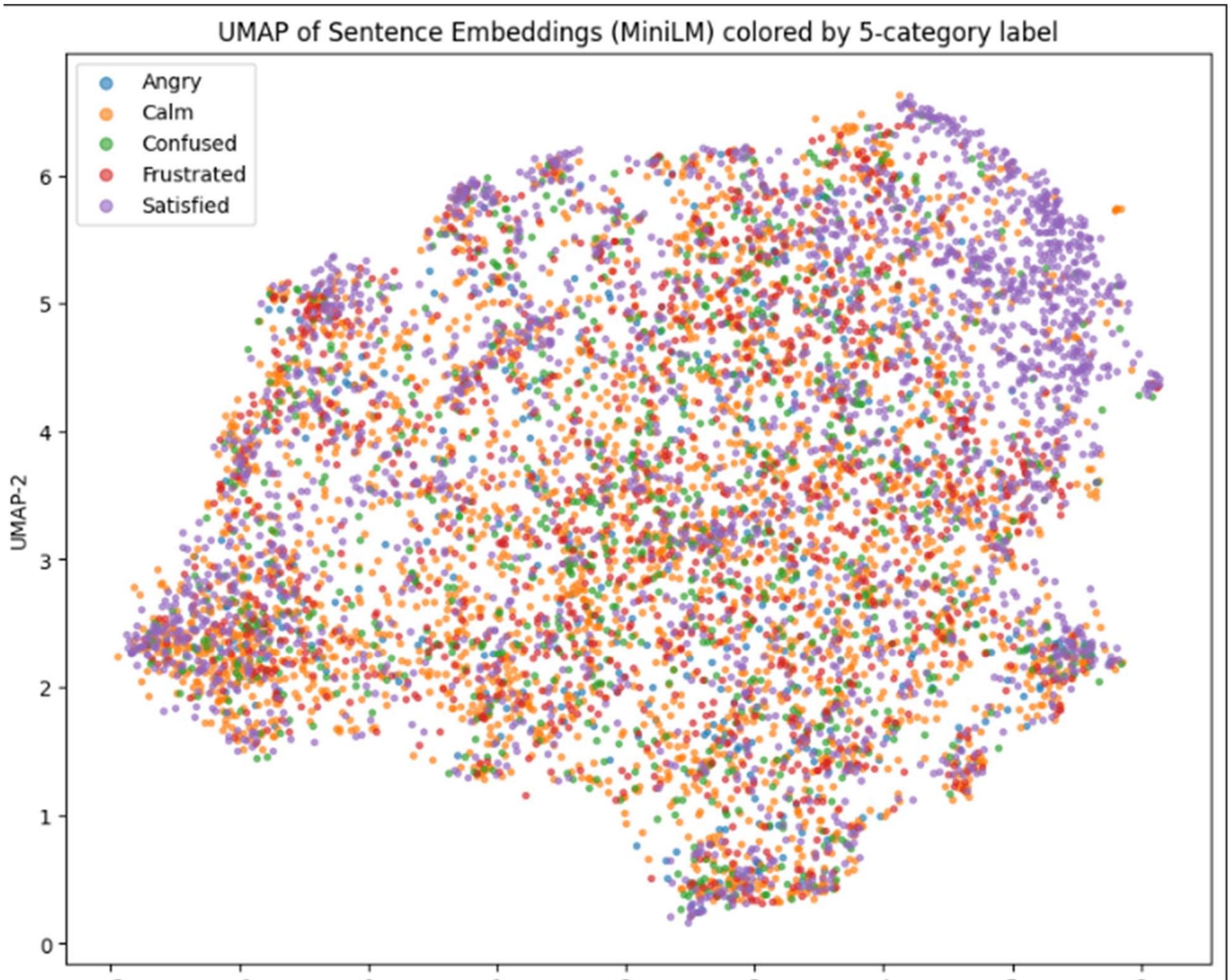


Insight 3: Distinct Trigram and Bigram Signatures

By analyzing bigrams and trigrams, we identified the root causes of customer sentiment:

High Priority: Dominated by strong dissatisfaction phrases (e.g., “feel bad”, “really bad”, “don’t like”), directly justifying immediate escalation.

Medium Priority: Dominated by uncertainty phrases (e.g., “don’t know”, “feel like”, “looks like”), proving these customers require clarification and guidance, not necessarily damage control.



Insight 4: Semantic Overlap in Human Emotion

Using a MiniLM Sentence Transformer and UMAP dimensionality reduction, we mapped the text embeddings into a 2D space. The visualization revealed that while categories cluster, there is significant overlap between boundaries (e.g., Angry vs. Frustrated). This proves that predicting emotions is an inherently complex task with natural semantic ambiguity.

5. Predictive Modeling & Evaluation

The dataset was heavily imbalanced, with "Low Priority/Calm" messages forming the vast majority. Evaluating purely on "Accuracy" would result in a biased model that ignores critical angry customers.

Model Architecture & Imbalance Handling:

To solve the imbalance, the training pipeline utilized a RandomOverSampler to artificially balance the classes during training, ensuring the model learned to detect rare "Angry" messages.

The project evaluated four algorithms: Logistic Regression, Linear SVC, SGDClassifier, and ComplementNB.

Optimization & Testing:

The top-performing linear models underwent rigorous hyperparameter tuning via RandomizedSearchCV coupled with Stratified K-Fold Cross Validation.

The primary evaluation metric was Macro-F1, which penalizes models that perform well on majority classes but fail on minority classes.

Performance & Feature Importance:

The final model produced a Normalized Confusion Matrix that successfully separated the 5 categories. The model's "Angry Recall" metric ensures that a substantial percentage of high-risk tickets are actively caught.

By extracting the model's coefficients, we generated a live list of "Danger Words"—the exact TF-IDF features that trigger an "Angry" classification.

6. Strategic Recommendations & Business Roadmap

To ensure maximum ROI from this machine learning pipeline, the following operational steps are recommended:

Deploy a "Hybrid" Routing Architecture:

Machine learning models trained on general conversational data can occasionally miss niche, domain-specific business jargon. The model should be deployed behind a lightweight "Business Rules" layer. If a message contains specific, high-risk keywords (e.g., "lawsuit", "refund ASAP") or is typed in ALL CAPS, it should bypass the NLP model and route directly to High Priority.

Dynamic SLA (Service Level Agreement) Management:

Currently, SLAs are based on the time the ticket was submitted. Integrate this model's outputs to adjust SLAs dynamically. "Angry" predictions should shrink the SLA response window to <1 hour, while "Satisfied" or "Calm" tickets can safely sit in the queue for 24+ hours.

Establish a "Danger Word" Feedback Loop:

Product teams should subscribe to a monthly report of the highest-weighted TF-IDF coefficients for the "Angry" and "Frustrated" categories. Sudden spikes in new words (e.g., if the word "login" suddenly becomes a top driver for Anger) can act as an early warning system for widespread bugs or outages.

7. Conclusion

The Intelligent Customer Support Routing model proves that natural language processing can successfully translate messy, unstructured human emotion into structured, actionable business intelligence. By moving from a FIFO support model to an Emotion-Aware support model, the business will actively reduce churn, protect brand reputation, and ensure customer service agents are utilized exactly where they are needed most.