**Technical Report**

**Automated Analysis of Customer Satisfaction from Audio Call Recordings Using Sentiment Analysis**

**1. Introduction**

Customer satisfaction is a key performance indicator for any business. Traditionally, customer satisfaction from phone interactions has been measured through post-call surveys or manual review of call recordings. However, with the advent of natural language processing (NLP) and machine learning techniques, it is now possible to automate the analysis of customer satisfaction from audio call recordings. This report explores the use of sentiment analysis, keyword detection, and trend analysis to determine customer satisfaction from audio calls.

**2. Objectives**

The main objective of this project is to develop an automated system that can analyze audio recordings of customer interactions and determine the level of customer satisfaction. The system should:

* Convert audio recordings to text.
* Perform sentiment analysis on the transcribed text.
* Detect keywords indicative of satisfaction or dissatisfaction.
* Analyze sentiment trends over the course of the conversation.
* Provide a final classification of the customer's satisfaction level.

**3. Methodology**

**3.1. Audio-to-Text Conversion**

The first step in analyzing customer satisfaction from audio calls is to convert the spoken content into text. This is achieved using the Google Speech Recognition API, which processes the audio file and returns a text transcription of the conversation.

**3.2. Sentiment Analysis**

Sentiment analysis is performed on the transcribed text to determine the emotional tone of the conversation. Using the VADER (Valence Aware Dictionary for Sentiment Reasoning) sentiment analysis tool, each sentence in the conversation is assigned a sentiment score, which is classified as positive, negative, or neutral. The percentage of positive, negative, and neutral sentiment is then calculated.

**3.3. Keyword Detection**

In addition to sentiment analysis, specific keywords that are commonly associated with satisfaction or dissatisfaction are detected in the conversation. Keywords such as "happy," "satisfied," and "thank you" indicate positive sentiment, while words like "disappointed," "frustrated," and "not happy" suggest negative sentiment.

**3.4. Sentiment Trend Analysis**

To capture the dynamics of the conversation, sentiment trends are analyzed. This involves tracking changes in sentiment over the duration of the call to identify whether the customer's sentiment improves, worsens, or remains stable. An upward trend may indicate successful issue resolution, while a downward trend could suggest increasing dissatisfaction.

**3.5. Customer Satisfaction Assessment**

The final step is to assess customer satisfaction based on the combined results of sentiment analysis, keyword detection, and trend analysis. A decision-making algorithm classifies the call as positive, negative, or neutral based on the following criteria:

* If positive keywords are detected without negative keywords, the call is classified as positive.
* If negative keywords are detected without positive keywords, the call is classified as negative.
* If the sentiment trend shows improvement, the call is classified as positive; if it worsens, the call is classified as negative.
* If there is no clear trend or keyword match, the sentiment percentages are used to make the final classification.

**4. Implementation**

The system is implemented using Python, leveraging libraries such as speech\_recognition for audio-to-text conversion, vaderSentiment for sentiment analysis, and pydub for handling audio files. The system processes an input audio file, performs the necessary analysis, and outputs a classification of the customer satisfaction level.

**5. Results**

The system was tested on various audio recordings of customer interactions. The results demonstrated that the system could accurately classify the level of customer satisfaction in most cases. Positive trends in sentiment and the presence of positive keywords were strong indicators of customer satisfaction, while negative trends and keywords were reliable indicators of dissatisfaction.

**6. Conclusion**

The automated analysis of customer satisfaction from audio call recordings offers a scalable and efficient alternative to manual review processes. By combining sentiment analysis, keyword detection, and trend analysis, the system provides a comprehensive understanding of customer satisfaction. Future work could involve enhancing the model with more sophisticated emotion detection techniques and expanding the keyword database to improve accuracy further.

**7. Future Work**

* **Emotion Detection**: Integrate more advanced models capable of detecting a wider range of emotions beyond basic sentiment.
* **Keyword Expansion**: Develop a more extensive keyword library to capture subtle expressions of satisfaction or dissatisfaction.
* **Contextual Analysis**: Incorporate context-aware NLP models to understand the nuances of the conversation better.

**8. References**

* Hutto, C.J., & Gilbert, E. (2014). VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text.
* Google Speech Recognition API Documentation.
* Python Pydub Documentation.