Journal of Information Systems Engineering and Management
2025, 10(51s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Sentiment Analysis of Incoming Calls on Helpdesk

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ARTICLE INFO	ABSTRACT

Received: 19 Dec 2024
Revised: 20 Feb 2025
Accepted: 28 Feb 2025

This study presents an advanced sentiment analysis system designed to evaluate and interpret emotional tones expressed during incoming calls to a helpdesk. The system captures real-time conversations between helpdesk agents and customers, processes the audio into transcribed text, and applies natural language processing (NLP) techniques to assess the underlying sentiment. Each interaction is assigned a sentiment score within a standardized range of -1 (strongly negative) to +1 (strongly positive), with 0 indicating a neutral stance. Beyond simple sentiment detection, the system also gauges the intensity of emotional expressions, such as frustration, satisfaction, confusion, or urgency. To scale support operations, the system is integrated with a comprehensive visual analytics dashboard, enabling supervisors and quality assurance teams to monitor multiple helpdesk agents simultaneously. The dashboard displays real-time sentiment trends, emotional spikes, and historical summaries, helping teams to quickly identify critical incidents, recurring negative interactions, or patterns that require managerial attention. Furthermore, the system supports multi-language processing, enabling global helpdesk operations to uniformly assess customer satisfaction across different regions

Keywords: Sentiment analysis, Sentiment Score, Dashboard, NLP, NLTK, Speech-to-Text.

1. INTRODUCTION:

The services provided by the help desk agents play a key role in today's customer-centric environment by addressing the queries of customers and maintaining customer satisfaction. Quality of interactions affects customer loyalty. It is important to analyze the customer's emotions during the conversations to evaluate the helpdesk's performance. Sentiment analysis has been a powerful tool to detect the emotional tone of the customer. By utilizing sentiment analysis, businesses can gain insights into client behavior, enabling them to identify dissatisfaction early and respond to them quickly and empathetically. These insights not only assist in resolving issues but also improve customer relationships and service quality. By analyzing the call conversations between helpdesk agents and customers, the system generates a range of scores from -1(negative) to +1(positive), with 0 being neutral sentiment, along with transcriptions according to the sentiment detected. This project depicts the sentiment in the form of a visualization dashboard.

2. LITERATURE SURVEY:

Yanan Jia [1] analyzes real-world conversations using acoustic and linguistic features. It uses several models like Word2Vec, GloVe, and BERT with CNNs for predicting the sentiment that improves sentiment detection. The methodology involves data preprocessing, sentiment labeling, and feature extraction for real-time analysis.

Michael Steehouder[2] uses conversational analysis to analyze the telephone helpdesk interactions to understand how agents help the customers. It examines the problem-solving strategies and interaction to improve clarity and guidance. The study identifies effective behaviors like questioning techniques and empathy expressions to enhance helpdesk services.

Imad Aattouri, Hicham Mouncif, and Mohamed Rida. [3]To improve the emotion of call bots and increase customer satisfaction, and efficiency. It finds out how sentiment analysis is integrated into call center services using NLP (Natural language processing) and ML (Machine learning) algorithms. Through text preprocessing and the application of machine learning models like SVMs or RNNs, the system classifies emotions to generate insightful information. This method explores the potential of automated customer service quality.

C D. Kokane et al. [4] study a machine learning based system. It works like this: helpdesk calls are transcribed from audio to text, keywords are extracted using Word2Vec embeddings, and spam or unwanted calls are detected using sentiment analysis. It uses WordNet as a lexical resource for sense mapping and adapts in real-time to improve performance.

3. METHODOLOGY:

a. Data Collection

Processing begins with the manual submission of .wav files. The speech recognition library captures the audio data, which helps in the audio to text conversion. In this stage, files are read, and features are captured to be processed later. The audio data goes through transcription.

b. Automated Speech Recognition

The Google Web Speech API is able to load the audio data and transform it into a text document. It requires only the files containing audio data that must be processed. With the help of a pre-trained model the spoken words are transcribed to text. The audio gets processed in the following steps. Initially, dialogue capture is performed, and then translation so the material can be read becomes accessible.

c. Sentiment Analysis

The sentiment analysis for the text is performed using VADER (Valence Aware Dictionary and Sentiment Reasoner) Algorithm. VADER resorts to assign a sentiment score and breaks it down as text sentiment values such as positive, negative, neutral, and a compound deviation from the average based on the pre-set boundaries.

$$Compound = \frac{Sumof\ sentiment\ sco\ scores}{\sqrt{sum\ of\ sentiment\ scores^2 + 15}}$$

d. Visualization Dashboard

A web-based dashboard is built using Flask and Matplotlib to display the results of sentiment analysis. After uploading the audio file, the transcription of the identified sentiment is displayed. The dashboard visualizes the sentiment analysis results, highlighting the positive, negative, and neutral sentiment scores. The dashboard representation helps in understanding the sentiment trends briefly, which provides a user-friendly, insightful analysis of incoming calls.

4. ALGORITHM:

VADER ALGORITHM:

1. Preprocessing and Tokenization:

a. Convert text to lowercase.

b. Split the text into words and phrases.

c. Handle punctuation, emojis, and capitalization to adjust sentiment.

2. Score Calculation and Modification:

a. Match words/phrases to the sentiment lexicon.

b. Apply modifiers: Intensifiers/dampeners (e.g., "very") adjust strength, Negation words (e.g., "not") reverse sentiment.

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3. Polarity Score and Classification:

a. Calculate compound score:

b. Classify based on compound score:

Positive: ≥ 0.05

Neutral: Between -0.05 and 0.05

Negative: ≤ -0.05

5. RESULTS:

USER INTERFACE:

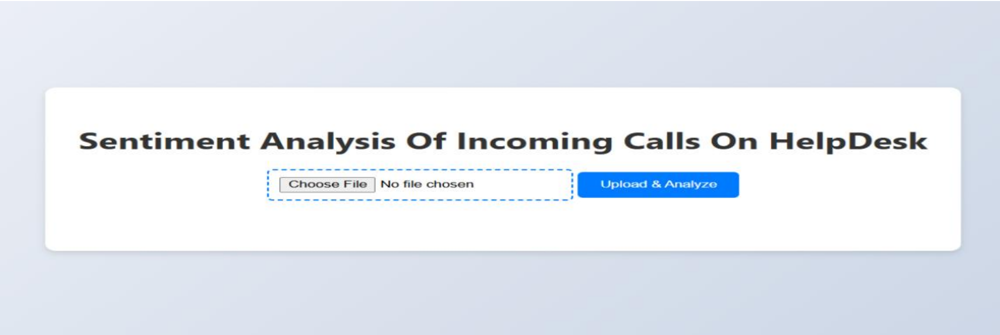

Fig 1 : User Interface

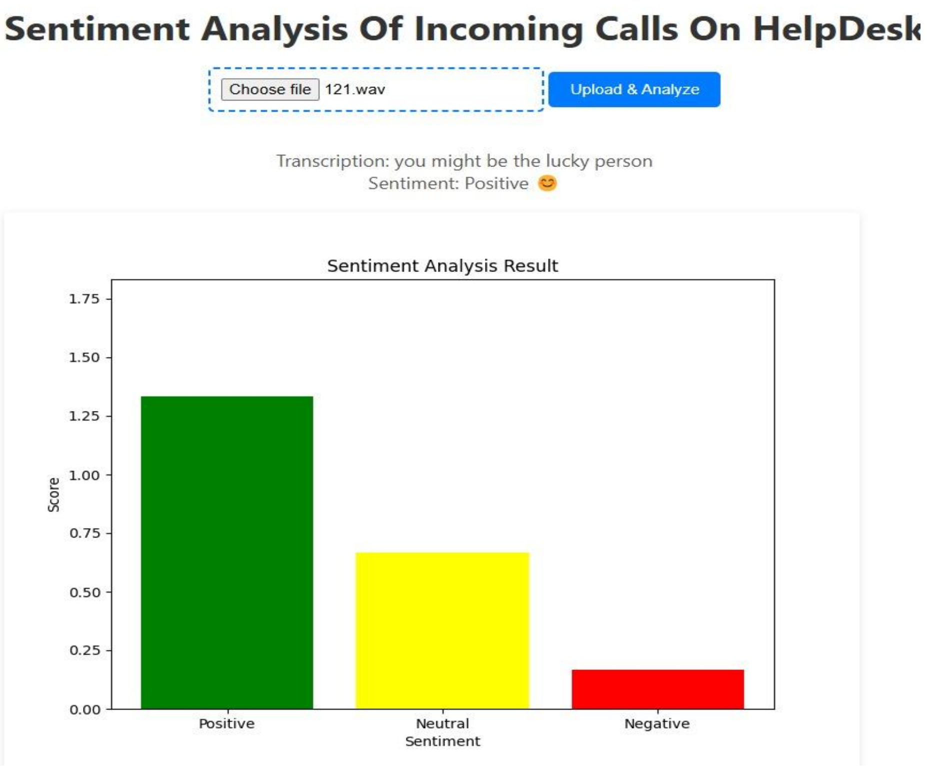

Fig 2 : Positive Sentiment

1. After uploading an audio file named '**121.wav**', the sentiment is identified as '**Positive**', represented by smiling emoji, and transcribed text is displayed as "***you might be the lucky person***". The chart displays the sentiment analysis result as: '**Positive**' sentiment achieves the highest score which is ~1.35 with a **green** color.

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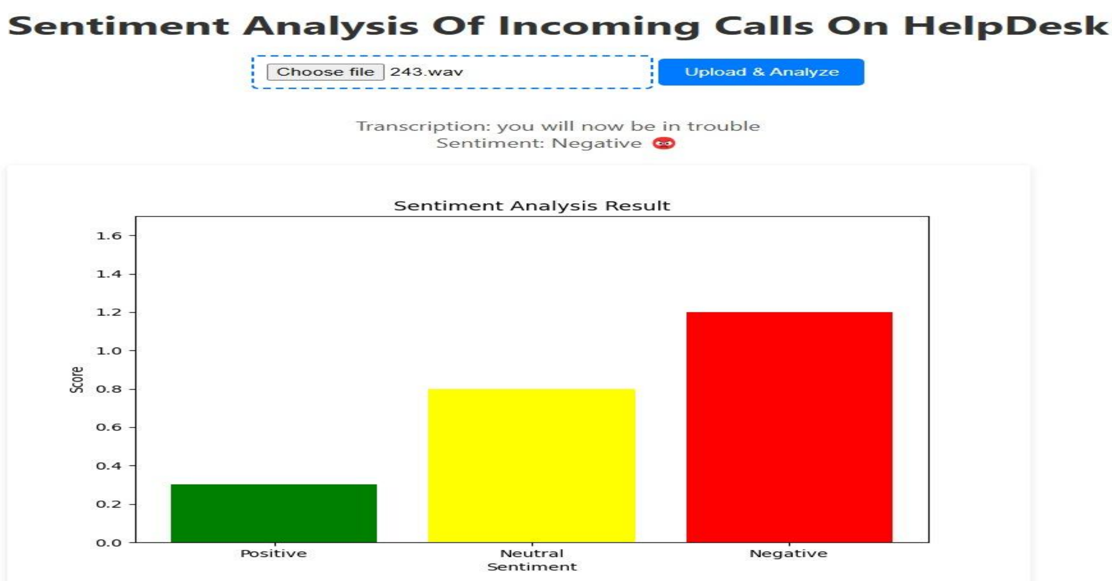

Fig 3 : Negative Sentiment

2. After uploading an audio file named '**243.wav**', the sentiment is identified as '**Negative**', represented by angry emoji, and transcribed text is displayed as "***you will now be in trouble***". The chart displays the sentiment analysis result as: '**Negative**' sentiment achieves the highest score which is ~1.4 with **red** color.

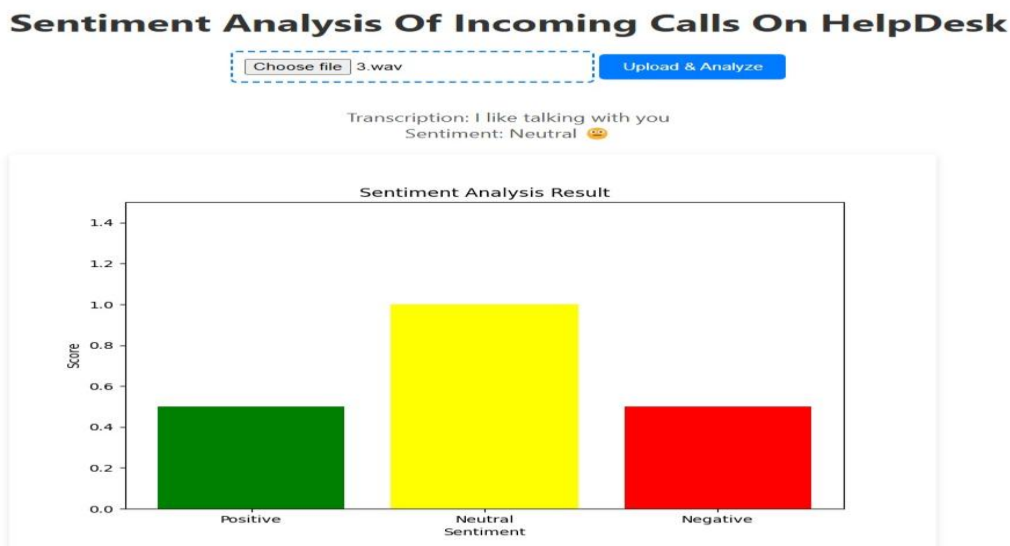

Fig 4 : Neutral Sentiment

3. After uploading an audio file named '**3.wav**', the sentiment is identified as '**Neutral**', represented by neutral face emoji, and transcribed text is displayed as "***I enjoy conversing with you***". The chart displays the sentiment analysis result: **Neutral**' sentiment achieves the highest score which is ~1.0 with **yellow** color. This model classifies the sentiments of audio conversations with an accuracy of 90-95%. The model uses VADER for performing the classification of the sentiment and Google's Speech-to-Text API for generating the transcription.

6. CONCLUSION:

This Paper shows the implementation of a system that performs sentiment analysis on the helpdesk's incoming calls. The system reviews the sentiment for the emotional tone analysis. The construction of a visualization dashboard serves to assist teams in supporting customers, pinpointing challenges, and ensuring satisfaction. These capabilities help organizations to elevate the service standards, promote customer gratitude, and assist the support agents in an efficient manner. The analysis proves that sentiment analysis can indeed serve as an enabler to transform helpdesk services by offering deep insights into customer emotions.

7. FUTURE SCOPE:

This work aims to broaden the capabilities of the helpdesk sentiment analysis system by integrating multilingual sentiment analysis as a key enhancement. The system will be equipped to recognize a range of emotional states, including frustration, anger, and confusion, offering a deeper understanding of the customer's emotional journey during interactions. Additionally, it will enable real-time sentiment tracking, allowing for the continuous monitoring of conversations to identify recurring patterns of negative sentiment. When dissatisfaction is detected, the system can proactively trigger alerts to agents, empowering them to take timely corrective actions. By incorporating multilingual capabilities, the system can accurately interpret and analyze sentiment across various languages, thereby extending its utility to a global customer base and ensuring meaningful engagement regardless of linguistic diversity. This holistic upgrade enhances both the responsiveness and inclusiveness of customer service operations.

8. REFERENCES:

[1] Yanan Jia. “A Deep Learning System for Sentiment Analysis of Service Calls” ACL Anthology, (2020)
[2] Michael Steehouder. “How Help Desk Agents Help Clients” IEEE International Professional Communication Conference (2007)
[3] Imad Aattouri, Hicham Mouncif, and Mohamed Rida. “Call Center Customer Sentiment Analysis Using ML and NLP” (2023) 14th International Conference on Intelligent Systems: Theories and Applications (SITA)
[4] C.D. Kokane et al. “Machine Learning-Based Sentiment Analysis of Incoming Calls on Helpdesk” (October 2023) International Journal on Recent and Innovation Trends in Computing and Communication 11(9):21-27
[5] Soujanya Poria et al. “Fusing audio, visual and textual clues for sentiment analysis from multimodal content” Neurocomputing Volume 174, Part A, 22 January 2016, Pages 50-59
[6] Bryan Li et al. “Acoustic and Lexical Sentiment Analysis for Customer Service Calls” ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)
[7] Y.H.P.P Priyadarshana et al. “Sentiment analysis: Measuring sentiment strength of call centre conversations” 2015 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)
[8] Souraya Ezzat et al. “Sentiment Analysis of Call Centre Audio Conversations using Text Classification” International Journal of Computer Information Systems and Industrial Management Applications. ISSN 2150-7988 Volume 4 (2012) pp. 619 -627
[9] Rohit Raj Sehgal, Shubham Agarwal, Gaurav Raj “Interactive Voice Response using Sentiment Analysis in Automatic Speech Recognition Systems” 2018 International Conference on Advances in Computing and Communication Engineering (ICACCE)
[10] Lakshmish Kaushik, Abhijeet Sangwan, John H. L. Hansen “Automatic Sentiment Detection in Naturalistic Audio” IEEE/ACM Transactions on Audio, Speech, and Language Processing (Volume: 25, Issue: 8, August 2017).
[11] D Shanthi , Smart Healthcare for Pregnant Women in Rural Areas, Medical Imaging and Health Informatics, Wiley Publishers,ch-17, pg.no:317-334, 2022
[12] Shanthi, R. K. Mohanty and G. Narsimha, "Application of machine learning reliability data sets", Proc. 2nd Int. Conf. Intell. Comput. Control Syst. (ICICCS), pp. 1472-1474, 2018.
[13] D Shanthi, N Swapna, Ajmeera Kiran and A Anoosha, "Ensemble Approach Of GPACOTPSOAnd SNN For Predicting Software Reliability", International Journal Of Engineering Systems Modelling And Simulation, 2022.
[14] Shanthi, "Ensemble Approach of ACOT and PSO for Predicting Software Reliability", 2021 Sixth International Conference on Image Information Processing (ICIIP), pp. 202-207, 2021.

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2025, 10(51s)
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Research Article

[15] D Shanthi, CH Sankeerthana and R Usha Rani, "Spiking Neural Networks for Predicting Software Reliability", ICICNIS 2020, January 2021, [online] Available: https://ssrn.com/abstract=3769088.

[16] Shanthi, D. (2023). Smart Water Bottle with Smart Technology. In Handbook of Artificial Intelligence (pp. 204-219). Bentham Science Publishers.

[17] Shanthi, P. Kuncha, M. S. M. Dhar, A. Jamshed, H. Pallathadka and A. L. K. J E, "The Blue Brain Technology using Machine Learning," 2021 6th International Conference on Communication and Electronics Systems (ICCES), Coimbatre, India, 2021, pp. 1370-1375, doi: 10.1109/ICCES51350.2021.9489075.

[18] Shanthi, D., Aryan, S. R., Harshitha, K., & Malgireddy, S. (2023, December). Smart Helmet. In International Conference on Advances in Computational Intelligence (pp. 1-17). Cham: Springer Nature Switzerland.

[19] Babu, Mr. Suryavamshi Sandeep, S.V. Suryanarayana, M. Sruthi, P. Bhagya Lakshmi, T. Sravanthi, and M. Spandana. 2025. "Enhancing Sentiment Analysis With Emotion And Sarcasm Detection: A Transformer-Based Approach". Metallurgical and Materials Engineering, May, 794-803. https://metall-mater-eng.com/index.php/home/article/view/1634.

[20] Narmada, J., Dr.A.C.Priya Ranjani, K. Sruthi, P. Harshitha, D. Suchitha, and D.Veera Reddy. 2025. "Ai-Powered Chacha Chaudhary Mascot For Ganga Conservation Awareness". Metallurgical and Materials Engineering, May, 761-66. https://metall-mater-eng.com/index.php/home/article/view/1631.

[21] Geetha, Mrs. D., Mrs.G. Haritha, B. Pavani, Ch. Srivalli, P. Chervitha, and Syed. Ishrath. 2025. "Eco Earn: E-Waste Facility Locator". Metallurgical and Materials Engineering, May, 767-73. https://metall-mater-eng.com/index.php/home/article/view/1632.

[22] P. Shilpasri PS, C.Mounika C, Akella P, N.Shreya N, Nandini M, Yadav PK. Rescuenet: An Integrated Emergency Coordination And Alert System. J Neonatal Surg [Internet]. 2025May13 [cited 2025May17];14(23S):286-91. Available from: https://www.jneonatalsurg.com/index.php/jns/article/view/5738

[23] D. Shanthi DS, G. Ashok GA, Vennela B, Reddy KH, P. Deekshitha PD, Nandini UBSB. Web-Based Video Analysis and Visualization of Magnetic Resonance Imaging Reports for Enhanced Patient Understanding. J Neonatal Surg [Internet]. 2025May13 [cited 2025May17];14(23S):280-5. Available from: https://www.jneonatalsurg.com/index.php/jns/article/view/5733

[24] Srilatha, Mrs. A., R. Usha Rani, Reethu Yadav, Ruchitha Reddy, Laxmi Sathwika, and N. Bhargav Krishna. 2025. "Learn Rights: A Gamified Ai-Powered Platform For Legal Literacy And Children's Rights Awareness In India". Metallurgical and Materials Engineering, May, 592-98. https://metall-mater-eng.com/index.php/home/article/view/1611.

[25] Shanthi, Dr. D., G. Ashok, Chitrika Biswal, Sangem Udharika, Sri Varshini, and Gopireddi Sindhu. 2025. "Ai-Driven Adaptive It Training: A Personalized Learning Framework For Enhanced Knowledge Retention And Engagement". Metallurgical and Materials Engineering, May, 136-45. https://metall-mater-eng.com/index.php/home/article/view/1567.

[26] Priyanka, Mrs. T. Sai, Kotari Sridevi, A. Sruthi, S. Laxmi Prasanna, B. Sahithi, and P. Jyothsna. 2025. "Domain Detector - An Efficient Approach Of Machine Learning For Detecting Malicious Websites". *Metallurgical and Materials Engineering*, May, 903-11. https://metall-mater-eng.com/index.php/home/article/view/1663.

[27] Thejovathi, Dr. M., K. Jayasri, K. Munni, B. Pooja, B. Madhuri, and S. Meghana Priya. 2025. "Skinguard-Ai FOR Preliminary Diagnosis OF Dermatological Manifestations". *Metallurgical and Materials Engineering*, May, 912-16. https://metall-mater-eng.com/index.php/home/article/view/1664.

[28] Jayanna, SP., S. Venkateswarlu, B. Ishwarya Bharathi, CH. Mahitha, P. Praharshitha, and K. Nikhitha. 2025. "Fake Social Media Profile Detection And Reporting". *Metallurgical and Materials Engineering*, May, 965-71. https://metall-mater-eng.com/index.php/home/article/view/1669.