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Automated Sentiment and Emotion Analysis of Client Feedback

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Abstract

This research contributes to automate the analysis of customer feedback with the help of sophisticated machine learning methods like tokenization, sentiment analysis, emotion recognition, and text classification to gain significant insights from answers. Instead of classifying feedback into rigid categories such as compliments or complaints, the system seeks to recognize repeating patterns and emotional tints to provide thorough analysis at the submission stage. It produces graphical reports that facilitate swift data-based decision-making, minimizing manual work and maximizing operational effectiveness. Automated processes enable the organization to respond swiftly to feedback, resulting in ongoing real-time improvement and improved customer satisfaction. The system is designed to scale efficiently with increasing user data, ensuring consistent performance. It also enhances transparency by offering clear visual insights that help stakeholders understand customer needs better. Ultimately, it empowers organizations to refine their services and strengthen customer relationships.

Keywords

Machine Learning, Sentiment Analysis, Emotion Detection, Text Classification, Data Visualization, Tokenization, Keyword Extraction

Introduction

Understanding customer and user feedback has become increasingly important for organizations operating in sectors such as education, healthcare, corporate training, and public services. However, prior studies indicate that traditional feedback evaluation approaches are largely manual, subjective, and inefficient, making it difficult to manage large volumes of unstructured textual data such as open-ended survey responses and online reviews (Santhosh et al., 2016). As a result, organizations often struggle to obtain timely and reliable insights. Moreover, many existing feedback analysis tools primarily focus on basic sentiment polarity and fail to capture deeper emotional or contextual information, leading to fragmented insights and limited decision-making support (Ojo et al., 2020).

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To overcome these limitations, intelligent feedback analytics platforms have emerged that employ Natural Language Processing (NLP) and Machine Learning (ML) techniques. These platforms enable automated sentiment analysis, emotion detection, keyword extraction, and text categorization, allowing organizations to derive actionable insights and gain a deeper understanding of user opinions (Jamatia et al., n.d.). Further enhancements are achieved through real-time feedback classification and aspect-based sentiment analysis, which help identify specific attributes or topics discussed by users and improve the interpretability of feedback data (Suneetha & Row, 2023).

Recent research highlights the effectiveness of deep learning techniques in text mining for improving the accuracy and scalability of feedback analysis. Such approaches enable the discovery of underlying patterns and trends in user opinions that are not easily captured using traditional methods (Rahman et al., 2022). Additionally, emotion-based sentiment analysis using advanced NLP models provides a richer understanding of user feedback by capturing emotional nuances beyond simple positive or negative sentiment classifications (Prasetyo et al., 2024).

To support practical adoption, modern feedback analytics platforms allow users to design customized feedback forms, upload responses in formats such as Excel or CSV, and visualize analytical outcomes through interactive charts, graphs, and word clouds. These visualization techniques simplify interpretation and promote data-driven decision-making (Skoghäll & Öhman, 2022). Enhanced keyword extraction and sentiment clustering further assist in identifying dominant themes and improving service quality (Babina & Sheremetyeva, 2026).

Despite these advancements, existing studies report ongoing challenges such as fragmented analytical tools, manual intervention, and inconsistent result interpretation, which may introduce delays and analytical bias (Banoth et al., 2020). Earlier research in sentiment analysis also emphasizes the necessity for integrated and automated systems to efficiently manage and analyze large-scale feedback data (Pal et al., 2021).

In response to these challenges, the proposed platform presents a centralized and user-friendly solution that integrates advanced NLP and ML techniques with intuitive visual analytics. By combining sentiment and emotion analysis, aspect-based evaluation, keyword extraction, and interactive dashboards, the platform enables accurate, scalable, and efficient feedback analysis without requiring extensive AI expertise. This approach supports informed and data-driven decision-making across diverse application domains (Krishna et al., 2025)).

Methodology

User input is collected either via specially designed forms or batch uploaded through Excel or CSV files. The text data is cleaned to eliminate noise such as punctuation, digits, and stop words to ensure higher-quality analysis. After cleaning, the data is tokenized and normalized so it can be efficiently processed by machine learning models. As depicted in Fig. 1, the architecture of FeedbackXpert consists of three primary components: Frontend - form creation, data entry, and file uploads; Backend - ML processing, analytics, and report generation; and Database - storage for form templates, user responses, and authentication details, thereby ensuring a smooth and reliable end-to-end data flow. Additional validation and preprocessing layers help maintain data consistency and support scalable real-time processing.

The entire process is demonstrated in Fig. 2, where users either create a form via Firebase or upload responses directly. The collected data is securely stored, processed using Python and Pandas, and then analyzed through ML models built with Scikit-learn for sentiment, emotion, and keyword extraction. The resulting insights are visualized through Chart.js and rendered within a Flask-driven analytical dashboard. This integrated pipeline enables organizations to instantly interpret patterns, monitor customer perceptions, and make well-informed, timely decisions that enhance overall service quality.

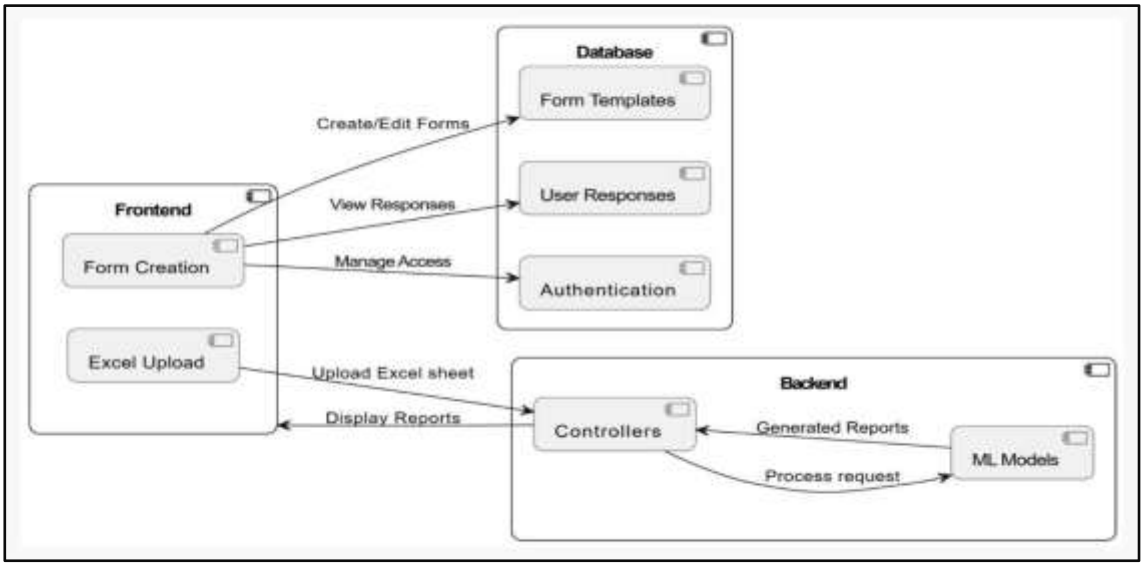

Fig 1: System Architecture

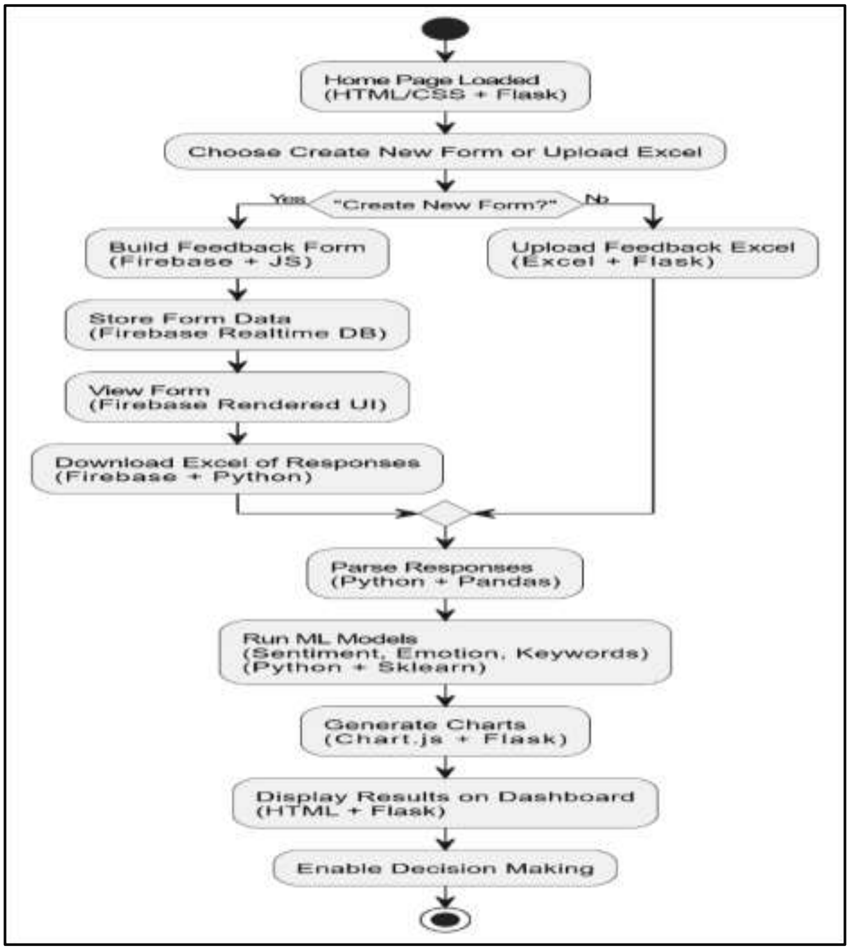

Fig 2: Flow of the application

Results and Discussion

The results show that the sentiment and emotion analysis models achieved high training and validation accuracy, indicating strong generalization to unseen feedback. The convergence of loss curves confirms that the models are not overfitting and are learning effectively. Evaluation through confusion matrices and classification reports reveals high precision, recall, and F1-scores across sentiment categories, demonstrating consistent and reliable performance. Visual outputs like bar charts and word clouds further validate the system's ability to extract meaningful insights from user feedback. Additional evaluation across diverse datasets also showed stable behavior, confirming the robustness and adaptability of the analytical pipeline.

The visual and interactive components of the system also contributed to its effectiveness. Fig. 3 displays the list of feedback forms created by users, while Fig. 4 presents a template interface used to design new feedback forms. Once forms are created, users can upload response data through the interface shown in Fig. 5, which allows Excel or CSV file uploads. Finally, Fig. 6 provides a comprehensive visual report of the analyzed feedback, including pie charts for sentiment distribution and emotion analysis, and word clouds for keyword extraction. These outputs not only support the technical performance of the system but also highlight FeedbackXpert's capabilities to deliver meaningful, insightful, and actionable analytics. The intuitive visualization ensures that even non-technical users can easily interpret trends, enabling faster decision-making and improving overall user engagement with the platform. Fig 7 shows the results generated from the feedback form responses.

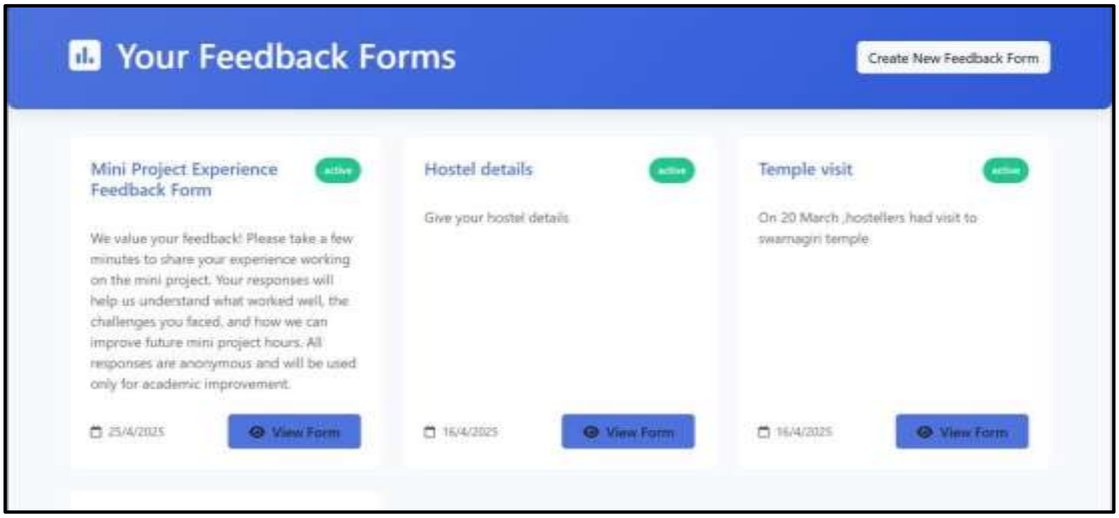

Fig 3: Feedback forms by the user

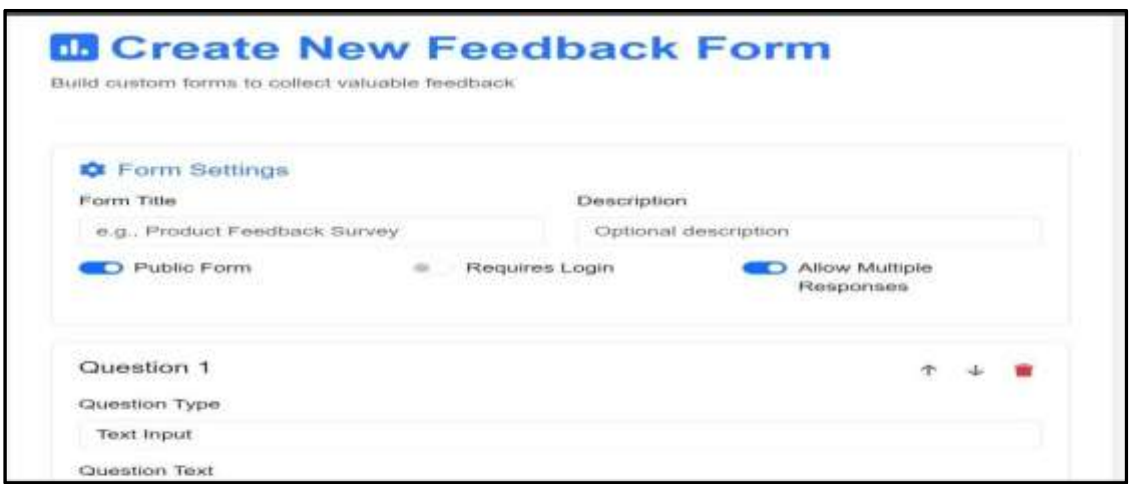

Fig 4: Creation of custom feedback form on feedbackXpert system

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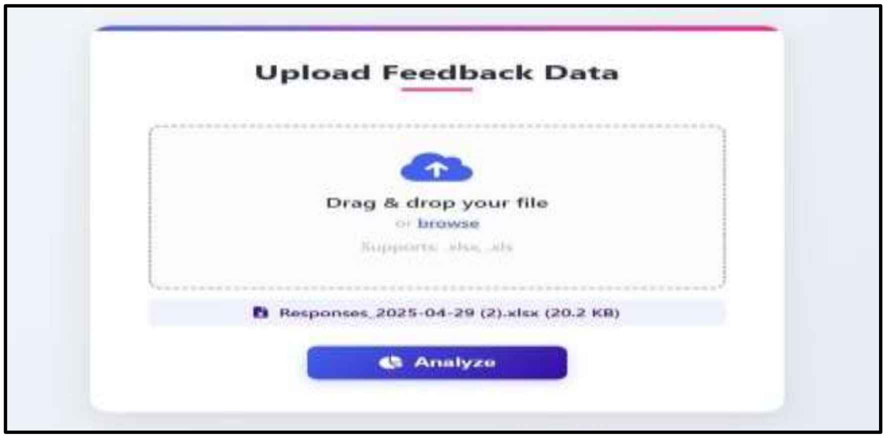

Fig 5: option to upload excel/csv feedback files

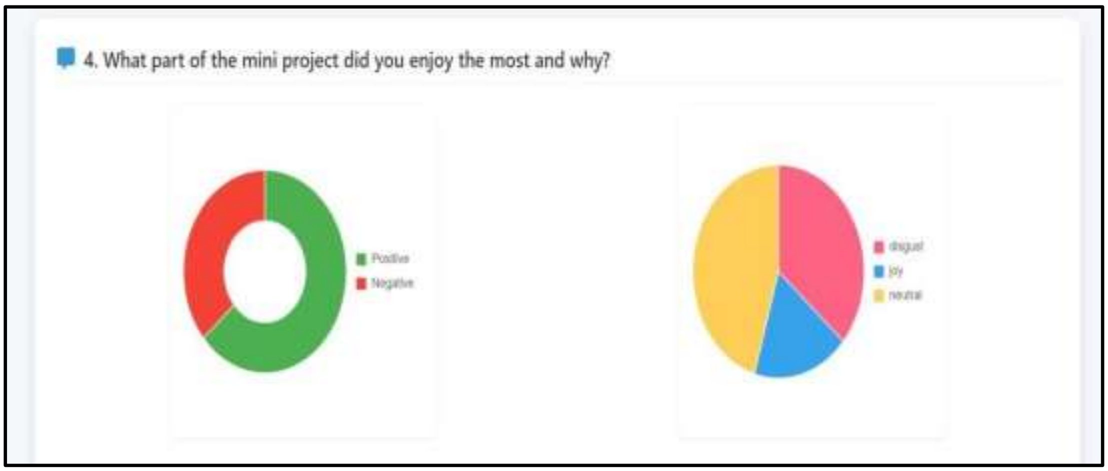

Fig 6: Visual representation of results

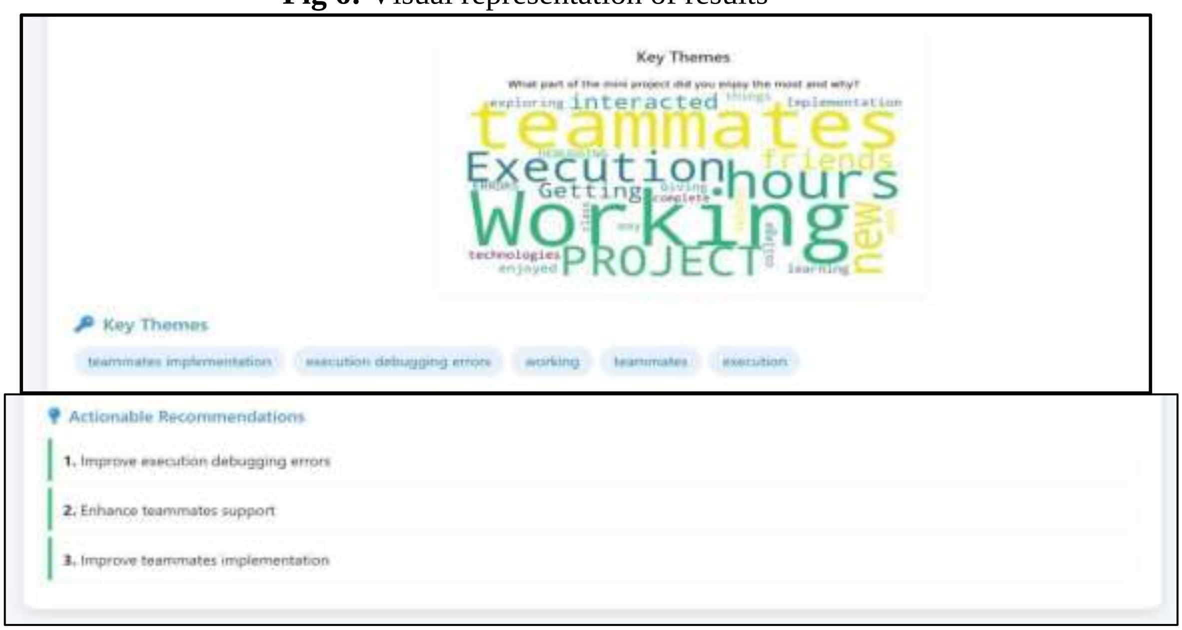

Fig 7: Results generated from the feedback form responses

Conclusion

In conclusion, this project successfully demonstrates the effective use of NLP and ML in automating feedback analysis by converting unstructured responses into accurate, actionable insights through sentiment, emotion, and keyword analysis, supported by clear visual reports. The system reduces manual effort, improves decision-making efficiency, and proves to be a reliable solution for intelligent feedback management across diverse sectors. It also showcases how advanced analytics can be integrated seamlessly into a user-friendly workflow, making sophisticated ML insights accessible even to non-technical stakeholders.

As a future enhancement, developing a mobile application will enable on-the-go access, real-time feedback processing, and wider usability, further strengthening the platform's accessibility and impact. Incorporating features such as push notifications, offline data capture, and instant visual dashboards can expand its functionality, ensuring that organizations remain responsive and informed at all times.

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References

Andi Prasetyo, Rina Dwi Lestari, & Rudi Hartono. (2024). Using Natural Language Processing to Enhance Customer Sentiment Analysis in Ecommerce. International Journal of Information Engineering and Science, 1(2), 19–25. https://doi.org/10.62951/ijies.v1i2.90

Babina, O., & Sheremetyeva, S. (2025). Emotion-Sentiment Profiling of Customer Feedback Through Cluster-Driven Analysis. Communications in Computer and Information Science, 101–116. https://doi.org/10.1007/978-3-032-04958-2_8

Banoth, S., Kumar Reddy, N., & Naidu, K. (2020). Deep learning for sentiment analysis based on customer reviews. Proceedings of the International Conference on Computing, Communication and Networking Technologies (ICCCNT), 1–5. https://doi.org/10.1109/ICCCNT49239.2020

Jamatia, J., Dalal, B., Kumar, M., & Devhare, D. (2024). Letter to Editor. Indian Journal of Medical Microbiology, 51, 100667. https://doi.org/10.1016/j.ijmmb.2024.100667

Krishna, J., Lakshmi Narayana, A., Juber, S. M. K., Mothilal Yadav, Y., Siva Karthik, G., & Pavan Kumar, V. (2025). Analyzing Customer Feedback on Amazon to Reveal Sentiment Trends using Machine Learning. 2025 International Conference on Computer, Electrical & Communication Engineering (ICCECE), 1–7. https://doi.org/10.1109/iccece61355.2025.10941446.

Ogundele, I. O., Akinade, A. O., & Alakiri, H. O. (2020). Detection and Prevention of Session Hijacking in Web Application Management. IJARCCE, 9(7), 1–10. https://doi.org/10.17148/ijarcce.2020.9601

Pal, S. (2021). Customer Feedback Analysis using NLP. Indian Journal of Computer Science, 6(1), 17. https://doi.org/10.17010/ijcs/2021/v6/i1/158186

Rahman, N. A., Idrus, S. D., & Adam, N. L. (2022). Classification of customer feedbacks using sentiment analysis towards mobile banking applications. IAES International Journal of Artificial Intelligence (IJ-AI), 11(4), 1579. https://doi.org/10.11591/ijai.v11.i4.pp1579-1587

Sampathirao Suneetha, Et. al. (2023). Cross-Domain Aspect Extraction using Adversarial Domain Adaptation. International Journal on Recent and Innovation Trends in Computing and Communication, 11(11s), 672–682. https://doi.org/10.17762/ijritcc.v11i11s.9658

Santhosh, K. L., Desai, J., & Majumdar, J. (2016). Opinion mining and sentiment analysis on online customer reviews. Proceedings of the International Conference on Computational Intelligence and Computing Research (ICCIC), 1–4. https://doi.org/10.1109/ICCIC.2016.7919584

Skoghäll, T., & Öhman, D. (2022). Summarization and keyword extraction on customer feedback data : Comparing different unsupervised methods for extracting trends and insight from text. In umu.diva-portal.org. https://urn.kb.se/resolve?urn=urn:nbn:se:umu:diva-196780