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Feedback Management System

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ABSTRACT: Effective feedback management is critical for organizational success, driving product innovation, enhancing customer satisfaction, and identifying operational inefficiencies. However, traditional methods of collecting and processing feedback are often manual, slow, and incapable of handling the sheer volume and unstructured nature of modern data sources like social media, support tickets, and surveys. This paper presents the design and implementation of an intelligent, AI powered Feedback Management System (FMS). The proposed system automates the entire feedback lifecycle: from multichannel collection and preprocessing to intelligent analysis using Natural Language Processing (NLP) for sentiment analysis and topic modelling. The system automatically categorizes and routes feedback to the appropriate teams, provides a real-time analytics dashboard, and facilitates closing the feedback loop with customers. We discuss the system architecture, the core AI components, and a case study demonstrating its effectiveness in reducing response times and identifying actionable insights from user feedback.

Keywords — Feedback Management, Natural Language Processing (NLP), Sentiment Analysis, Customer Satisfaction, System Design, Machine Learning.

1. Introduction

Feedback is nothing but expressing one’s opinion on a product, a person’s performance on a task etc., which can be used as the base of enhancement. It's useful information given at the right time and through the right means. Education plays a significant part in perfecting the living norms of the people. The largest educational system in the world is thought to be the advanced education system in India Privatization enhanced occasion for the private individualities to establish, Colleges and Private Universities feeding to the adding demand for education. During the end of the session, the staffs provides a Google form, and the overall scores for ***each*** area and each lecturer are determined. Following that, the (HOD) of the specific branch and the director sir/ma'am, who is provided by the faculty, view all of the grade summaries. However, this procedure allows students to provide feedback through an online system, saving time, and once the feedback has been given, it cannot be modified. Education The effect of tutoring methods is defined by the feedback framework. It defines the legitimacy and position of the teaching methods. As more students enrol in institutions, it becomes more challenging to handle feedback manually. A substantial amount of executive effort is required for data collecting in journal article tutoring performance evaluation. Additionally, paper-based tutoring performance assessment is quite time- and money-consuming. On the other hand, information technology is dramatically altering the teaching landscape. To show the fashion conscious practises and blights present in its system, educational institutions must create and buy or rent Feedback Management System (FMS). The input on preceptors has been mandated by the University Subventions Commission. In order to gauge the effectiveness of educational delivery, it has instructed the National Accreditation and Assessment Council (NAAC) to solicit input from the students. This essay discusses the nonsupervisory ethics, procedures, opportunities, and difficulties of India's Advanced Education System. without human intervention . This automation enables organizations to act on feedback faster, prioritize improvements based on data, and ultimately improve the customer experience.

The remainder of this paper is structured as follows: Section II reviews related work in feedback analysis and existing systems. Section III details the proposed system architecture and the feedback lifecycle. Section IV discusses the core implementation components, focusing on the NLP engine. Section V presents a case study and evaluation results. Finally, Section VI concludes the paper and outlines future work.

2. Related Work

The field of automated feedback analysis builds heavily on advancements in Natural Language Processing. Early systems relied on keyword spotting and rule-based methods, which were often brittle and difficult to maintain [3]. With the rise of machine learning, sentiment analysis models, typically using algorithms like Support Vector Machines (SVM) or Naive Bayes, became common.

More recently, deep learning models, particularly transformerbased architectures like BERT (Bidirectional Encoder Representations from Transformers), have shown state-of-theart performance in understanding context and nuance in text [4]. These models can be fine-tuned on domain-specific data (e.g., software reviews) to achieve high accuracy in both sentiment classification and topic extraction.

While many commercial tools (e.g., Zendesk, UserVoice) offer feedback collection capabilities, they often provide limited analytical depth. Academic research, on the other hand, has focused heavily on the analysis models [5] but less on the endto-end system architecture for integrating these models into a practical, real-time workflow. Our work aims to bridge this gap by presenting a complete system that integrates advanced NLP with a robust workflow engine.

3. System Architecture

The proposed FMS is designed as a modular, scalable system built on a microservices architecture. The core of the system is a central processing pipeline that orchestrates the flow of feedback from collection to resolution. The complete feedback lifecycle, as managed by the system, is illustrated in Fig. 1.

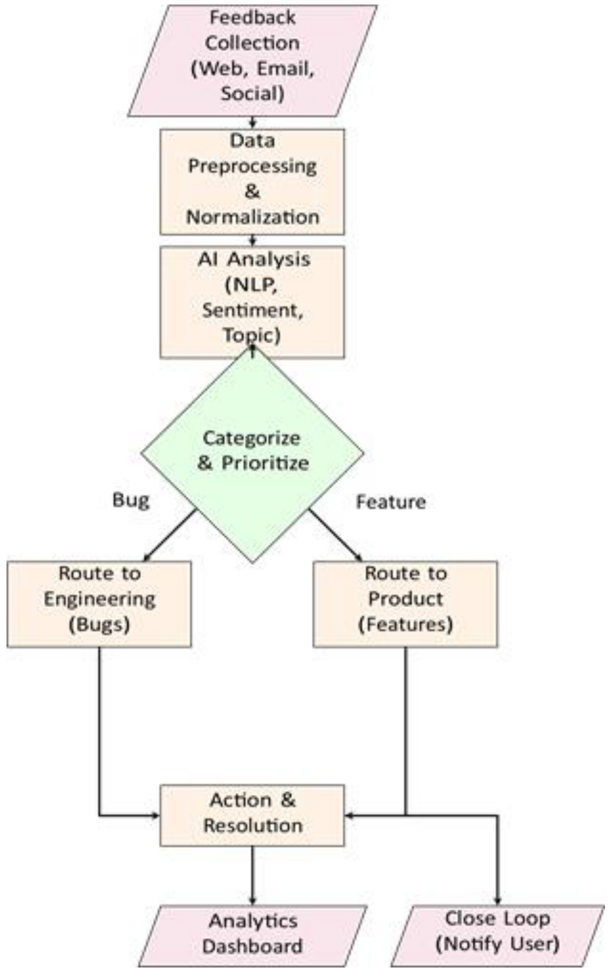

Fig. 1. The AI-Powered Feedback Management Lifecycle

The workflow begins with the Data Collection Module, which aggregates feedback from various APIs and input forms. This unstructured data is then passed to the "Preprocessing Module", which cleans the text (e.g., removes HTML, converts to lowercase).

The cleaned text is fed into the AI Analysis Engine, the core of the system. This engine performs three tasks:

- Sentiment Analysis: Classifies the feedback as positive, negative, or neutral.

- Topic Modelling: Identifies the primary theme (e.g., ”UI,” ”billing,” ”performance”).
- Intent Classification: Determines the user’s intent (e.g., ”bug report,” ”feature request,” ”question”).

Based on these classifications, the **Routing Module** automatically creates a ticket and assigns it to the correct team (e.g., a ”negative” bug report about ”billing” is routed to the finance and engineering teams). All data is stored in a central database and visualized on the **Analytics Dashboard**, allowing managers to track trends and KPIs. Finally, the system includes a module to ”close the loop” by sending automated or manual follow-ups to users when their feedback has been acted upon.

4. Implementation and Core Components

The system was implemented using Python for the backend services, with Flask as the API framework. The NLP models

were built using the Hugging Face ‘transformers‘ library.

A. *NLP Engine*

We fine-tuned a Distil BERT model on a custom dataset of 10,000 feedback entries, which were manually labelled for sentiment, topic, and intent. This custom-trained model achieved an accuracy of 92% on sentiment classification, outperforming generic pre-trained models.

B. *Analytics Dashboard*

The dashboard was built using a modern web framework. It provides real-time visualizations of key metrics, such as:

- Feedback volume over time, by channel.
- Overall customer sentiment (CSAT score).
- Top feedback topics and keywords.
- Average time to resolution for feedback tickets.

5. Case Study and Results

We deployed the FMS in a medium-sized SaaS company for a trial period of three months. The company previously used a shared email inbox to manage feedback. We collected data on two key metrics: average response time to new feedback and the number of actionable insights identified by the product team.

As shown in Fig. 2, the results were significant. The average time to first response decreased by over 70%, as the system eliminated the need for manual triage.

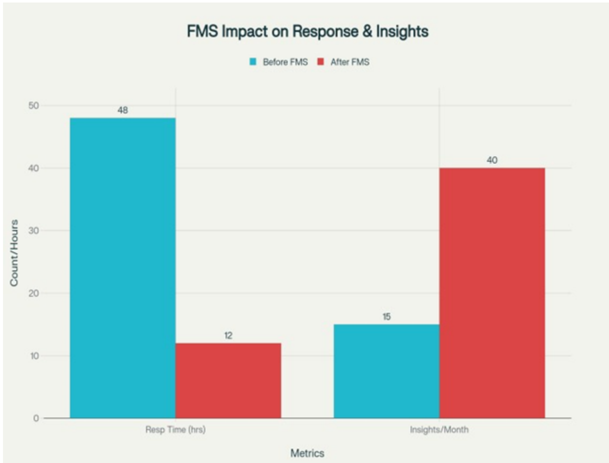

Fig. 2. Key Performance Metrics Pre- and Post-FMS Implementation.

Furthermore, the product team reported a 150% increase in the number of actionable insights derived from feedback. By using the dashboard to filter for ”negative” sentiment feedback tagged with the ”UI/UX” topic, the team was able to quickly identify and fix three major Data Graph Placeholder usability issues that had been repeatedly mentioned by users but were previously missed.

6. Conclusion

This paper presented the design and implementation of an AI-powered Feedback Management System. By integrating modern NLP techniques into a cohesive, end to-end workflow, the system successfully automates the collection, analysis, and routing of user feedback. Our case study demonstrates that this approach can significantly reduce operational overhead and, more importantly, unlock valuable, actionable insights from unstructured customer data.

Future work will focus on expanding the system's analytical capabilities. We plan to incorporate multi-lingual models to process feedback from a global user base and develop a proactive alerting system to notify teams of sudden spikes in negative sentiment or emerging critical issues in real-time.

7. Future Work

While the current Feedback Management System provides a robust foundation for AI-powered analysis, several areas remain for expansion:

- Multi-lingual Support: Future iterations will focus on incorporating multi-lingual NLP models to allow organizations to process and analyze feedback from a global, linguistically diverse user base.
- Proactive Alerting Systems: We plan to develop real-time monitoring capabilities that trigger proactive alerts for management teams whenever sudden spikes in negative sentiment or critical emerging issues are detected.
- Advanced Predictive Analytics: Beyond classification, future work will explore using deep learning to predict future customer satisfaction (CSAT) trends based on historical feedback patterns, allowing for more strategic organizational planning.
- CRM Integration: Expanding the system's interoperability by building native connectors for popular Customer Relationship Management (CRM) tools will further streamline the process of "closing the feedback loop"

References

[1] R. G. Cooper and S. J. Edgett, ”Best practices in the ideatolaunch process and its governance,” Research-Technology Management, vol. 55, no. 2, pp. 43-54, 2012.

[2] B. Liu,”Sentiment analysis and opinion mining,” Synthesis lectures on human language technologies, vol. 5, no. 1, pp. 1-167, 2012.

[3] E. Roloff and J. Wiebe, ”Learning extraction patterns for subjective expressions,” in Proceedings of the 2003 conference on Empirical methods in natural language processing, 2003, pp. 105-112.

[4] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, ”Bert: Pretraining of deep bidirectional transformers for language understanding,” arXiv preprint arXiv:1810.04805, 2018.

[5] P. Wang, Y. Fan, and P. Wang, ”Comparative analysis of text classification algorithms,” in 2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA), 2017, pp. 73-77.

[6] M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[7] N. Soni, N. Nigam, "Recent Advances in Artificial Intelligence and Machine Learning: Trends, Challenges, and Future Directions", International Journal of Engineering Trends and Applications (IJETA), Vol. 12, Issue. 1, pp. 9-12, 2025.

[8] S. A. Saiyed, N. Sharma, H. Kaushik, P. Jain, G. K. Soni and R. Joshi, "Transforming portfolio management with AI and ML: shaping investor perceptions and the future of the Indian investment sector," Parul University International Conference on Engineering and Technology 2025 (PiCET 2025), pp. 1108-1114, 2025.

[9] M. K. Jha, K. Kumar, N. Hemrajani, D. S. Rao, A. Goyal, and R. Ajmera, “AI Powered Student Performance Prediction using Explainable ML,” in Proceedings of the 4th International Conference on Automation, Computing and Renewable Systems (ICACRS), pp. 1140–1144, 2025.

[10] I. Yadav, V. Shekhawat, K. Gautam, G. Kumar Soni and R. Yadav, "Artificial Intelligence for Cybersecurity: Emerging Techniques, Challenges, and Future Trends," 2025 3rd International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), pp. 1176-1180, 2025.

[11] P. Upadhyay, K. K. Sharma, R. Dwivedi and P. Jha, "A Statistical Machine Learning Approach to Optimize Workload in Cloud Data Centre," 2023 7th International Conference on Computing Methodologies and Communication (ICCMC), pp. 276-280, 2023.

[12] P. Jha, D. Dembla and W. Dubey, "Crop Disease Detection and Classification Using Deep Learning-Based Classifier Algorithm", Emerging Trends in Expert Applications and Security. ICETEAS 2023. Lecture Notes in Networks and Systems, Vol 682. 2023.

[13] P. Jha, G. K. Soni, H. Dogra, D. Goswami, K. Choudhary, and H. Vaishnav, "Plant Disease Detection and Classification using Convolutional Neural Network," in Proceedings of the 4th International Conference on Automation, Computing and Renewable Systems (ICACRS), pp. 1442–1446, 2025.

[14] S. Soni, K. Paliwal, and G. K. Jain, "Reinforcement Learning in Autonomous Systems: Advancing Intelligent Decision-Making," International Journal of Global Research in Science and Technology, vol. 10, pp. 321–325, 2025.

[15] H. Sharma and R. Ajmera, "Comprehensive review and analysis on machine learning based Twitter opinion mining framework," Tuijin Jishu/Journal of Propulsion Technology, vol. 44, no. 5, 2023.

[16] M. Kumar, R. Ajmera, and D. Kumar, "Statistical analysis and accuracy assessment of improved machine learning based opinion mining framework," Advances in Nonlinear Variational Inequalities, vol. 27, no. 1, 2024.

[17] K. Paliwal, P. Jha, S. Kumari, V. Vaish, N. Vishwakarma, and A. Bansal, "Machine Learning in Electric Vehicle Consumption Modelling," in Proceedings of the 9th International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 727–730, 2026.

[18] S. Soni, M. K. Jha, and D. Jangid, "A Comprehensive Review of Blockchain and Machine Learning Convergence," International Journal of Global Research in Science and Technology, vol. 10, pp. 242–249, 2025.