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Design and Implementation of a Smart Feedback System for Lecturers Using Sentiment

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Abstract

Traditional feedback methods are often manual, time-consuming, and susceptible to subjective interpretation, which limits their effectiveness for timely instructional improvement. To address these challenges, a web-based system was developed to streamline feedback collection and management. The system integrates a Flask-based sentiment analysis engine powered by Natural Language Processing (NLP) techniques to automatically classify student feedback into positive, negative, or neutral categories. The proposed system includes a user-friendly student feedback interface, a secure lecturer dashboard, automated sentiment classification, and graphical visualization of feedback trends using charting tools. These features work together to provide an efficient and structured approach to feedback analysis. System testing confirmed accurate sentiment classification, seamless integration between components, and effective real-time processing of feedback data. The system demonstrates how artificial intelligence can enhance teaching evaluation by providing lecturers with timely, data-driven insights that support continuous improvement in instructional delivery.

Keywords:

Smart Feedback, Evaluation, Sentiment Analysis, Lecturers, NLP.

Introduction

Higher education institutions face significant challenges in effectively processing and analysing student feedback to improve teaching quality and educational outcomes. The primary problems include the time-intensive nature of manual feedback analysis and subjective interpretation issues. Educational institutions collect vast amounts of textual feedback from students, but manual processing is labour-intensive and often results in delayed responses to teaching quality issues, limiting the potential for real-time pedagogical improvements (Kastrati et al., 2021). Hattie and Timperley's (2007) seminal work established feedback as one of the most powerful influences on learning and achievement, with their meta-analysis demonstrating significant effect sizes for well-designed feedback interventions. This foundational research has been consistently validated by subsequent empirical studies across diverse educational contexts and institutional settings. Recent research has continued to affirm the powerful influence of feedback on student learning, with studies emphasizing that feedback must be timely, specific, and actionable to maximize its positive impact on academic performance (Winstone & Nash, 2016). Carless and Boud (2018) conducted extensive research on sustainable feedback approaches, proposing a model that shifts focus from teacher-generated feedback to student uptake and utilization of feedback information. Their empirical findings demonstrated that feedback effectiveness depends not only on the quality of information provided but also on students' capacity to process and act upon that information. In contemporary higher education, the quality of teaching and learning experiences has become increasingly critical for institutional success and student outcomes. Traditional feedback mechanisms, particularly end-of-semester evaluations, have long served as the primary means of assessing lecturer performance and course effectiveness. However, these conventional approaches present significant limitations, including delayed feedback processing, subjective interpretation challenges, and the inability to provide real-time insights for immediate pedagogical improvements (Altrabsheh et al., 2013). The computational foundation of sentiment analysis in educational feedback systems relies on advanced natural language processing theories and models that enable machines to understand, interpret, and analyze human language. These theoretical frameworks and computational models provide the technical basis for developing sophisticated systems capable of processing and analyzing textual feedback with high accuracy and reliability. Ellis and Herrington (2024) investigated the use of artificial intelligence in delivering effective feedback in higher education settings. Their study examined the implementation of AI-powered feedback systems across multiple institutions and found that automated feedback mechanisms can significantly reduce instructor workload while maintaining or even improving feedback quality. The research revealed that delivering feedback effectively, especially in large educational settings, is challenging due to time and resource constraints, making automated systems particularly valuable for scalable feedback provision. However, the study also identified important limitations, including the need for careful calibration of AI systems to ensure feedback appropriateness and the importance of maintaining human oversight in complex feedback scenarios. Transformer Architecture represents a revolutionary advancement in natural language processing that has transformed the field of text analysis and sentiment classification. The transformer model, introduced by Vaswani et al. (2017), established a new paradigm for sequence-to-sequence learning that relies entirely on attention mechanisms, eliminating the need for recurrent or convolutional layers. BERT (Bidirectional Encoder Representations from Transformers) has emerged as one of the most influential models in natural language processing, particularly for sentiment analysis applications. BERT-based models outperformed other methods in e-commerce and code-mixed language sentiment analysis (Yin et al., 2024; Tripty et al., 2024). Hybrid Models and Advanced Architectures have emerged as powerful approaches for improving sentiment analysis performance by combining multiple theoretical frameworks and computational techniques. ArabBert-LSTM improves Arabic sentiment analysis based on transformer model and Long Short-Term Memory (Alosaimi et al., 2024). Van der Schaaf et al. 2024 conducted a systematic review of online peer feedback practices in higher education, analysing 67 empirical studies published between 2018 and 2023. Their review identified key components of effective peer feedback systems, including structured protocols, training interventions, and technological scaffolding. The research demonstrated that there is a growing body of literature acknowledging peer feedback as a crucial learning practice in online settings, with evidence suggesting that well-designed peer feedback interventions can enhance both feedback provision and reception skills. Kastrati et al. (2021) conducted a systematic mapping study of sentiment analysis applications in student feedback, reviewing 83 empirical studies that employed NLP and deep learning techniques. Their comprehensive analysis revealed that in the education domain, dealing with and processing students' opinions is complicated due to the nature of the language used by students and the large volume of information. The study identified predominant use of pure NLP techniques, including lexicon-based approaches, with increasing adoption of deep learning methods in more recent studies. The research mapped various sentiment analysis techniques used in educational contexts, including rule-based methods, machine learning classifiers, and neural network architectures, providing a comprehensive overview of methodological approaches and their relative effectiveness. A recent comprehensive review by (Rodriguez et al., 2025) examined the generalization of sentiment analysis across multiple domains, including education. Their meta-analysis of 156 empirical studies explored the trajectory of sentiment analysis research from traditional machine learning approaches to state-of-the-art deep learning models, including transformers and hybrid architectures.

Methodology

The Smart Feedback System was developed using a modular architecture to ensure a clear separation of concerns among the frontend, backend, and sentiment analysis components. This approach enhances system scalability, maintainability, and ease of integration, allowing each module to be developed, tested, and updated independently without affecting the overall system performance. The development process followed the Prototype Model of the Software Development Life Cycle (SDLC). This model was selected due to its suitability for systems requiring continuous user interaction and feedback (Zhang etal, 2024; Jahin et al, 2024). An initial prototype of the system was designed and implemented to demonstrate core functionalities, after which it was presented to users for evaluation. Based on user feedback, iterative refinements were carried out to improve system usability, functionality, and performance. This cycle of prototyping, testing, and enhancement continued until the system met both user expectations and defined technical requirements. The use of the Prototype Model ensured early detection of design flaws, reduced development risks, and resulted in a more user-centered and efficient final product.

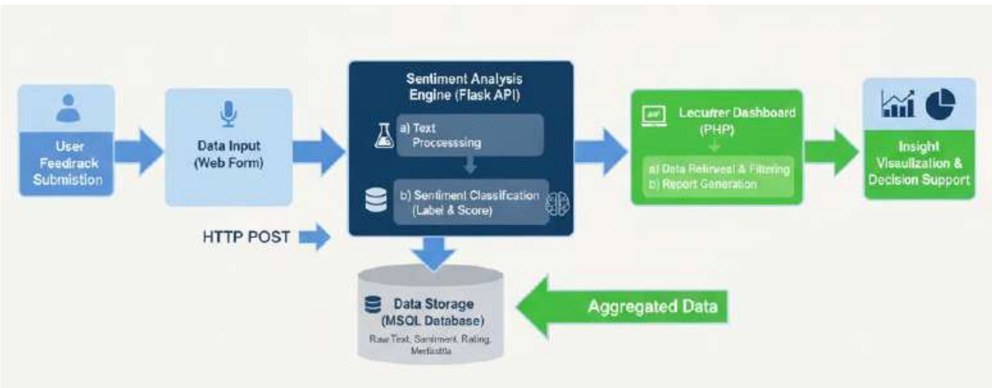

Figure 1: System Design Framework

The architecture of the Smart Feedback System is based on a three-tier structure comprising the presentation layer, application layer, and database layer. The Smart Feedback System is composed of the following modules:

Student Feedback Module

The Student Feedback Module provides a user-friendly and responsive interface that enables students to submit feedback efficiently. The interface is developed using PHP, HTML, and Bootstrap, ensuring accessibility across different devices and screen sizes. Each feedback submission includes key details such as the course name, lecturer name, an optional rating, and textual comments (Zhang etal, 2024; Jahin et al, 2024). Upon submission, the system securely stores the feedback data in a MySQL database for record-keeping and further analysis. In addition, the textual feedback is automatically transmitted to a Flask-based API, where it undergoes sentiment analysis. This process classifies the feedback into predefined sentiment categories, enabling the system to generate meaningful insights from student responses in real time.

Lecturer Dashboard

The Lecturer Dashboard provides an interactive interface for visualizing and analyzing student feedback. It presents sentiment analysis results through concise summaries and intuitive graphical representations, enabling lecturers to quickly interpret overall student perceptions. The dashboard categorizes feedback into positive, negative, and neutral sentiments, allowing lecturers to identify trends and areas that may require improvement (Zhang etal, 2024; Jahin et al, 2024). Additionally, users can filter feedback based on specific courses or date ranges, making it easier to perform targeted analysis. To support further evaluation and documentation, the system also includes functionality for exporting feedback reports in a structured format. This enhances decision-making and facilitates continuous improvement in teaching effectiveness.

Sentiment Analysis Engine

The Sentiment Analysis Engine is implemented as a Flask-based service responsible for processing and classifying textual feedback. It leverages natural language processing (NLP) libraries and techniques to analyze the polarity of submitted comments. Upon receiving feedback from the main application, the engine evaluates the text and assigns it to a predefined sentiment category (e.g., positive, negative, or neutral). This automated classification enables real-time analysis of student opinions and supports data-driven insights within the system.

Analytics and Visualization

The Analytics and Visualization component is responsible for aggregating and presenting feedback data in a clear and interpretable format. The system transforms raw feedback into meaningful insights through the use of visual elements such as charts, graphs, and summary metrics. This enables lecturers to easily understand student opinions, identify trends, and detect areas that require improvement (Zhang etal, 2024; Jahin et al, 2024). To support this functionality, Natural Language Processing (NLP) libraries are employed to analyze the polarity of submitted feedback. Once the textual data is processed by the sentiment analysis

API, it returns a sentiment classification—positive, negative, or neutral along with an optional confidence score indicating the reliability of the prediction. The PHP backend captures the API response and stores the sentiment label and confidence score in the database alongside the original feedback. This design ensures efficient data management and enables quick retrieval for visualization purposes.

The system adopts a clear separation of concerns by decoupling the sentiment analysis engine from the main application logic. This allows the analytics engine to operate independently while maintaining seamless integration with the overall system, thereby improving scalability, flexibility, and maintainability.

Result and Discussion

The student feedback interface was designed with a strong emphasis on usability, responsiveness, and accessibility. It provides a clean and intuitive platform through which students can submit feedback efficiently. Users are required to input key details, including the course name, lecturer name, and textual feedback, while also having the option to provide a star rating on a scale of one to five (Zhang etal, 2024; Jahin et al, 2024). To ensure data integrity and improve user experience, both client-side and server-side validation mechanisms were implemented. These validations verify that all required fields are correctly completed before the feedback is submitted, thereby reducing errors and incomplete entries.

Upon successful submission, the feedback data is securely stored in a MySQL database for future reference and analysis. Simultaneously, the textual component of the feedback is transmitted to a Flask-based sentiment analysis API for processing and classification. The interface is fully responsive and optimized for use across a variety of devices, including desktops, tablets, and mobile phones. This ensures that students can conveniently provide feedback at any time and from any location, thereby enhancing overall system usability and engagement.

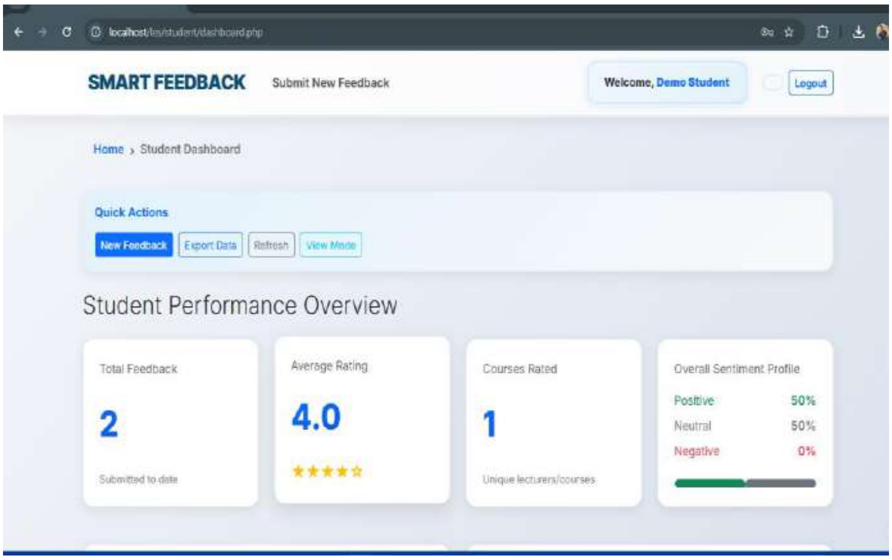

Figure 2: Student Feedback Form Interface

Sentiment Analysis Module Implementation

The Sentiment Analysis Module was implemented as a standalone, service-oriented component to ensure modularity and scalability. It operates as an independent application that exposes a RESTful API endpoint, which accepts textual feedback via HTTP POST requests from the main system. The module leverages Natural Language Processing (NLP) libraries and techniques to evaluate the polarity of the submitted feedback (Zhang etal, 2024; Jahin et al, 2024). Upon receiving the input text, the system preprocesses and analyzes the content before assigning it to a predefined sentiment category positive, negative, or neutral. In addition, the API returns an optional confidence score that indicates the reliability of the classification.
Once the analysis is completed, the API sends the result back to the main application. The backend component captures this response and stores the sentiment label and confidence score in the database alongside the original feedback data. This enables efficient retrieval and supports downstream analytics and visualization processes. By adopting a clear separation of concerns, the sentiment analysis module operates independently of the core application logic. This design enhances system flexibility, allowing the sentiment engine to be updated, scaled, or replaced without disrupting other system components, while still maintaining seamless integration with the general architecture.

Lecturer Dashboard Implementation

The Lecturer Dashboard was implemented with a session-based authentication mechanism to ensure secure and restricted access. This approach guarantees that only authorized lecturers can log into the system and access feedback to the courses they teach, thereby maintaining data privacy and integrity. The dashboard provides a well-organized and user-friendly interface for viewing student feedback. Feedback entries are displayed in a clear and structured format, with sentiment labels positive, negative, or neutral visibly attached to each entry to facilitate quick interpretation (Zhang etal, 2024; Jahin et al, 2024). To enhance usability and support targeted analysis, the system includes filtering capabilities that allow lecturers to sort feedback based on course name, date, or sentiment category. Additionally, lecturers can view detailed information for individual feedback entries, enabling a deeper understanding of specific student concerns or commendations. The dashboard also supports exporting feedback reports in formats such as CSV and PDF, making it easier to archive data or conduct further external analysis. These features collectively empower lecturers to effectively analyze student feedback and make data-driven decisions aimed at improving teaching quality.

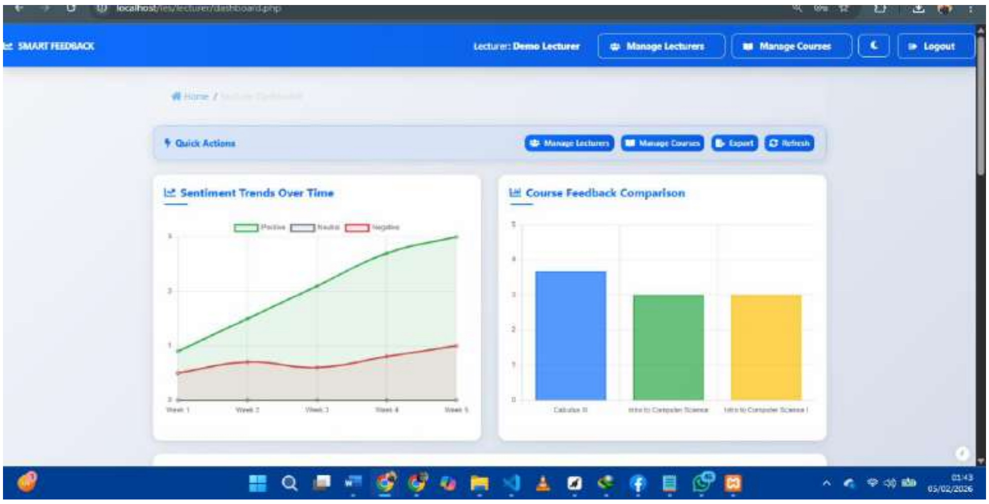

Figure 3: Lecturer Dashboard Interface

Data Visualization and Analytics

To enhance the interpretation of feedback results, data visualization tools were integrated into the Lecturer Dashboard. These tools present feedback data through intuitive graphical representations such as charts and summary metrics, providing lecturers with a clear and immediate overview of student sentiment. The system enables the visualization of sentiment trends over time, allowing users to monitor patterns and track changes in student opinions across different academic periods (Zhang etal, 2024; Jahin et al, 2024). This functionality supports trend analysis, helping lecturers identify recurring issues, improvements, or shifts in student perception. By transforming complex feedback data into easily interpretable visual formats, the system reduces analytical effort and improves decision-making efficiency. As a result, lecturers are better equipped to derive actionable insights and implement strategies aimed at enhancing teaching effectiveness

Figure 4: Sentiment Distribution and Trend Charts

To enhance interpretation of feedback results, data visualization tools were integrated into the system. These visual representations provide a quick overview of student sentiment trends over time. The system also supports trend analysis, allowing lecturers to observe changes in sentiment across different periods. By presenting feedback data graphically, the system simplifies complex data and improves decision-making efficiency for lecturers. The system underwent several testing stages to ensure reliability and effectiveness. Functional testing was conducted to verify that all modules, including feedback submission, sentiment processing, dashboard display, and report export, operated as expected. Integration testing confirmed smooth communication between the PHP backend and the Flask sentiment analysis API. Performance testing showed that sentiment analysis requests were processed within an acceptable time frame, ensuring real-time feedback analysis. The results demonstrated accurate sentiment classification for most feedback entries, confirming the effectiveness of the selected NLP techniques (Zhang etal, 2024; Jahin et al, 2024). The system met the objectives of providing automated, timely, and meaningful feedback insights for lecturers. The results obtained from system implementation and testing indicate that the Smart Feedback System successfully achieved its primary objectives. The system automated the collection and analysis of student feedback, eliminating the delays and subjectivity associated with traditional manual methods. The integration of sentiment analysis provided lecturers with immediate insights into student perceptions, enabling data-driven improvements in teaching practices. The visual analytics further enhanced understanding by summarizing large volumes of feedback into simple charts and trends. These results demonstrate that sentiment-driven feedback systems can significantly improve feedback utilization and teaching evaluation processes in higher education institutions.

Conclusion

This study presented the design and implementation of a Smart Feedback System for lecturers using sentiment analysis techniques. The motivation for this work stemmed from the limitations of traditional feedback methods, which are often manual, time-consuming, and subjective. To address these challenges, a web-based system was developed to support efficient feedback collection and management, alongside a Flask-based sentiment analysis engine for automated analysis of students' textual responses. The system provides a user-friendly interface that enables students to submit feedback conveniently, while lecturers access sentiment-driven insights through a secure and interactive dashboard. By applying Natural Language Processing (NLP) techniques, the system classifies feedback into positive, negative, and neutral categories. In addition, data visualization tools were integrated to present the analyzed results in graphical formats, thereby improving interpretability and supporting informed decision-making. System evaluation through functionality, integration, performance, and usability testing demonstrated that the solution effectively automates feedback analysis and delivers timely insights. The system enhances the efficiency of feedback management and contributes to improved teaching and learning outcomes.

Future research should focus on improving sentiment analysis accuracy using advanced transformer-based models, enhancing system scalability through cloud deployment, and supporting multilingual feedback analysis. Additionally, aspect-based sentiment analysis and real-time analytics can be integrated to provide more detailed and actionable insights for lecturers, improving decision-making in teaching evaluation.

Based on the findings of this study, several recommendations are proposed to enhance the effectiveness, usability, and impact of the developed system in improving student feedback evaluation processes in higher education institutions.

1. Higher education institutions should adopt automated feedback systems to improve the efficiency, speed, and objectivity of student feedback collection and analysis.
2. Artificial Intelligence and Natural Language Processing (NLP) tools should be integrated into academic systems to enhance accurate sentiment analysis and support data-driven decision-making.
3. Lecturers and administrative staff should receive proper training to effectively use the system and interpret sentiment analysis results for instructional improvement.
4. Regular system maintenance and updates should be carried out to ensure optimal performance, security, and reliability of the feedback system.
5. Institutions should encourage continuous student participation in feedback processes to ensure consistent data collection for improving teaching and learning quality.

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