

## Enhancing faculty evaluation through NLP-based sentiment analysis of student feedback

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### Abstract

Faculty performance evaluation is crucial for maintaining high teaching standards in academic institutions. Traditional feedback mechanisms often rely on numerical ratings or manually reviewed responses, which lack depth in capturing student sentiments. This paper presents an NLP-powered sentiment analysis system that extracts meaningful insights from textual student feedback. The system classifies sentiments to highlight faculty strengths and areas for improvement. The analysis results are visualized through interactive dashboards, enabling faculty to track their performance trends and administrators to manage faculty data efficiently. By automating sentiment analysis and integrating data-driven feedback loops, this system fosters continuous faculty development and enhances the overall academic environment.

**Keywords:** Natural Language Processing (NLP); Sentiment Analysis; Faculty Evaluation; Feedback System; Machine Learning; Text Analysis; Data-Driven Insights; Academic Performance Assessment; Educational Technology; Automated Feedback System.

### 1. Introduction

In higher education, faculty performance plays a vital role in shaping student learning outcomes. To ensure quality teaching, institutions rely on faculty evaluation systems that gather student feedback. However, traditional evaluation methods—such as numerical rating scales and manually reviewed responses—often fail to capture the nuanced sentiments behind student opinions. These limitations hinder institutions from deriving meaningful insights that could drive faculty improvement.

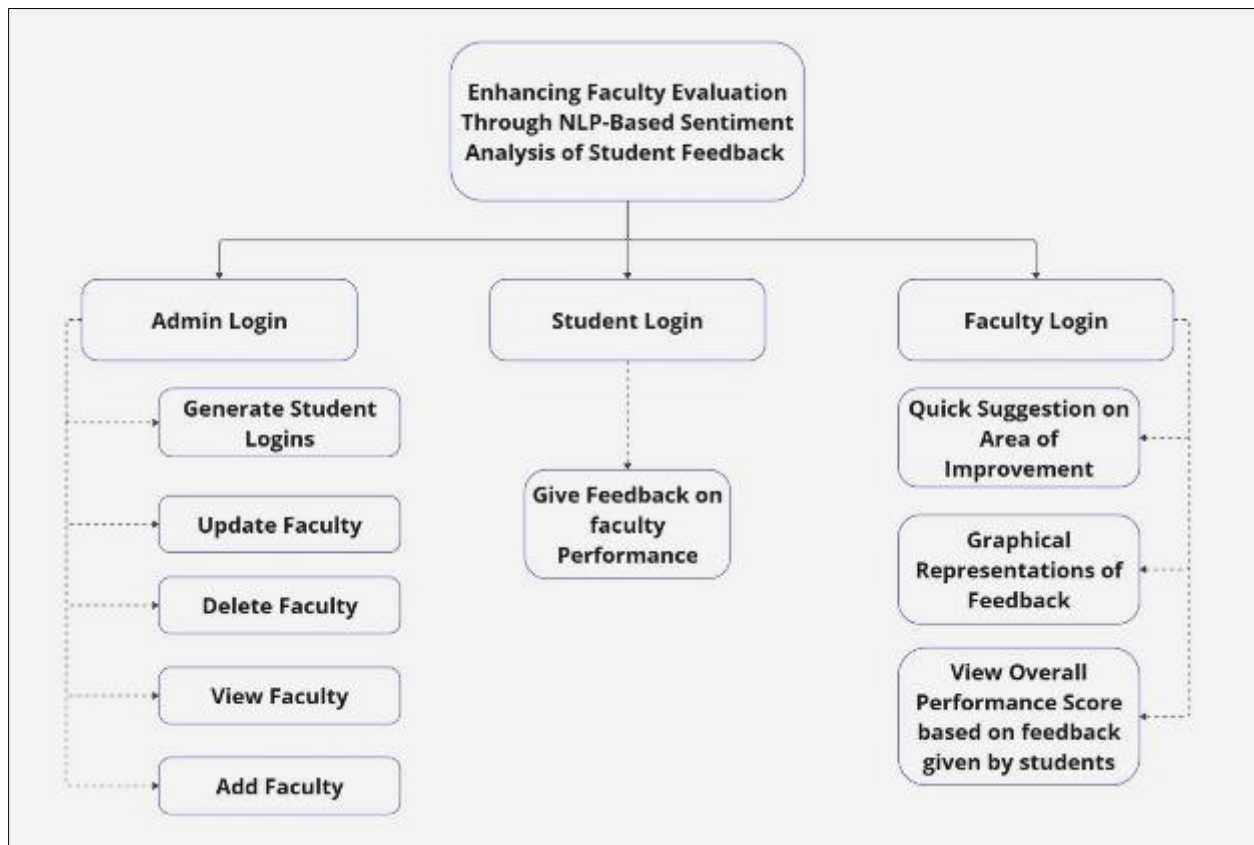
Recent advancements in Natural Language Processing (NLP) have introduced new possibilities for automated feedback analysis [1]. Sentiment analysis, a subfield of NLP, enables systems to categorize textual feedback into positive, negative, and neutral sentiments, providing deeper insights into faculty performance [2]. This paper presents an NLP-driven faculty evaluation system to analyze student feedback, extracting key performance indicators and identifying areas for improvement.

The system not only automates sentiment analysis but also visualizes results through interactive performance dashboards, helping faculty track their progress over time. Additionally, administrators can leverage the system to manage faculty feedback data efficiently and implement data-driven decision-making processes. By integrating machine

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learning-based sentiment classification with real-time data visualization, this approach fosters a structured feedback loop, ensuring continuous improvement in teaching quality.

### 1.1. Block Diagram



**Figure 1** Block Diagram showing user roles and their functionalities within the system.

## 2. Literature review

Faculty evaluation plays a crucial role in ensuring high-quality education and continuous improvement in teaching methodologies. Traditionally, student feedback has been collected using numerical rating scales or manually reviewed textual responses. However, these approaches often fail to capture the depth of student sentiments, leading to subjective or incomplete assessments [3]. With advancements in Natural Language Processing (NLP), automated sentiment analysis has emerged as an effective solution for processing and interpreting student feedback.

Several studies have explored sentiment analysis techniques in the education domain. Early research primarily focused on lexicon-based methods, which rely on predefined sentiment scores for words. While these approaches provide quick insights, they often struggle with understanding context, negation, and domain-specific language [4]. Later, machine learning-based models, such as Support Vector Machines (SVM) and Naïve Bayes, were introduced to classify feedback into positive, neutral, or negative sentiments. Although these models improved accuracy, they required large, labeled datasets for training, making them less adaptable to varying academic environments [5].

The adoption of deep learning techniques, such as Long Short-Term Memory (LSTM) networks and BERT-based transformers, further enhanced sentiment classification by capturing contextual meanings in textual data [6]. However, these models often demand high computational power and extensive fine-tuning, which may not be practical for real-time faculty evaluation systems [7].

To address these challenges, StanfordNLP has been recognized as a powerful linguistic tool for sentiment analysis, offering pre-trained models that efficiently process text while preserving contextual meanings. Unlike traditional methods, StanfordNLP enables aspect-based sentiment classification, allowing institutions to categorize feedback into specific teaching attributes such as communication skills, subject knowledge, engagement, and explanation clarity.

While existing research has contributed significantly to sentiment analysis in faculty evaluation, there remains a gap in real-time feedback visualization, automated improvement suggestions, and structured faculty performance tracking. Our proposed system integrates StanfordNLP-powered sentiment analysis with an interactive faculty dashboard, providing a data-driven approach to faculty evaluation. By offering real-time insights, personalized feedback, and trend analysis, this system aims to bridge the gap between student feedback collection and meaningful faculty development.

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### **3. Methodology**

This section describes the approach used to design and implement the NLP-powered Faculty Evaluation System. The methodology consists of four key components: System Architecture, Data Collection, Sentiment Analysis, and Performance Visualization.

#### **3.1. System Architecture**

The system follows a three-tier architecture, consisting of:

- Frontend – Developed using HTML, CSS, and JavaScript, allowing students to submit feedback and faculty to view performance insights.
- Backend – Implemented in Spring Boot, handling feedback processing, faculty management, and sentiment analysis.
- Database – Uses MySQL to store faculty data, student feedback, and sentiment analysis results.

The frontend communicates with the backend via RESTful APIs, while the backend interacts with the MySQL database to retrieve and store data efficiently.

#### **3.2. Data Collection**

Student feedback is collected through an interactive web-based form. The feedback includes:

- Structured Questions – Multiple-choice questions rated on a Likert scale (e.g., 1-5) covering faculty performance aspects like teaching effectiveness, subject knowledge, and engagement.
- Open-Ended Comments – Free-text responses where students provide detailed feedback about faculty strengths and areas of improvement.

All responses are securely stored in the MySQL database, ensuring data integrity and easy retrieval for analysis.

The screenshot displays a web form titled "Faculty Feedback". At the top, it shows the faculty member's details: "Faculty ID: 1", "Name: Ram", and a small profile picture. Below this is a section titled "Provide Your Feedback". The form includes several input fields and text areas:

- Enter Current Semester:** A text box containing the number "6".
- Select Subject:** A dropdown menu with "mean stack" selected.
- Regularity to Class:** A text area containing the comment: "The faculty member never misses a class and is always on time, setting a great example for students."
- Knowledge Depth:** A text area containing the comment: "The instructor possesses an exceptional depth of knowledge and often provides advanced insights."
- Communication:** A text area containing the comment: "Communication is outstanding; the instructor explains concepts in a way that captivates the class."
- Engagement:** A text area containing the comment: "The instructor fosters an incredibly engaging environment, encouraging all students to participate."

**Figure 2** Students providing detailed feedback on faculty performance.

### 3.3. Sentiment Analysis Process

The core of this system is the custom NLP-based sentiment analysis model, which processes student feedback using StanfordNLP. The analysis pipeline consists of the following steps:

- Text Processing - Tokenization, stop word removal, and lemmatization to clean the feedback [8].
- Sentiment Classification – Using StanfordNLP’s sentiment model to categorize feedback into Positive, Neutral, or Negative.
- Aspect-Based Sentiment Analysis – Breaking down comments into faculty performance aspects and assigning sentiment scores accordingly [8].
- Score Aggregation – Converting classified sentiments into numerical scores for visualization.

By leveraging StanfordNLP, the system ensures high accuracy in identifying the tone of student feedback.

### 3.4. Performance Visualization

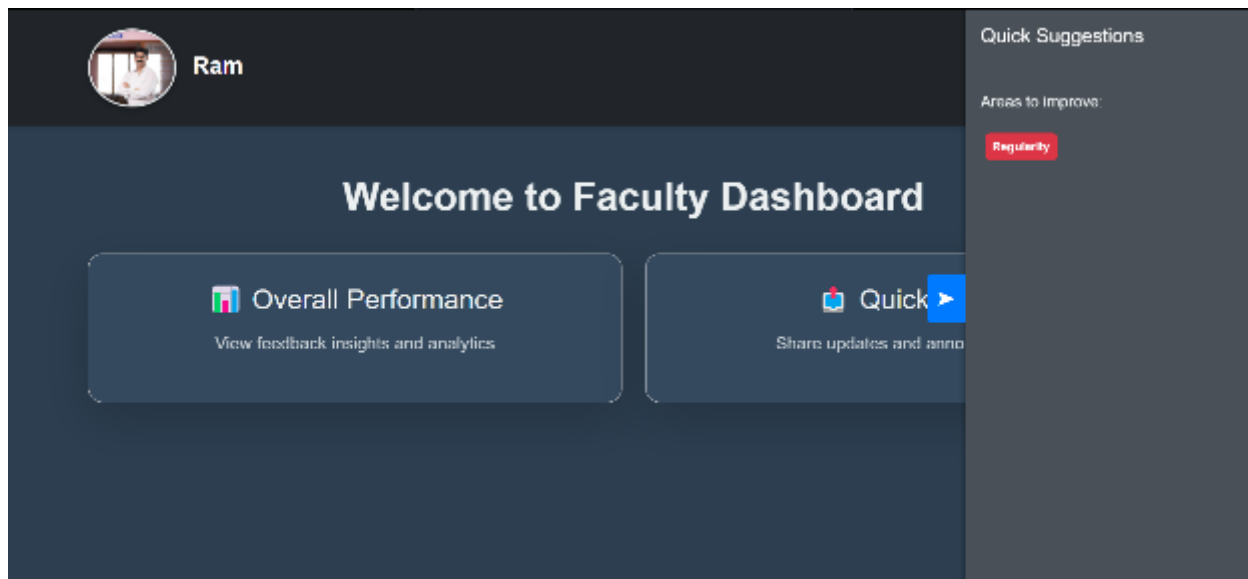
The analyzed feedback is presented through interactive dashboards that provide:

- Overall Sentiment Scores – A faculty’s average score based on student feedback.
- Category-Based Insights – Performance breakdown across aspects like communication, engagement, and subject knowledge.
- Trend Analysis – Time-based comparisons to track faculty improvement over semesters.

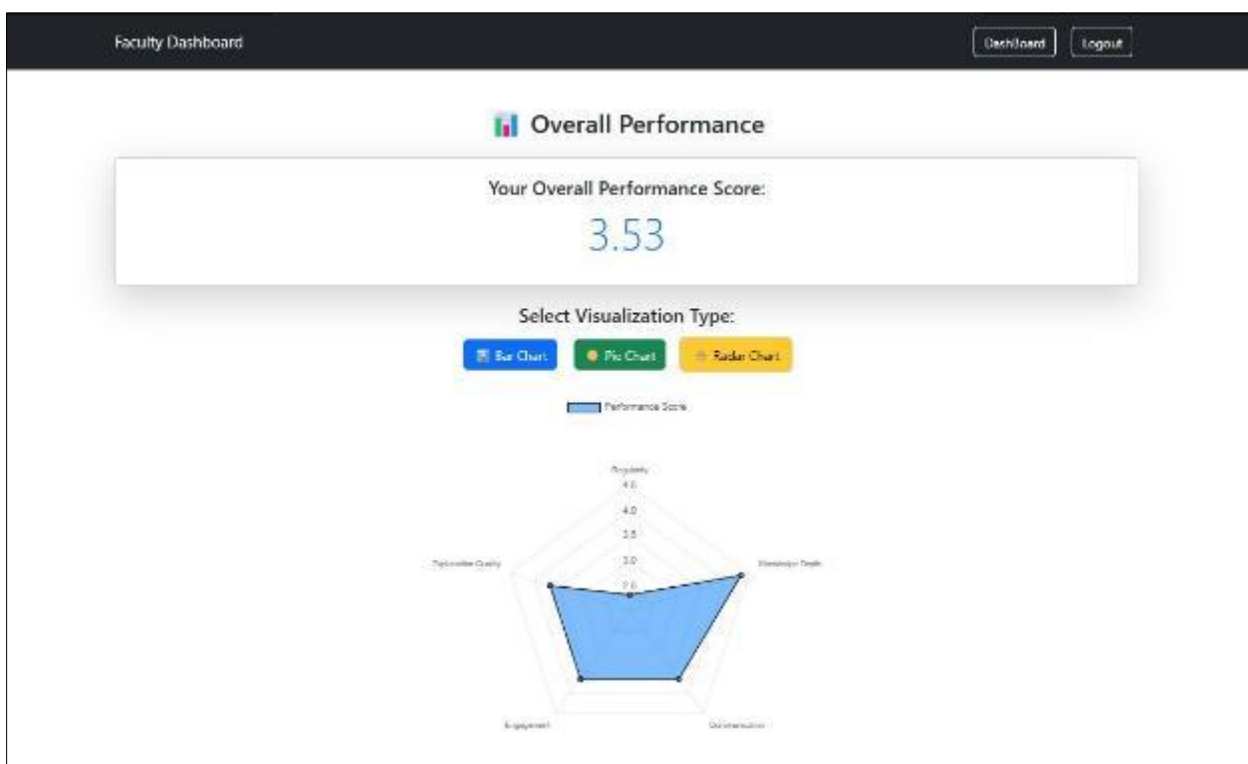
The faculty dashboard allows individual faculty members to access their feedback, while administrators can view overall faculty performance trends for data-driven decision-making.

#### 4. Results

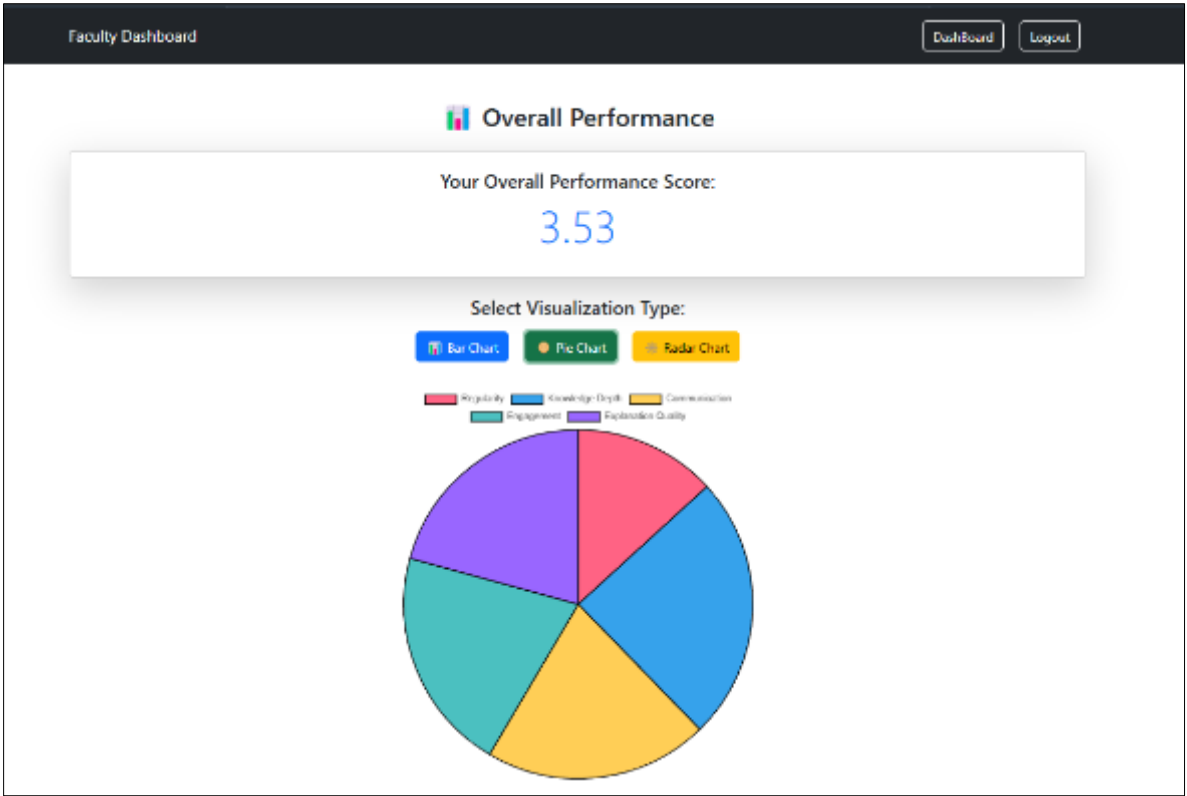
The proposed Faculty Feedback System effectively processes student feedback using StanfordNLP-based sentiment analysis, classifying responses into predefined performance categories. Unlike traditional systems, it dynamically generates real-time visual representations such as bar graphs and sentiment distribution charts, ensuring up-to-date performance tracking [9]. Additionally, automated abusive feedback handling ensures cleaner, more reliable reports by categorizing inappropriate responses separately and assigning them the lowest score. The system's actionable insights and real-time data visualization empower faculty members to improve their teaching methods, while administrators benefit from long-term performance tracking for informed decision-making.



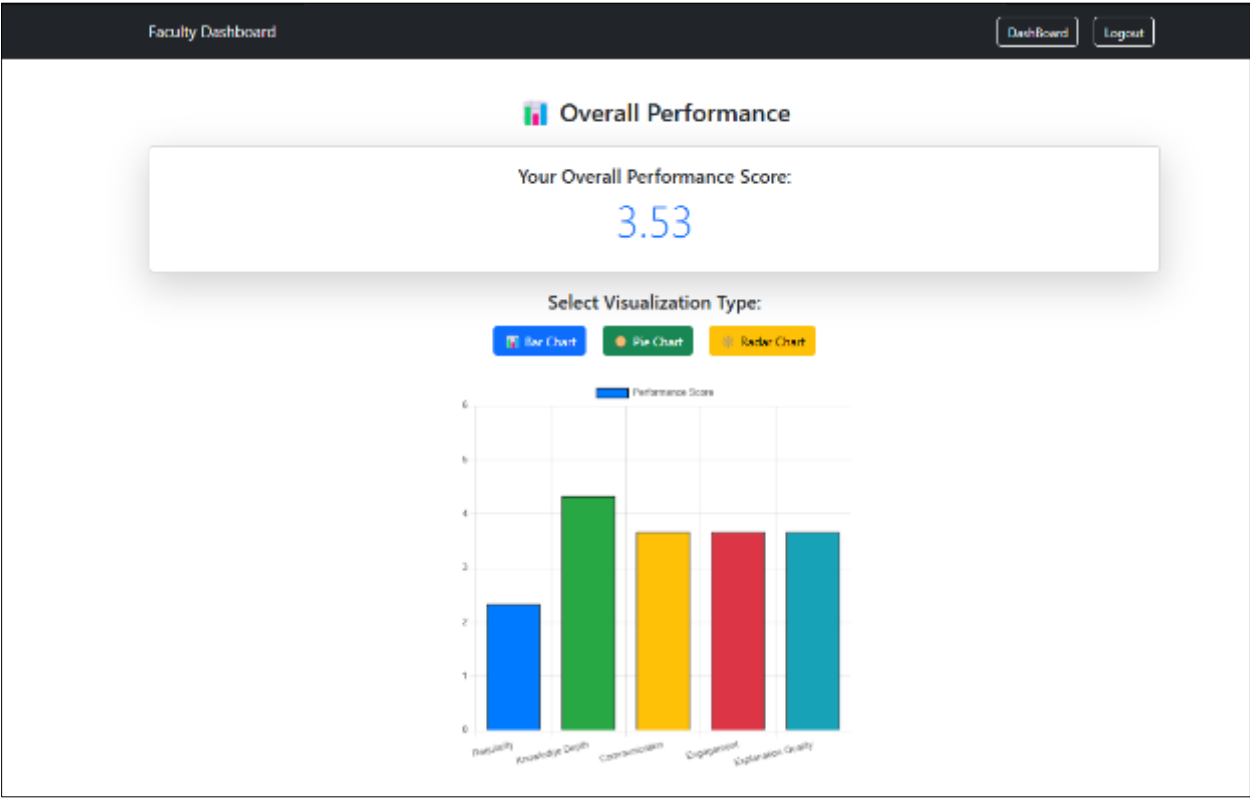
**Figure 3** Faculty Dashboard displaying overall performance insights and improvement suggestions



**Figure 4** Faculty Performance Dashboard showing the overall score with a radar chart & other visualization options



**Figure 5** Faculty Performance Dashboard showing the overall score with a pie chart & other visualization options



**Figure 6** Faculty Performance Dashboard showing the overall score with a bar graph & other visualization options

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## 5. Conclusion

The Faculty Feedback System, powered by StanfordNLP-based sentiment analysis, provides a data-driven, automated, and dynamic approach to faculty evaluation. By leveraging real-time sentiment classification, dynamic visual representations, and automated handling of inappropriate feedback, the system offers a more insightful and efficient alternative to traditional evaluation methods. Faculty members gain actionable insights into their strengths and areas for improvement, while administrators benefit from structured performance tracking for institutional decision-making. The system not only enhances the quality of feedback analysis but also fosters a continuous improvement culture in academia. Future work can explore advanced NLP techniques and deep learning models to further refine sentiment accuracy and expand functionality.

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## Compliance with ethical standards

### *Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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