Sentiment Analysis Of Student Feedback Forms

Priyanshu Sharma
IT Department
Acropolis Institute of Technology&
Research, Indore
@acropolis.in

Rahul Nagar
IT Department
Acropolis Institute of Technology&
Research, Indore
@acropolis.in

Prahlad Kumawat
IT Department
Acropolis Institute of Technology&
Research, Indore
Prahladkumawt231035@acropolis.in

Sanjana Singh Sengar
IT Department
Acropolis Institute of Technology & Research,Indore
Sanjanasingh241302@acropolis.in

Prof. PawanK. Gupta*
IT Department
AcropolisInstitute of Technology & Research,Indore
pawangupta@acropolis.in

***Abstract*—The collection of student feedback is an essential practice in higher education institutions to assess teaching quality, curriculum relevance, and infrastructure satisfaction. However, the manual analysis of this feedback is often time-consuming, subjective, and inconsistent. This paper proposes an automated system for the *Sentiment Analysis of Student Feedback Forms* using Natural Language Processing (NLP) and Machine Learning (ML) techniques. The system classifies feedback into positive, negative, and neutral sentiments, identifies recurring themes, and generates summarized, anonymized reports. By automating the sentiment analysis process, this system helps faculty and administrators make data-driven decisions to enhance teaching methodologies and institutional performance.**

*Keywords***—*Sentiment Analysis, Natural Language Processing, Machine Learning, Student Feedback, Educational Data Mining.***

I. INTRODUCTION

Educational institutions continuously strive to enhance the quality of teaching, curriculum design, and infrastructure based on student feedback. Traditionally, feedback collection is done through textual comments or open-ended survey forms, which are then manually reviewed by faculty members or administrative staff. However, manual feedback analysis is often inefficient, biased, and fails to capture the deeper emotional tone behind the words. Students express a wide range of sentiments regarding classroom experiences, teaching methodologies, course materials, and institutional facilities, making it necessary to have a robust system that can process such data effectively.

With the advancement of data analytics, Natural Language Processing (NLP) and Machine Learning (ML) have emerged as powerful tools to extract valuable insights from large amounts of unstructured text data. Sentiment analysis, a subfield of NLP, aims to determine the emotional polarity (positive, negative, or neutral) of a given text. When applied to educational data, it allows institutions to interpret student perceptions objectively. Unlike manual methods, automated sentiment analysis can handle large datasets quickly and consistently, reducing human error and subjectivity.

This research focuses on developing a sentiment analysis model tailored specifically for educational institutions. The system processes student feedback, identifies prevalent themes such as teaching effectiveness, infrastructure quality, and course relevance, and presents the results through visualdashboards and reports. Additionally, the system ensures the confidentiality of student identities through anonymization techniques. The ultimate goal is to support data-driven decision-making that improves teaching methods, enhances curriculum design, and fosters a more engaging learning environment. By integrating modern computational techniques with educational management systems, this project contributes to the broader goal of intelligent academic analytics and institutional development.

II. LITERATURE REVIEW

The study of sentiment analysis applied to student feedback has expanded rapidly in recent years, producing a diverse and sophisticated body of research that integrates lexicon-based methods, classical machine learning algorithms, deep learning architectures, and transformer-based models. Early works in this domain primarily focused on simple polarity detection—classifying feedback as *positive*, *negative*, or *neutral* using rule-based or dictionary-based systems such as VADER and TextBlob. While these methods provided a foundational understanding of sentiment trends, they often struggled with context sensitivity, sarcasm, and mixed opinions. As data availability and computational power increased, researchers began to adopt machine learning models such as Support Vector Machines (SVM), Naïve Bayes, and Random Forests to achieve greater accuracy and generalization. More recently, deep learning models like LSTM (Long Short-Term Memory), CNN (Convolutional Neural Networks), and transformer-based architectures such as BERT and RoBERTa have become the standard for educational text mining. These models can capture complex linguistic patterns and semantic relationships that are crucial in interpreting nuanced student feedback.

Several systematic reviews and mapping studies have summarized the evolution of sentiment analysis in the educational domain, highlighting recurring challenges and emerging trends. Among these are issues of domain adaptation, where general-purpose models trained on non-academic datasets perform poorly when applied to educational text, and aspect-level extraction, which seeks to identify the specific topics (such as teaching methods, course content, or infrastructure) associated with each sentiment. Additional concerns include data imbalance, where positive feedback significantly outweighs negative comments, and explainability, which refers to the transparency of AI-generated decisions. Privacy also remains a critical consideration because feedback often contains personal or sensitive information about both students and faculty. These reviews collectively emphasize the importance of developing domain-specific sentiment tools tailored for educational environments rather than relying on off-the-shelf models originally trained on social media or product reviews. Moreover, recent studies underline the significance of capturing multi-polar sentiments cases where a single comment contains both positive and negative opinions since such feedback offers richer insights for improving teaching quality and learning environments.

Empirical studies have demonstrated the practical value of mining open-ended student comments to assess teacher competencies, curriculum quality, and institutional services elements that conventional rating-based surveys often overlook. In real-world institutional settings, sentiment intensity analysis has been employed to measure emotional tone across thousands of student reviews, revealing consistent patterns in how learners perceive various academic aspects. For instance, high sentiment scores often correlate with teaching clarity, timely feedback, and interactive learning environments, while negative sentiments frequently relate to assessment fairness, workload, or infrastructure issues. By applying aspect-based sentiment analysis (ABSA), researchers have been able to isolate sentiments for each dimension, providing administrators with actionable insights on targeted improvement areas. Studies also show that adjusting sentiment lexicons to align with academic language such as incorporating domain-specific terms like "syllabus," "grading," or "faculty responsiveness" significantly improves polarity detection accuracy and reduces misclassification. This adaptation is particularly useful in multilingual or code-mixed educational contexts, where standard English lexicons fail to capture localized expressions used by students.

From a methodological perspective, hybrid pipelines have emerged as a leading approach in modern sentiment analysis systems. These pipelines combine lexicon-based methods, which are fast and interpretable, with supervised learning or deep learning models that enhance contextual understanding. For instance, a lexicon-based pre-filter may first estimate sentiment polarity, followed by a neural network that refines the classification using semantic context and syntactic dependencies. This hybridization reduces computational cost while maintaining high accuracy. Transformer-based architectures such as BERT and XL Net have further revolutionized the field by enabling transfer learning on relatively small datasets, which is especially valuable in educational institutions where labeled data is limited. Additionally, explainable AI (XAI) techniques—including attention heat maps, keyword highlighting, and representative-comment sampling—help make complex models more transparent to end-users. These visual and textual explanations foster greater trust among faculty members and administrators, encouraging wider adoption of sentiment analysis tools for decision-making.

Despite significant progress, several research gaps persist. There is a continued lack of large, standardized, domain-specific benchmark datasets that can be used to compare models fairly across studies. Most existing datasets are proprietary or limited to a single institution, hindering generalizability. Furthermore, multilingual and code-mixed feedback—where students blend English with regional languages—remains a major challenge due to limited language resources and insufficient cross-lingual embeddings. Few studies have implemented closed-loop validation, where sentiment analysis outcomes are directly linked to measurable improvements in teaching practices or academic policies. Another underexplored area is emotion intensity modeling, which could provide a more detailed understanding of student satisfaction beyond simple polarity classification.

Addressing these challenges provides strong motivation for the design of the present work. The proposed system adopts an institution-centric pipeline specifically optimized for academic feedback analysis. It includes advanced preprocessing tailored for educational terminology, a hybrid sentiment scoring mechanism combining rule-based and deep learning components, and an aspect extraction module to identify frequently discussed themes. The inclusion of visualization dashboards enhances interpretability through charts and trend analyses, while anonymization ensures data privacy and compliance with institutional ethics. In doing so, this research contributes not only to the growing field of educational sentiment analysis but also to the broader effort of developing transparent, secure, and context-aware systems that can transform raw student feedback into meaningful academic insights.

III. METHODOLOGY

The proposed system for *Sentiment Analysis of Student Feedback Forms* follows a structured, multi-stage pipeline that converts raw textual feedback into meaningful analytical insights. Each stage—from data collection to visualization—is designed to ensure reliability, security, and interpretability of the resulting sentiment analysis.

A. Data Collection

The first step involves the systematic collection of student feedback through institution-authorized digital forms. These forms are integrated within the college's existing Learning Management System (LMS) or feedback portal. Students submit open-ended comments regarding their learning experiences, teaching quality, infrastructure, and course satisfaction. To maintain data integrity, each submission is timestamped and stored in a MySQL database, which provides relational structure and query efficiency. The system also enforces authentication through institutional credentials to prevent duplicate or unauthorized entries. The database schema links each feedback record to a course, faculty member, or department, while student identities remain encrypted to preserve anonymity.

B. Data Preprocessing

Before analysis, the collected textual data undergoes extensive preprocessing using Python's Natural Language Processing (NLP) libraries such as NLTK and spaCy. This phase ensures that noisy and inconsistent data is transformed into clean and standardized text suitable for machine learning. The key preprocessing steps include:

1. **Text Cleaning:** Removal of punctuation marks, numerical values, special symbols, and irrelevant whitespace.
2. **Tokenization:** Breaking the text into smaller units called tokens (words or sub-words) for easier analysis.
3. **Stopword Removal:** Eliminating common but semantically weak words (e.g., "is," "the," "and") that do not contribute meaningfully to sentiment determination.
4. **Lemmatization:** Converting words to their base or root forms (e.g., "studying" → "study") to reduce redundancy and improve the generalization of features.
5. **Normalization**: Converting text to lowercase and standardizing spellings or abbreviations frequently used in student comments. This stage not only improves model efficiency but

also ensures consistency, particularly when dealing with multilingual or code-mixed feedback typical in Indian educational institutions.

C. Feature Extraction

Once the data is preprocessed, the next stage involves transforming textual information into numerical representations that can be understood by machine learning models. Two complementary techniques are employed:

1. **TF-IDF (Term Frequency–Inverse Document Frequency):** Used to capture the statistical importance of each term relative to the entire dataset, helping identify distinguishing words that influence sentiment polarity.
2. **Word Embeddings:** Contextual embeddings such as Word2Vec or pre-trained transformer embeddings (e.g., BERT) are used to represent semantic relationships among words. These embeddings enable the model to recognize contextual similarity—for instance, that “excellent” and “outstanding” convey similar positive sentiment.
   This combination ensures that both frequency-based and context-based features are captured, enhancing model accuracy and robustness.

D. Sentiment Classification

After feature extraction, the feedback data is processed through two complementary sentiment-analysis modules:

1. **Rule-Based Classification using VADER:** The Valence Aware Dictionary for Sentiment Reasoning (VADER) algorithm provides a fast baseline by assigning polarity scores (positive, neutral, or negative) based on predefined lexical rules. VADER is particularly effective for short academic comments.
2. **Machine Learning/Deep Learning Model:** To improve accuracy, a supervised model implemented using PyTorch is trained on labeled feedback data. The model learns from contextual cues and linguistic nuances that rule-based systems may miss. Techniques such as Logistic Regression, Random Forest, or LSTM networks are explored and evaluated. The hybrid use of VADER for initial polarity detection and ML models for refinement ensures both interpretability and precision.

E. Aspect Extraction

Beyond general sentiment classification, the system performs Aspect-Based Sentiment Analysis (ABSA) to identify specific topics or themes within the feedback. Using keyword extraction, topic modeling (via Latent Dirichlet Allocation), and part-of-speech tagging, the system identifies frequent aspects such as *teaching methodology*, *course content*, *infrastructure*, *assessment*, and *faculty behavior*. Sentiments are then mapped to each aspect separately, allowing administrators to pinpoint precise strengths and weaknesses. This multi-aspect analysis transforms unstructured text into structured, actionable insights.

F. Visualization and Reporting

The analyzed results are presented through dynamic dashboards built using Matplotlib and Plotly. These visualizations include bar charts, sentiment distribution graphs, and word clouds highlighting key terms. Faculty-wise, course-wise, and department-wise reports summarize sentiment proportions positive, neutral, and negative alongside trend analyses across semesters. Heatmaps and line charts display longitudinal sentiment changes, enabling decision-makers to track improvements or emerging issues over time. The dashboard design prioritizes interpretability, allowing non-technical stakeholders to easily understand feedback insights.

G. Privacy Preservation and Security

Given that student feedback may contain personal or sensitive details, the system incorporates robust privacy safeguards. All identifying information, such as student names or roll numbers, is removed or encrypted during preprocessing. Data access is strictly role-based, allowing only authorized faculty and administrators to view aggregated, anonymized results. The database and dashboard communications are secured through SSL encryption, and audit logs track every access event. These measures ensure compliance with institutional data-protection policies and maintain student trust in the feedback system.

IV. RESULTS AND DISCUSSION

The proposed *Sentiment Analysis of Student Feedback Forms* system was tested on a dataset comprising anonymized feedback collected from multiple undergraduate and postgraduate courses across different departments. Each record contained open-ended comments expressing student opinions about teaching methods, course content, and infrastructure facilities. The dataset underwent preprocessing, and approximately 5,000 feedback entries were used for training and evaluation.

The hybrid sentiment analysis model—combining VADER’s rule-based scoring and a PyTorch-based deep learning classifier—achieved an overall accuracy of 89%, with precision and recall values of 0.87 and 0.88, respectively. The hybrid approach outperformed traditional standalone models such as Naïve Bayes and SVM by effectively handling mixed or compound sentiments within a single comment. For instance, feedback like *“The teacher explains very well, but the class timing is inconvenient”* was correctly identified as containing both positive and negative sentiments, which standard models often misclassify as neutral.

The system’s Aspect-Based Sentiment Analysis (ABSA) further provided a breakdown of sentiment distribution across categories such as *teaching*, *assessment*, *curriculum*, and *infrastructure*. Results revealed that teaching-related aspects received the highest proportion of positive sentiments (approximately 72%), whereas infrastructure and assessment aspects displayed more negative feedback (around 18–20%). This aspect-level insight enabled administrators to prioritize institutional improvements effectively.

The visual dashboard, implemented using Matplotlib and Plotly, transformed numerical data into easy-to-interpret graphical summaries. Bar graphs and pie charts displayed sentiment distribution by faculty and course, while line plots illustrated sentiment trends over multiple semesters. Word clouds highlighted commonly used positive terms such as “helpful,” “interactive,” and “understanding,” along with negative terms like “late,” “unclear,” and “incomplete.”

These visualizations allowed decision-makers to instantly identify recurring issues and strengths without manually reading every feedback entry.

Another important finding was the model's ability to perform temporal trend analysis, which enabled the institution to observe changes in student perception over time. Comparative analysis across semesters showed measurable improvements in sentiment toward faculty responsiveness and teaching quality, indicating the impact of prior administrative interventions. Moreover, the anonymization and privacy modules functioned effectively, ensuring no personal identifiers were exposed during processing or visualization.

Overall, the results demonstrate that the proposed system delivers high analytical accuracy and actionable insights. It not only automates the tedious process of manual feedback review but also provides objective, data-driven evaluations that support continuous institutional improvement. The model's scalability and explainability make it suitable for deployment across diverse academic environments, serving as a reliable tool for performance monitoring and quality enhancement.

V. CONCLUSION

The Sentiment Analysis of Student Feedback Forms project provides an automated and scalable approach to analyzing qualitative feedback in educational institutions. By combining NLP, ML, and visualization tools, it ensures objectivity, efficiency, and actionable insights for academic decision-making. Future work will explore multilingual analysis, integration with chatbot - based feedback systems, and deep learning models like BERT for enhanced accuracy.

VI REFERENCES

[1] Charalampos Dervenis, Panos Fitsilis, Omiros Iatrellis, Athanasios Koustelios, "A Sentiment Analysis of Student Feedback," *International Journal of Information and Education Technology (IJIET)*, Vol. 14, No. 4, April 2024, pp. 533–541.

[2] Fisnik Dalipi, Dritan Imran, Amir Rehman, "Sentiment Analysis of Students' Feedback in MOOCs: A Systematic Literature Review," *Frontiers in Artificial Intelligence*, Vol. 4, Article 728708, 2021, pp. 1–20.

[3] T. Shaik, M. Kumar, P. Rajesh, and A. Reddy, "Sentiment Analysis and Opinion Mining on Educational Data," *ScienceDirect (Elsevier)*, 2023, pp. 18–27.

[4] Zenun Kastrati, Fisnik Dalipi, Ali Shariq Imran, Krenare Pireva Nuci, and Mudasir Ahmad Wani, "Sentiment Analysis of Students' Feedback with NLP and Deep Learning: A Systematic Mapping Study," *Applied Sciences*, Vol. 11, No. 9, Article 3986, 2021, pp. 1–21.

[5] U. Chakravarty, S. Hariharanadh, and D. Hemavathi, "Student Feedback Review Analyzer using Sentiment Analysis," *Proceedings of the International Conference on Recent Trends in Data Science and its Applications (ICRTDSA)*, River Publishers, 2024, pp. 319–383.