Journal of Effective Teaching and Learning Practices. 2026;3(Sp1):69-77
eISSN: 3048-9601

AI-Assisted Platform for Centralized Teaching and Learning Student Feedback Analysis

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Abstract

In outcome-oriented higher education, feedback from students is essential to ensure the teaching–learning (T-L) quality and continual improvement. The majority of Higher Education Institutions (HEIs) still rely on manual analysis, despite the fact that feedback can often be collected online. This leads to delayed actions and a lack of actionable insights. In order to solve this, we have integrated the Student LMS Portal to an AI-assisted feedback analysis system. This article presents the technical details and implementation of the proposed feedback analysis system. The system instantly generates quantitative ratings and AI-derived qualitative insights using Natural Language Processing (NLP) for sentiment and thematic analysis once processing 23 multiple-choice questions and one open-ended response. Timely pedagogical interventions and accreditation requirements are supported by automated dashboards, recurring reports, and action-taken documentation. This automation greatly lessens the administrative workload and improves the teaching-learning process's entire efficacy, efficiency, and transparency.

***Keywords*—AI-assisted feedback; educational analytics; LMS; NLP; quality assurance; student feedback system.**

***JETLP Category*—Research**

Introduction

The feedback is the heart of any quality system which requires a continuous check on Teaching-Learning (TL) process (Mousavi, Mares, & Stonham, 2015). The learner's feedback is a vital mechanism for continuous improvement in higher education that outcome-based education relies. Though online collection of feedback is usual, the automation of analysis and consolidation of collected data is conventionally manual in the most of the Higher Education Institutions (HEIs) (Yeap, 2008; Saha, 2016). The conventional manual feedback analysis of bulk response data often suffers from delayed actions, and lack of actionable insights or recommendation for faculty or courses in the stipulated time (Norris et. al, 2008; Chatti et. al, 2012). To address these challenges, our institution was set to implement an AI-assisted feedback analysis system that collects feedback data through a framework that collects feedback through Student's LMS Portal, Self-analyses scores for well-defined TL questionnaire including 23 Multiple Choice Questions (MCQs) for quantifying comprehensive TL behaviour and 1 Open-ended feedback question.

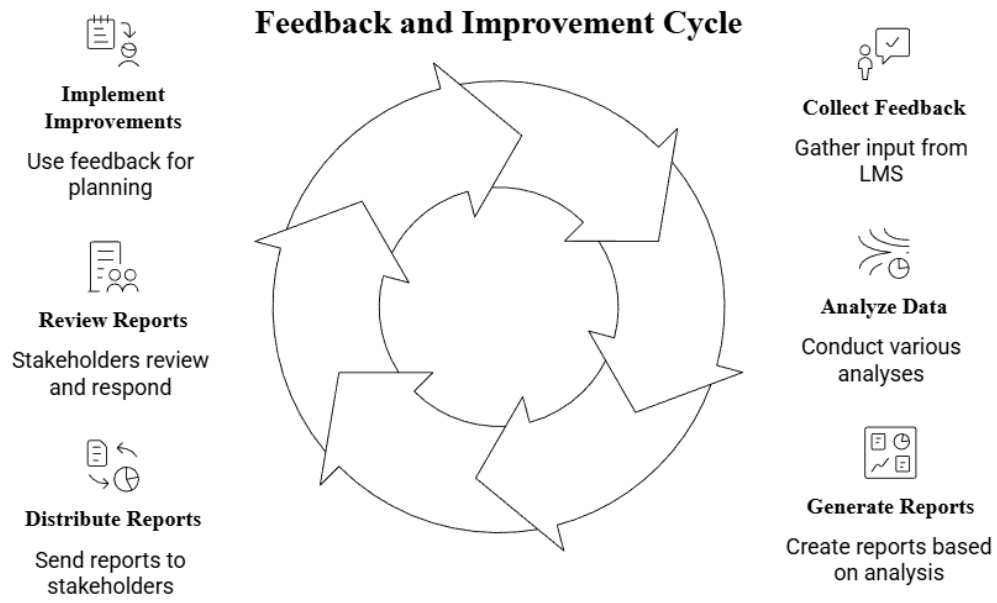


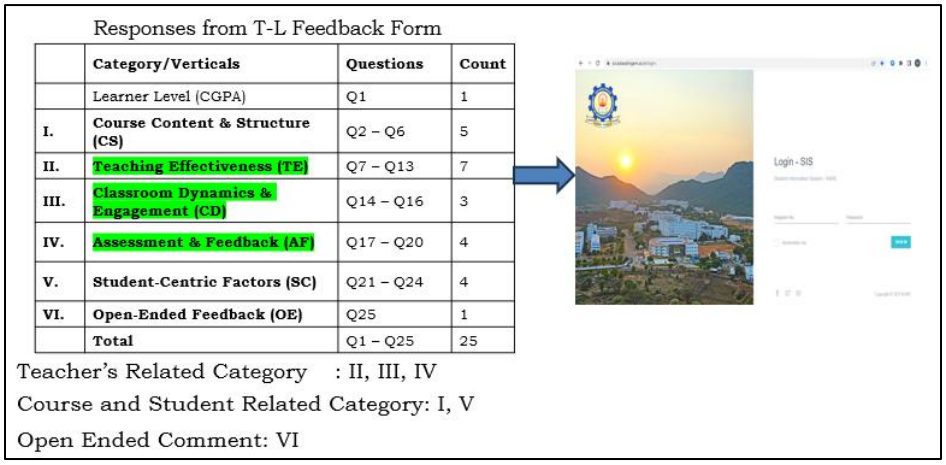
Figure 1: Functionality of the proposed feedback analysis portal

Figure 1 illustrates the complete workflow of the proposed feedback analysis portal, beginning with the collection of student feedback from the LMS and progressing through automated data export, upload, storage, and analysis. The system then generates detailed reports that are distributed to stakeholders for review, enabling timely decision-making and academic improvements. The closed-loop cycle highlights how the portal streamlines every stage from raw data acquisition to actionable insights, ensuring a continuous and efficient feedback-driven enhancement of the TL process. The implemented system record improvements every academic year and capable of self-generating report for documentation including action taken reports and electronic submission of compliance report by the faculty. This automation extremely reduces manual efforts for central administrators and ensures timely interventions to improve teaching quality. By making feedback more meaningful, transparent, and efficient, the initiative strengthens trust between students and teachers for an effective outcome-based education and proper historical reporting for records that contributes to academic excellence. The Teaching–Learning (T-L) student feedback questionnaire, which is organized across guidelines from governing bodies including AICTE, UGC, NAAC etc. aligned verticals covering course content, teaching effectiveness, engagement, assessment, and student-centric factors, is categorized in Table 1. In order to ensure a systematic, criterion-based analysis of both quantitative ratings and qualitative student feedback, each question (Q1–Q25) is mapped to a particular parameter and question type.

Table 1: T-L student feedback questions details and analysis verticals.

S.No.	CATEGORY/VERTICALS	Questions Number	Question Type
0	Learner Level (CGPA)	Q1	Likert
1.	Course Content & Structure (CS)	Q2 – Q6	MCQ/Likert
2.	Teaching Effectiveness (TE)	Q7 – Q13	MCQ/Likert
3.	Classroom Dynamics & Engagement (CD)	Q14 – Q16	MCQ/Likert
4.	Assessment & Feedback (AF)	Q17 – Q20	MCQ/Likert
5.	Student-Centric Factors (SC)	Q21 – Q24	MCQ/Likert

6.	Open-Ended Feedback (OE)	Q25	Open-ended
	Total	Q1 -Q25	



Responses from T-L Feedback Form

	Category/Verticals	Questions	Count
	Learner Level (CGPA)	Q1	1
I.	Course Content & Structure (CS)	Q2 – Q6	5
II.	Teaching Effectiveness (TE)	Q7 – Q13	7
III.	Classroom Dynamics & Engagement (CD)	Q14 – Q16	3
IV.	Assessment & Feedback (AF)	Q17 – Q20	4
V.	Student-Centric Factors (SC)	Q21 – Q24	4
VI.	Open-Ended Feedback (OE)	Q25	1
	Total	Q1 – Q25	25

Teacher's Related Category : II, III, IV

Course and Student Related Category: I, V

Open Ended Comment: VI

Figure 2: Category wise feedback questions collection through LMS.

In order to ensure a systematic, criterion-based analysis of both quantitative ratings and qualitative student feedback, each question (Q1–Q25) is mapped to a particular parameter and question type. The developed and implement portal instantly provide scores and summarizes student responses in terms of teacher's performance in a quantitative rating and student satisfaction by AI-analysed open-ended feedback as qualitative indicator (Shaikh et al., 2022).

Methodology

The novel implementation utilizes Natural Language Processing (NLP) to process open-ended comments, identify recurring themes, and detect sentiment propositions (Mohanty, 2025; Datnow & Hubbard, 2016). The proposed feedback analysis portal mechanism is depicted in Figure 3, which illustrates how the IQAC processes raw feedback through parallel quantitative score computation and qualitative open-comment analysis (Aleksendric, Batra, Palmer, & Ranjan, 2024). The system calculates scores across CGPA-based student groups, divides question categories related to teachers and courses, and produces combined reports for departmental compliance. In order to create a thorough qualitative report, open-ended comments are simultaneously categorized into positive and negative inputs and then subjected to AI-based sentiment analysis and summarization (Didolkar, & Lokulwar, 2025). In order to facilitate timely academic improvements and documentation, the outputs from both streams are ultimately integrated into department-wise, school-wise, course-wise, and teacher-wise observation reports

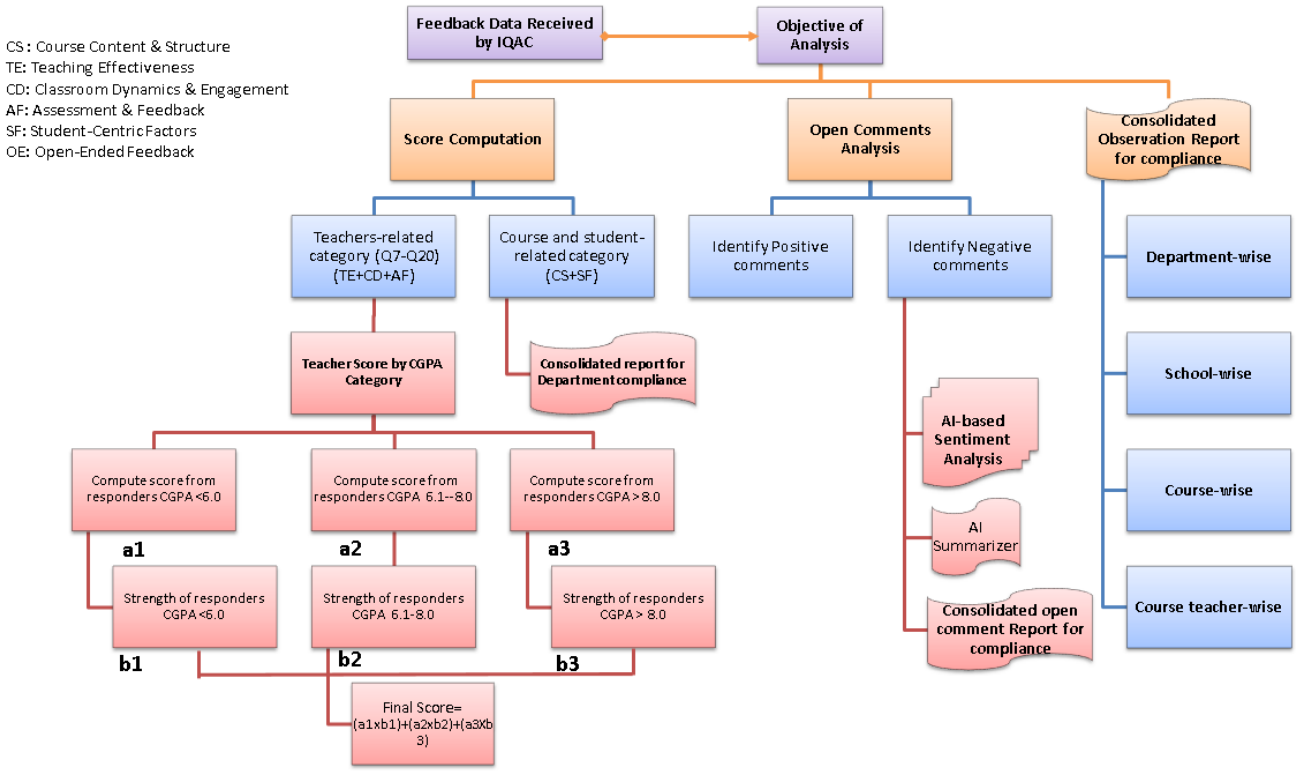


Figure 3: Mechanism of data analysis with score computation and Open comment analysis.

Implementation

The proposed not only strengthens faculty engagement with student perspectives but also institutionalizes a transparent, data-driven feedback culture aligned with quality assurance frameworks. The introduction of the system marks a significant shift from manual consolidation to structured, meaningful, and timely feedback-driven improvement. Instead of relying solely on quantitative ratings, it provides faculty with actionable dashboards highlighting strengths, gaps, and student suggestions and auto report for periodical semesters. In fact, accreditation bodies, cross examine the effectiveness of feedback analysis and implementation across the various departments and organizational system over academic periods. The implementation of the AI-assisted feedback analysis platform followed a structured, multi-phase methodology to ensure technical integration, academic acceptability, and alignment with IQAC requirements as described in phases below.

Phase 1: Need Analysis and Planning
IQAC and Academic Council committees identified persistent challenges in the existing feedback mechanism, including manual errors, inconsistent interpretation, and difficulty managing large data volumes. These insights informed the system specifications and integration requirements.

Phase 2: System Development and Integration
An AI-enabled feedback platform—developed through an in-house workflow and integrated with the institution's LMS—was configured to collect student responses automatically at the end of

each course module. The system supports structured (MCQ) and unstructured (open-text) feedback formats.

Phase 3: Data Collection
Students submit their feedback through the LMS portal. The portal ensures authenticity through secure login and collects responses across six key verticals covering course structure, teaching effectiveness, engagement, assessment, student-centric factors, and qualitative remarks.

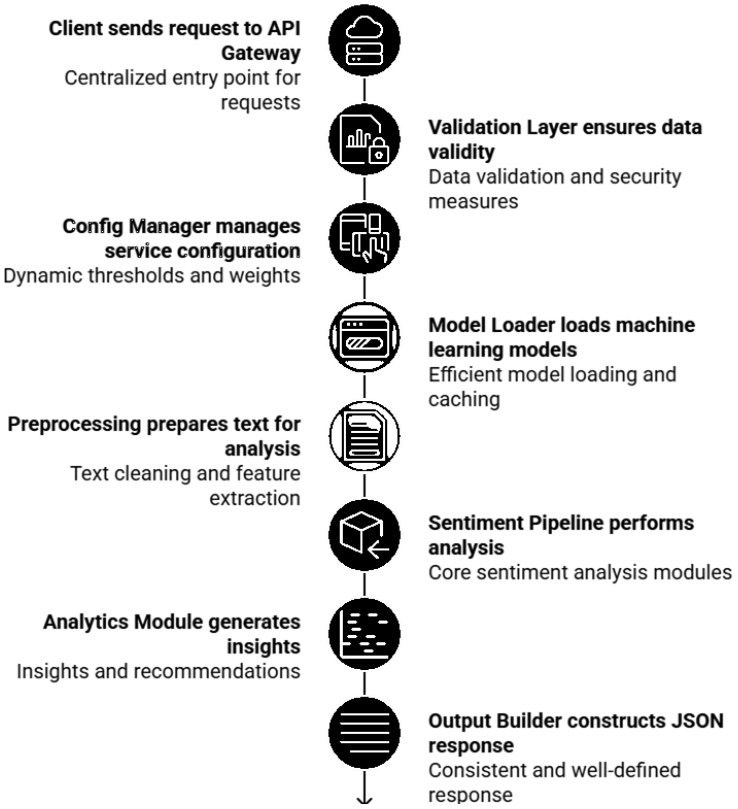


Figure 4: Fast API service architecture for sentiment analysis

Phase 4: AI-Driven Analysis
The modular Fast API architecture for sentiment analysis is shown in Figure 4. The API Gateway, which directs incoming requests to the Fast API service, is where the workflow starts (Yun, Lee, & Choi, 2025; Cetin, & Gundogmus, 2024). The Pre-processing Layer cleans and transforms the text before sending it to the Model Inference Engine, where the deployed NLP model produces sentiment scores (Wilson, Pollard, Aiken, Caballero, & Lewandowski, 2022). The Response Formatter organizes outputs, and Monitoring/Logging records anomalies and performance (Jamil & Hameed, 2023). For scalability and dependability, deployment is handled by standardized services, and all configuration and model artifacts are kept in Persistent Storage. The core of the system is an AI engine that performs:

- Sentiment Analysis: Identification of positive, neutral, and negative sentiments within comments as mentioned in Figure 4.
- Topic Clustering: Grouping of recurring instructional themes such as pace, clarity, technology use, and engagement.

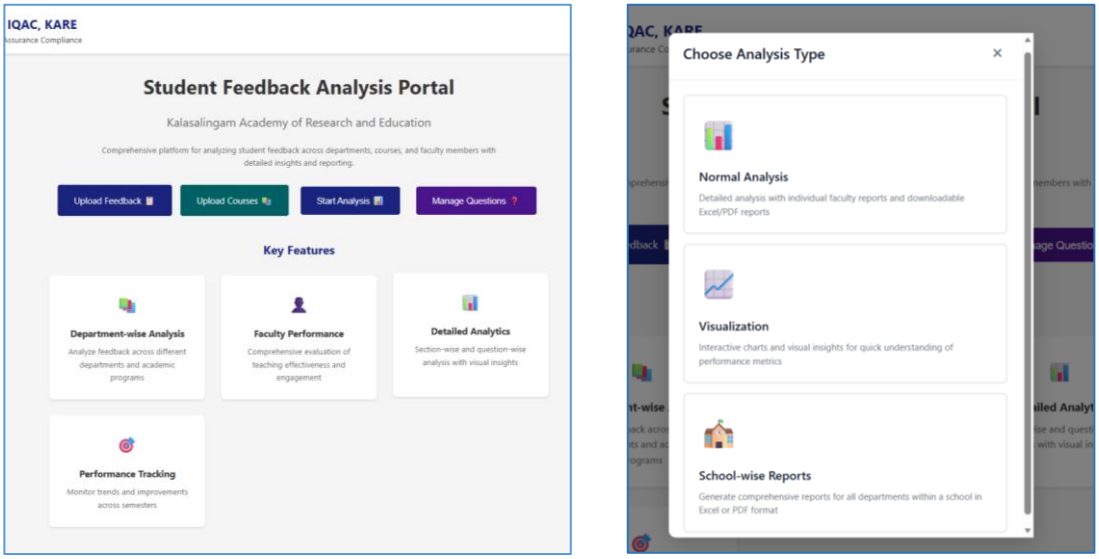
- Quantitative Score Computation: Automated calculation of vertical-wise performance ratings.
- Bias Mitigation: Detection and normalization of extreme or contextually irrelevant responses.

Phase 5: Reporting and Dashboards
Faculty receive consolidated dashboards highlighting strengths, areas requiring attention, student suggestions, and sentiment patterns. IQAC and administrators access institutional-level aggregates for cross-departmental review and accreditation documentation.

Phase 6: Feedback-Based Action
Departments and faculty utilize the reports to redesign teaching strategies, enhance assessment methods, and implement student-centric improvements. Follow-up reports track progress over academic periods for quality audits and accreditation requirements.

Results and Discussions

The developed feedback analysis portal demonstrates an efficient and streamlined mechanism for processing and interpreting student feedback data across multiple academic units. The home interface provides a unified access point for uploading feedback files, managing course information, initiating analysis, and navigating different reporting modules. The system modular workflow supports department-wise, course-wise, and faculty-wise analysis, ensuring comprehensive coverage for academic review as depicted in Figure 5.

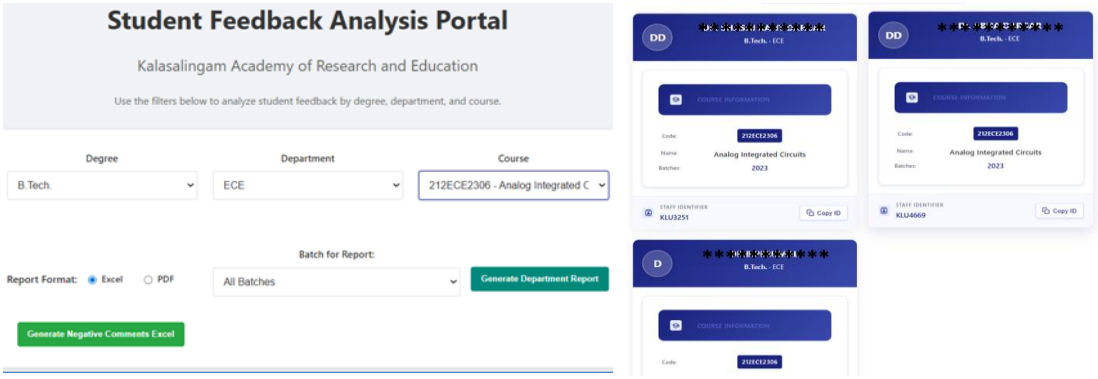


(a) (b)

Figure 5: Analysis portal dashboard- (a) home page and (b) types of analysis interface

As shown in Figure 6, the reporting interface allows users to filter feedback by program, department, and course, generating outputs in both Excel and PDF formats. This flexibility enables departments to extract tailored reports for internal quality reviews. The portal also provides options to access negative comments separately, which supports targeted improvement planning. The analysis type selector further allows users to choose between standard statistical reports, visual dashboards, and school-level consolidations, making the system adaptable to various quality assurance needs.

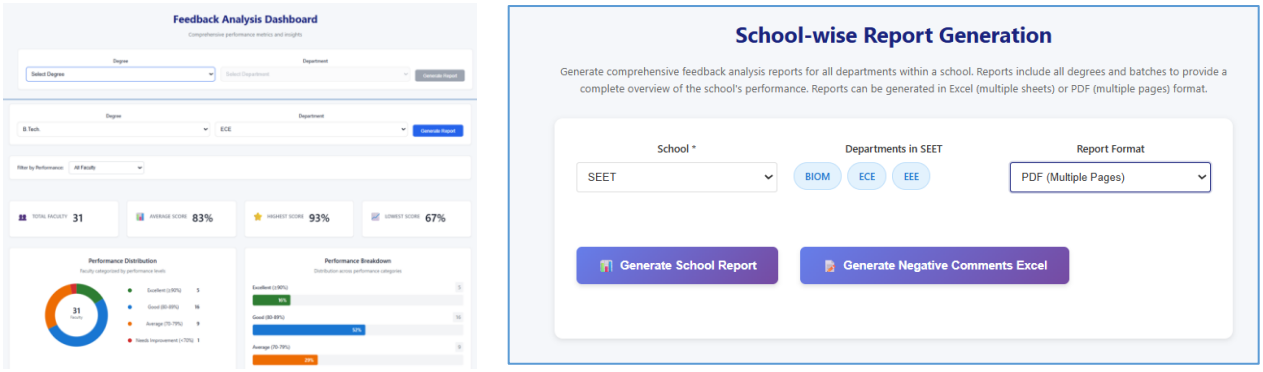
Faculty-level cards and course identifiers are automatically generated, allowing quick navigation to individual performance summaries. The visual analytics dashboard presents aggregated metrics such as average scores, highest and lowest performance levels, and distribution across performance categories. Graphical elements, including pie charts and bar charts provide clear insights into overall teaching effectiveness and student satisfaction patterns.



(a) (b)

Figure 6: Analysis portal dashboard-(a) course selection, and (b) teacher's display interface

The visual breakdown enables stakeholders to identify strengths, improvement areas, and variations across departments or faculty groups as shown in Figure 7.



(a) (b)

Figure 7: Analysis portal dashboard-(a) feedback score display and (b) report download interface

Overall, the results indicate that the portal successfully integrates automated scoring, sentiment-based comment analysis, and dynamic visualization to offer a holistic understanding of feedback trends. As comparison of various student satisfaction shown in figure 8, the centralized dashboard empowers academic administrators and faculty members to monitor performance, track semester-wise improvements, and make informed decisions for academic enhancement. The system's ability to consolidate and present complex feedback data in an accessible manner highlights its effectiveness as a quality assurance tool in supporting continuous improvement within the T-L ecosystem.

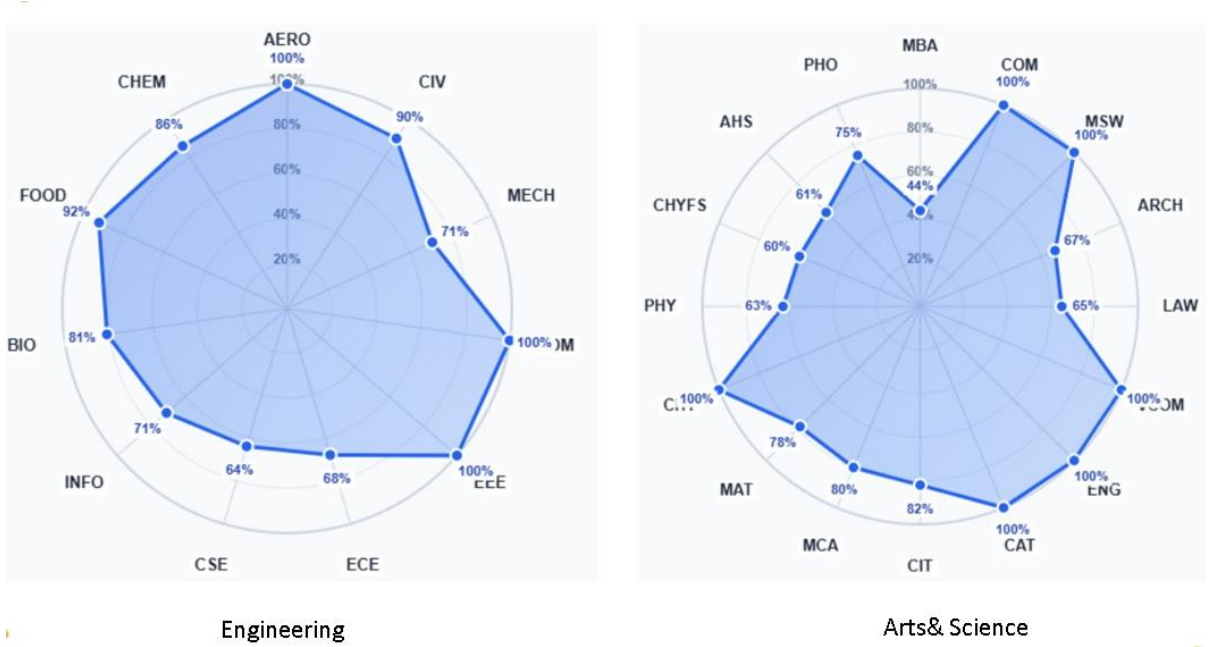


Figure 8: Analysis portal dashboard-radar chart quick visualization for Engineering and other disciplines in department wise comparison.

Conclusion

The effectiveness, precision, and transparency of teaching-learning evaluation in higher education are greatly improved by the AI-assisted feedback analysis system. The platform avoids the delays and mistakes of manual feedback processing by combining LMS-based data collection with automated score computation, sentiment analysis, and dynamic dashboards. It strengthens outcome-based education practices, empowers faculty with practical insights, and permits timely pedagogical interventions. Furthermore, the system generates compliance reports, ensures traceable documentation for audits, and maintains organized, year-by-year feedback records to support accreditation and ranking procedures. From data collection to multi-level reporting, the streamlined workflow creates a scalable, evidence-based system that supports ongoing academic improvement and institutional quality assurance.

Acknowledgments

The authors express their sincere gratitude to academic administration and the Internal Quality Assurance Cell (IQAC) for their cooperation and support during the feedback analysis system's development. We also want to express our gratitude to the instructors and students whose involvement and suggestions helped the platform be implemented and evaluated successfully.

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