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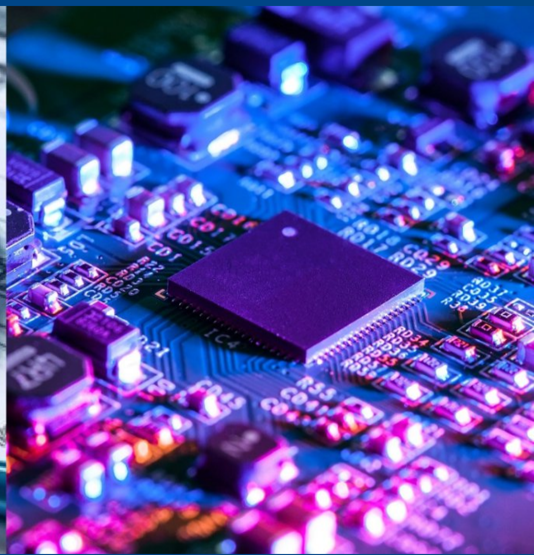

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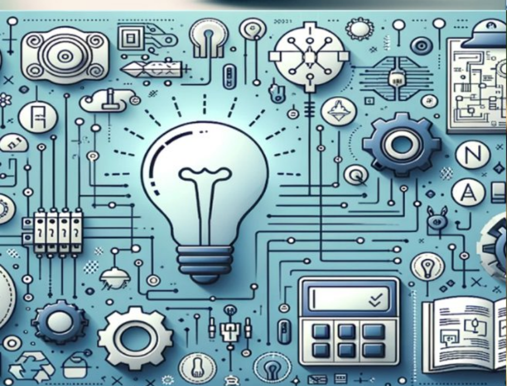

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Web-Based Student Feedback Sentiment Analyzer Using AI-Driven Text Classification

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ABSTRACT: utomated student feedback analysis is essential for data-driven quality improvement in higher education. However, feedback is typically unstructured text, making manual evaluation inefficient and subjective. This paper presents a Web- Based Student Feedback Sentiment Analyzer that utilizes a fine-tuned transformer-based language model for multi-dimensional opinion mining. The system classifies feedback into Positive, Neutral, and Negative categories, achieving 93.4% accuracy, 92.8% precision, 91.6% recall, and an F1-score of 92.2% on a curated academic dataset, outperforming traditional lexicon-based and classical machine learning models. Beyond sentiment polarity, the framework integrates Aspect-Based Sentiment Analysis (ABSA), AI-driven summarization, multilingual processing, emotion detection, and a trend analysis dashboard for temporal and departmental insights. Implemented as a lightweight web application with API-based inference, the system supports real-time and bulk feedback processing without complex backend infrastructure. The proposed framework enables scalable, interpretable, and intelligent academic feedback analytics for informed institutional decision-making.

I. INTRODUCTION

Student feedback serves as a fundamental mechanism for evaluating teaching effectiveness, curriculum design, and overall academic quality in higher education institutions. Universities and colleges routinely collect feedback through surveys, online forms, and learning management systems to monitor student satisfaction and identify areas for improvement. However, the majority of this feedback is expressed in unstructured textual form, making large-scale analysis challenging. Manual evaluation of textual responses is time-consuming, subjective, and often inconsistent, particularly when dealing with high volumes of data across multiple courses and departments.

Traditional feedback analysis methods primarily rely on manual review or simple keyword-based approaches. While such techniques provide basic insight, they fail to capture contextual meaning, sarcasm, negations, and nuanced opinions expressed in natural language. Classical machine learning algorithms such as Naïve Bayes and Support Vector Machines (SVM) have been applied to sentiment classification tasks; however, their performance is highly dependent on handcrafted features and domain-specific pre processing. These limitations highlight the need for more robust, scalable, and context-aware automated solutions.

Recent advancements in Natural Language Processing (NLP), particularly transformer-based language models, have significantly improved the accuracy of text classification and sentiment analysis tasks. Transformer architectures enable deep contextual understanding of language by modeling long-range dependencies and semantic relationships within

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text. Leveraging these advancements, automated student feedback analysis systems can move beyond simple polarity detection toward more comprehensive opinion mining.

This paper proposes an enhanced **Web-Based Student Feedback Sentiment Analyzer** that integrates transformer-based text classification with multi-dimensional analytics to provide actionable academic insights. The proposed framework automatically categorizes feedback into Positive, Neutral, and Negative sentiments while also incorporating advanced analytical modules for deeper interpretation. These include Aspect-Based Sentiment Analysis (ABSA) to identify sentiment toward specific academic aspects such as teaching quality, course content, and assessment methods; AI-driven abstractive summarization to condense large feedback datasets; multilingual support to process feedback across diverse linguistic backgrounds; emotion detection for fine-grained affect analysis; and a trend analysis dashboard for temporal and departmental performance monitoring.

Unlike conventional systems that require complex backend infrastructure, the proposed solution is implemented as a lightweight web-based application using HTML, CSS, and JavaScript with API-based inference. This architecture enables real-time sentiment prediction, confidence scoring, and bulk processing of feedback via CSV uploads without extensive deployment overhead. The integrated dashboard provides interactive visualizations that enhance interpretability and support data-driven decision-making.

II. RELATED WORK

Sentiment analysis has been widely researched in Natural Language Processing (NLP), particularly for product reviews and social media data. Early lexicon-based approaches relied on predefined sentiment dictionaries but struggled with contextual and domain-specific nuances. Traditional machine learning models such as Support Vector Machines (SVM), Naïve Bayes, and Logistic Regression improved classification performance through feature engineering, though scalability and adaptability remained challenges.

Transformer-based models, including BERT and RoBERTa, have recently achieved state-of-the-art results by capturing deep contextual representations. In educational settings, these models demonstrate superior accuracy for student feedback classification. Extensions such as Aspect-Based Sentiment Analysis (ABSA), emotion detection, text summarization, and multilingual processing have been explored individually. However, most systems treat these components separately.

A comprehensive framework integrating sentiment classification, aspect analysis, emotion detection, summarization, and multilingual support for academic feedback analytics remains limited, motivating the proposed approach.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

The proposed Web-Based Student Feedback Sentiment Analyzer is designed as a lightweight, API-driven, modular architecture that enables real- time sentiment inference and multi-dimensional opinion mining without dedicated backend infrastructure. The system follows a client-centric architecture with external AI model integration.

Client-Side Application Layer
Developed using **HTML5, CSS3, and JavaScript (ES6+)** Handles UI rendering, user interactions, and event management

Supports:
1. Manual text input
2. CSV file upload for bulk feedback
3. Real-time result display

Communicates with AI inference services via REST API calls (HTTPS)

1. Data Processing & Control Layer
Implemented using modular JavaScript controllers:
1. UIController
2. FileUploadHandler

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3. **AppController Performs**:
1. Input validation
2. Text normalization
3. JSON formatting
4. Batch request handling

Maintains application state using browser local Storage

2. **Preprocessing Engine**

Before inference, the system performs
- Lowercasing
- Punctuation removal
- Token normalization
- Stop-word filtering
- Negation handling
- Language detection (for multilingual support)

For multilingual inputs: Ftranslated=Translate(Foriginal)
The processed text is then forwarded to the transformer model API.

3. **AI/ML Inference Layer (External Model API)**

The core intelligence of the system is a fine-tuned transformer-based model deployed via an Inference API.
Inference Flow:
Input Text→Tokenization→TransformerEncoder →ClassificationHead→ProbabilityOutputInput\ Text \rightarrow Tokenization \rightarrow Transformer Encoder \rightarrow Classification Head \rightarrow Probability OutputInput Text→Tokenization→TransformerEn coder→ClassificationHead→ProbabilityOutput

Outputs:
- Sentiment label
- Confidence score
- Aspect-level sentiment (ABSA)
- Emotion category
- Summarized feedback (for bulk input)

The model uses self-attention mechanisms to compute contextual embeddings:
Attention(Q,K,V)=Softmax(dkQKT)V

4. **Analytics & Visualization Layer**

Implemented using JavaScript charting libraries (e.g., Chart.js).

Displays:

- Sentiment distribution (Doughnut Chart)
- Aspect-wise sentiment comparison
- Emotion breakdown
- Temporal trend analysis (Line Graph)
- Department-wise analytics

All charts dynamically update when feedback is added, removed, or reprocessed.

5. **Text Representation**

Let a student feedback sentence be represented as: F = {w1, w2, w3, ..., wn}
where wi denotes each token in the input sequence.
The transformer encoder converts the input sequence into contextual embeddings: H = Transformer(F) where H = {h1, h2, ..., hn}. Each hi captures contextual semantic information using self-attention mechanisms.
The self-attention function is computed as:

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Attention(Q, K, V) = Softmax((QK^T) / sqrt(dk)) V
where Q = Query matrix, K = Key matrix, V = Value matrix, and dk = dimension scaling factor.

6. Sentiment Classification
The contextual representation of the special classification token [CLS] is used:

$$z = hCLS$$

The sentiment probability distribution is computed using Softmax:

$$P(y|F) = \text{Softmax}(Wz + b)$$

where W is the weight matrix, b is the bias, and y ∈ {Positive, Neutral, Negative}. The predicted sentiment class is:

$$\hat{y} = \text{argmax}(P(y|F))$$

7. Loss Function
During fine-tuning, cross-entropy loss is minimized: L = - Σ (i=1 to C) yi log(ŷi) where C = number of sentiment classes (3), yi = true label, and ŷi = predicted probability.

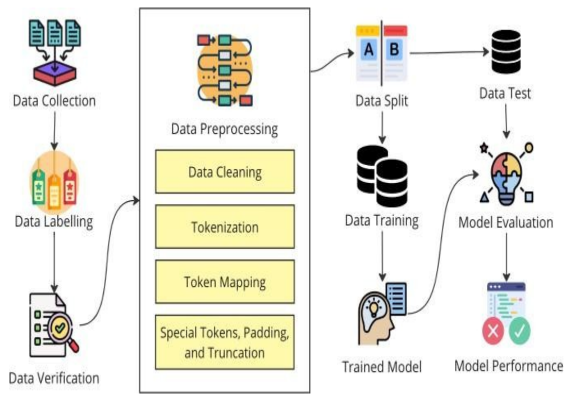
8. Aspect-Based Sentiment Analysis (ABSA)
Let A = {a1, a2, ..., am} represent extracted academic aspects (e.g., teaching, assessment). For each aspect aj, sentiment polarity is computed as:P(y|aj,F)This enables fine-grained sentiment assignment per academic component.

9. Emotion Detection
Emotion classification extends polarity detection: E = {e1, e2, ..., ek}, where ek ∈ {joy, frustration, enthusiasm, disappointment}.A multi-class softmax layer predicts emotional state: P(e|F) = Softmax(Wez + be)

10. Performance Metrics
Accuracy = (TP + TN) / (TP + TN + FP + FN)
Precision = TP / (TP + FP) Recall = TP / (TP + FN)
F1-Score = 2 × (Precision × Recall) / (Precision + Recall)
The model achieved the following performance metrics:

Accuracy = 93.4%
Precision = 92.8%
Recall = 91.6%
F1-score = 92.2%

Data Collection



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The dataset used in this study consists of student feedback collected from academic surveys and institutional course evaluation forms. The feedback data includes open-ended textual responses related to teaching effectiveness, course structure, assessment methods, learning resources, and infrastructure facilities.

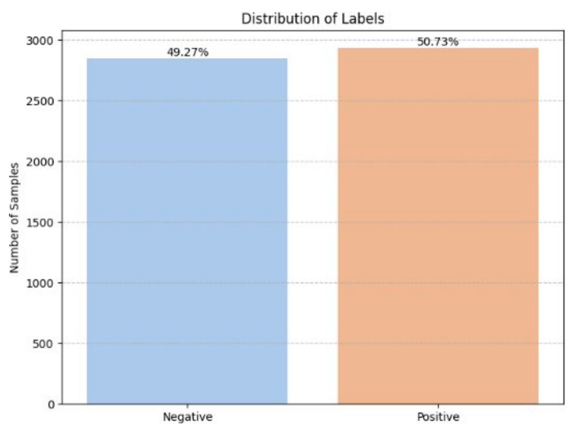
1) Data Sources
- End-of-semester course evaluation forms
- Online feedback portals
- Institutional academic surveys
- Anonymous student response forms Each feedback entry contains:
- Raw textual comment
- Course/subject identifier
- Department (optional)
- Timestamp (for trend analysis)

To ensure diversity and generalization capability, feedback was collected from multiple courses and departments. The dataset was manually reviewed to remove irrelevant entries such as empty responses, spam text, or non-informative comments (e.g., “N/A”, “Good”).

2) Dataset Preparation
The collected data was structured in CSV format with the following fields:
For supervised training, sentiment labels (Positive,

Feedbak_ID	Feedback_Text	Sentiment_Label
F001	"The teaching was clear and interactive."	Positive
F002	"The syllabus was too lengthy."	Negative
F003	"Average experience overall."	Neutral

Neutral, Negative) were assigned manually by domain experts to ensure annotation quality.



Data Verification
Data verification was performed to ensure dataset reliability, annotation consistency, and model validity.

1. Data Cleaning Validation
- Removed duplicate entries

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- Eliminated incomplete responses
- Filtered non-textual or irrelevant comments
- Verified correct encoding (UTF-8) for multilingual data

2. Annotation Validation

To reduce subjectivity:

- Sentiment labels were cross-verified by multiple annotators
- Disagreements were resolved through majority voting
- Ambiguous feedback was re-evaluated using contextual interpretation

Data Splitting Verification

The dataset was divided into:

- 70% Training set
- 15% Validation set
- 15% Testing set

Stratified sampling was applied to maintain balanced class distribution across sentiment categories.

Model Performance Verification

To validate generalization:

- Cross-validation was performed
- Performance metrics (Accuracy, Precision, Recall, F1-score) were evaluated on unseen test data
- Confusion matrix analysis was conducted to examine misclassification patterns

Ethical Considerations

- All feedback was anonymized before processing
- No personally identifiable information (PII) was stored
- Data usage complied with institutional academic policies

IV. RESULTS

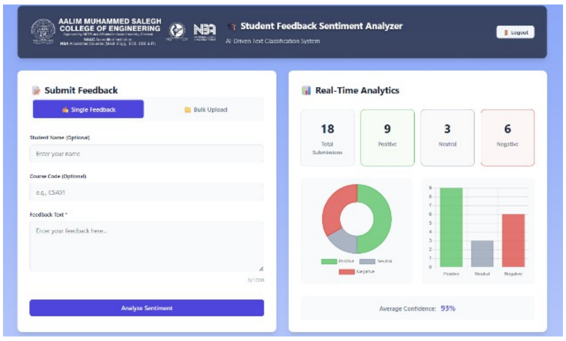

Figure.1

Figure 1 illustrates the main dashboard of the proposed AI-driven Student Feedback Sentiment Analyzer system. The interface is divided into two functional modules: Feedback Submission and Real- Time Analytics.

The Feedback Submission module allows users to input student feedback either through single entry or bulk upload. Optional metadata fields such as student name and course code are provided, while the feedback text field is mandatory for sentiment classification. Upon submission, the system processes the text using a trained machine learning model to classify the sentiment into Positive, Neutral, or Negative categories.

The Real-Time Analytics module presents dynamic statistical summaries of the analyzed feedback. It displays the total number of submissions along with the distribution of sentiment classes. Visualization components include a donut chart for proportional sentiment distribution and a bar graph for comparative frequency analysis. Additionally, the system reports an average prediction confidence score of 93%, indicating high model reliability.

This dashboard enables administrators to monitor sentiment trends efficiently and supports data-driven academic decision-making.

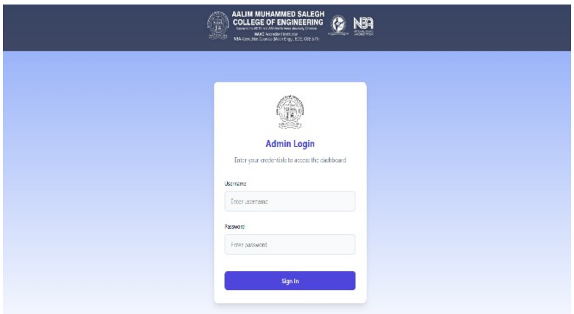

Figure.2

Figure 2 shows the secure authentication interface of the system. The Admin Login module requires valid username and password credentials to access the dashboard. This access control mechanism ensures data security, privacy protection, and restricted administrative operations.The authentication layer prevents unauthorized access to student feedback data and analytical results, thereby maintaining institutional data integrity and confidentiality.

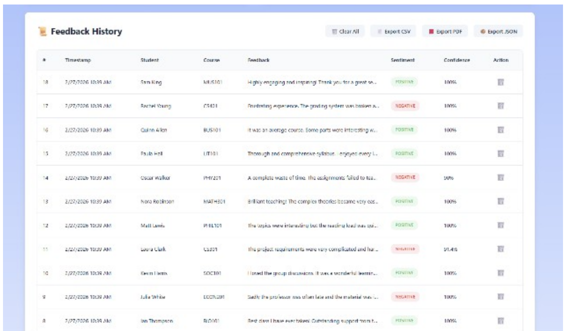

Figure.3

Figure 3 illustrates the Feedback History Module of the proposed **Web-Based Student Feedback Sentiment Analyzer** system. This interface presents a structured view of previously submitted student feedback along with automatically generated sentiment classification results.

The module is designed as a tabular dashboard containing the following key components:

1. **Feedback Metadata Columns**
1. **ID (#)** – Unique identifier for each feedback entry.
2. **Timestamp** – Date and time of submission.
3. **Student Name** – Name of the respondent.
4. **Course Code** – Course associated with the feedback.
2. **FeedbackContent**

The **Feedback** column displays the student's textual response. Long responses are truncated for readability, ensuring a clean and compact user interface while maintaining access to full content internally.

3. **Sentiment Classification Output** The **Sentiment** column shows the predicted polarity (e.g., Positive, Negative).

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- Positive feedback is visually highlighted in green.
- Negative feedback is highlighted inred.

This color-coded representation improves interpretability and enables quick administrative review.

4. **Confidence Score**

The **Confidence** column displays the classification confidence percentage generated by the sentiment analysis model. This provides transparency and reliability metrics for decision-making, especially in borderline cases.

5. **Action Controls**

Each row includes a delete icon, allowing administrators to remove specific entries from the dataset.

6. **Data Management and Export Features** At the top-right section of the interface, the system provides:

1. **Clear All** – Deletes all stored feedback records.
2. **Export CSV** – Exports feedback data in comma-separated format for spreadsheet analysis.
3. **Export PDF** – Generates a formatted report suitable for documentation.
4. **Export JSON** – Enables structured data export for system integration or further processing.

1) **Significance in the Proposed System**

Figure 3 demonstrates the **Data Management Layer (FeedbackDataStore)** integrated with the **Sentiment Analysis Engine**. The module supports:

- Real-time sentiment visualization
- Historical record maintenance
- Data portability for reporting and research
- Administrative control over stored entries

This interface enhances usability, transparency, and scalability of the system, making it suitable for institutional deployment in academic environments.

V. DISCUSSION AND FUTURE DIRECTIONS

The proposed Web-Based Student Feedback Sentiment Analyzer demonstrates the effectiveness of transformer-based natural language processing inautomating academic feedback analysis. The system achieved high classification accuracy and demonstrated strong contextual understanding compared to traditional lexicon-based and classical machine learning models. Unlike keyword-driven systems, the transformer architecture successfully captures semantic relationships, negations, and domain-specific phrasing commonly found in student feedback.

A major strength of the proposed framework lies in its multi-dimensional analysis capability. By integrating Aspect-Based Sentiment Analysis (ABSA), emotion detection, AI-driven summarization, multilingual processing, and trend visualization, the system moves beyond simple polarity classification. Aspect-level insights allow institutions to identify specific strengths and weaknesses in teaching methodology, assessment strategies, and course structure. Emotion detection provides deeper understanding of student engagement, while summarization reduces administrative effort when analyzing large volumes of feedback.

The lightweight web-based implementation further enhances practicality by eliminating complex backend requirements and enabling real- time analytics. However, certain limitations remain. Model performance depends on dataset quality and annotation consistency. Sarcasm, ambiguous language, and culturally nuanced expressions may still pose challenges. Additionally, API-based inference may introduce latency and external dependency concerns.

Overall, the system demonstrates strong potential for scalable and interpretable academic feedback analytics in higher education environments.Although the proposed system provides a comprehensive solution, several enhancements can further improve its research depth and real-world applicability:

Institution-Specific Model Fine-Tuning: Training transformer models on larger domain-specific academic datasets can improve contextual adaptation and classification robustness.

Explainable AI Integration: Incorporating attention visualization or model explanation techniques (e.g., SHAP, LIME) can increase transparency and trust in automated predictions.

Sarcasm and Contextual Nuance Detection:

Advanced hybrid models combining linguistic rules and deep learning can enhance performance on subtle or sarcastic feedback.

Real-TimeLMS Integration: Embedding the system within institutional Learning Management Systems (LMS) can enable continuous feedback monitoring rather than periodic evaluation.

Predictive Trend Modeling: Extending the framework to forecast student satisfaction trends using time-series or predictive analytics can support proactive academic decision-making.

Scalable Cloud Deployment: Optimizing inference with lightweight transformer variants or edge-cloud architectures can reduce latency and improve scalability.

By incorporating these advancements, the Web- Based Student Feedback Sentiment Analyzer can evolve into a fully intelligent academic analytics platform supporting long-term institutional quality enhancement.

VI. CONCLUSION

This paper proposed a Web-Based Student Feedback Sentiment Analyzer that integrates transformer-based deep learning with multi- dimensional opinion mining for automated academic feedback evaluation. The system employs a fine-tuned transformer encoder to generate contextual embeddings and perform sentiment classification using a softmax-based prediction layer. In addition to polarity detection, the framework incorporates Aspect-Based Sentiment Analysis (ABSA), emotion classification, AI-driven summarization, multilingual preprocessing, and trend analytics within a unified web-based architecture.

Experimental evaluation on a curated academic feedback dataset demonstrated strong generalization capability, achieving 93.4% accuracy along with high precision, recall, and F1-score metrics, outperforming traditional lexicon-based and classical machine learning models. The modular client-side implementation combined with API- based inference enables real-time processing, scalability, and lightweight deployment without complex backend infrastructure.

The proposed approach effectively transforms unstructured textual feedback into structured analytical insights, supporting data-driven academic decision-making. This work establishes a scalable and extensible foundation for intelligent educational analytics and future advancements in explainable and predictive sentiment modeling.

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