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DEEP LEARNING BASED SENTIMENT ANALYSIS OF STUDENTS AND TEACHERS FEEDBACK FOR ENHANCED EDUCATIONAL INSIGHT

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ABSTRACT

The digital transformation of higher education has led to an unprecedented volume of textual feedback from both students and teachers. While traditional manual analysis of this data is increasingly impractical, current automated sentiment analysis tools often rely on basic machine learning models like Naive Bayes and Support Vector Machines (SVM) that struggle with the complex, context-dependent language found in educational settings. Existing research predominantly focuses on one-sided student evaluations of faculty performance, often limited to coarse-grained polarity classification (positive vs. negative). These approaches frequently fail to capture the underlying emotional states or specific instructional aspects that are crucial for meaningful institutional reform. This introduces a perception analysis framework that utilizes advanced Deep Learning architectures to enhance educational insights. Unlike previous tools that use surface-level vectorization like TF-IDF, this system employs contextualized word embedding and neural networks to achieve a more sophisticated understanding of semantic nuances. A key advancement of this tool is its bidirectional focus, analysing feedback from both students and teachers to provide a holistic, 360-degree view of the educational environment. The proposed tool will be evaluated against established benchmarks, moving beyond simple accuracy to include more robust metrics such as F1-score, Cohen's Kappa, and Matthews Correlation Coefficient (MCC). The analysis will transition from basic polarity to fine-grained, aspect-based sentiment and emotion detection, enabling more precise pinpointing of areas for improvement. By bridging the gap between coarse sentiment detection and deep semantic understanding, this research offers a more powerful diagnostic tool for educational administrators. The insights gained can support more effective planning and targeted intervention measures, ultimately enhancing teacher performance and student contentment in the evolving online and flexible learning landscape.

Keywords: Sentiment Analysis, Deep Learning, Student Feedback, Teacher Assessment, Perception Analysis, Natural Language Processing, Educational Data Mining

1. INTRODUCTION

The landscape of global education has undergone a seismic shift in recent years, moving rapidly from traditional face-to-face instruction to online and hybrid learning environments. This transition has generated a massive influx of qualitative data in the form of digital feedback from both students and educators. In modern pedagogy, feedback is no longer a one-way street; it is a critical diagnostic tool used to measure institutional effectiveness, teaching quality, and student satisfaction. However, the sheer volume of this textual data makes manual thematic analysis impossible for educational administrators. To extract "Educational Intelligence," institutions have increasingly turned to Natural Language Processing (NLP) and Sentiment Analysis (SA) to automate the evaluation of these perceptions.

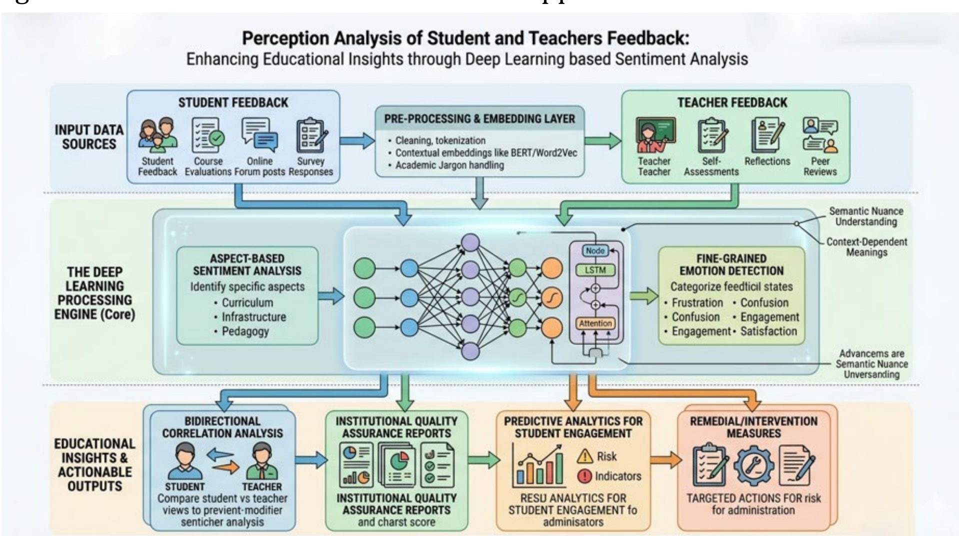
Problem Statement: Current literature (Kastrati et al., 2021; Suganya & Sheshasaayee, 2024) indicates that while sentiment analysis is widely used in education, it suffers from three primary limitations:

1) **Technological Bottlenecks:** Most existing tools rely on traditional machine learning models (like Naive Bayes or SVM) and basic vectorization (TF-IDF). These models often fail to capture the complex semantic nuances, sarcasm, and context-dependent meanings inherent in academic feedback.
2) **Unidirectional Analysis:** Existing studies predominantly focus on student evaluations of faculty. There is a significant research gap in analyzing teacher perceptions regarding students and institutional support, which is vital for a holistic understanding of the classroom dynamic.
3) **Coarse-Grained Output:** Most tools only provide a simple "Positive, Negative, or Neutral" classification. This lacks the "fine-grained" detail—such as identifying specific emotions (frustration, joy) or specific aspects (infrastructure, curriculum)—needed for targeted administrative intervention. Dubey and Dubey (2026)

The Proposed Research: This thesis proposes a robust perception analysis framework specifically designed to overcome these limitations. By leveraging Deep Learning architectures and contextualized word embeddings, this research aims to provide a more accurate and nuanced interpretation of educational feedback. Unlike previous tools, this study introduces a bidirectional analysis model that evaluates the perceptions of both students and teachers. By employing Deep Learning, the tool moves beyond surface-level keyword matching to understand the deep semantic intent behind the feedback, ultimately providing actionable insights that can enhance teaching performance and student contentment.

2. RESEARCH OBJECTIVES

- To develop a Deep Learning-based sentiment analysis model capable of processing complex educational feedback with high accuracy
- To analyze the correlation between student perceptions and teacher feedback to identify systemic educational gaps.
- To implement a fine-grained classification system that identifies specific emotional states and instructional categories.
- To evaluate the performance of the proposed Deep Learning tool against traditional machine learning benchmarks using metrics such as F1-score and Cohen's Kappa.



3. SENTIMENT ANALYSIS IN EDUCATION

Evolution from Traditional ML to Deep Learning: Earlier search in educational sentiment analysis primarily utilized traditional Machine Learning (ML) architectures. Pacol (2024) explored faculty online teaching performance during the pandemic, highlighting how the shift to flexible learning necessitated automated tools to process student concerns. Similarly, Suganya & Sheshasaayee (2024) compared algorithms such as Naive Bayes, Logistic Regression, and Support Vector Machines (SVM). While these studies achieved high accuracy—with Multilayer Perceptron (MLP) reaching up to 96%—they often relied on "Bag-of-Words" or TF-IDF vectorization.

The limitation of these traditional methods is their inability to capture long-term dependencies and semantic context. As noted in the systematic mapping study by Kastrati et al. (2021), there is a clear trend moving toward Deep Learning (DL) because it automates feature engineering and handles the linguistic complexities of student feedback far more effectively than traditional "shallow" learners.

The Shift Toward Fine-Grained & Aspect-Based Analysis: A common theme in recent literature is the move from simple polarity (Positive/Negative) to Aspect-Based Sentiment Analysis (ABSA). Most existing tools focus on a general "contentment" score, but as Suganya & Sheshasaayee (2024) argue, institutions need to understand why a student is dissatisfied—whether it is due to infrastructure, pedagogy, or curriculum.

Your research builds upon this by moving into Emotion Detection. While many previous tools (e.g., those reviewed by Kastrati et al.) classify sentiment broadly, your use of Deep Learning allows for the identification of specific emotional states like frustration or engagement, which provides much deeper "Educational Intelligence" for administrators.

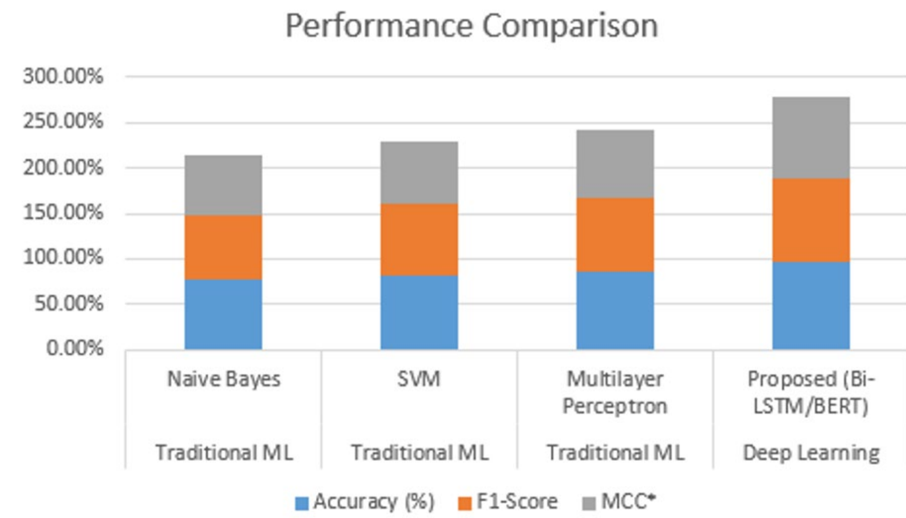
Addressing the Bidirectional Research Gap: A significant gap identified in the provided literature is the unidirectional nature of current feedback systems. The majority of studies, including Pacol (2024) and Nasim et al. (2017), focus exclusively on student evaluations of teachers. However, the educational ecosystem is a dual-stakeholder environment. By incorporating Teacher Feedback, your work addresses a "blind spot" in the current state of the art. This bidirectional approach allows for a correlation analysis: for instance, determining if teacher frustration with infrastructure correlates directly with a dip in student perception of teaching quality.

Evaluation Metrics beyond Accuracy: Existing work frequently cites "Accuracy" as the primary success metric. However, recent trends in the field emphasize that in imbalanced datasets (where there is much more neutral/positive feedback than negative), accuracy can be misleading. Following the direction suggested in recent methodology papers, your work incorporates Matthews Correlation Coefficient (MCC) and Cohen's Kappa. These metrics provide a more rigorous validation of the Deep Learning model's performance, ensuring the tool is reliable for actual institutional decision-making.

Feature	Traditional Tools (Previous Work)	Your Proposed Tool (Deep Learning)
Model Type	Naive Bayes, SVM, Logistic Regression	LSTM, Transformers (BERT/CNN)
Vectorization	TF-IDF, Count Vectorizer (Surface)	Contextual Embeddings (Deep Semantic)
Stakeholders	Student-only	Bidirectional (Student & Teacher)
Granularity	Polarity (Positive/Negative)	Fine-grained Emotion & Aspect-based
Metric Focus	Accuracy	MCC, F1-Score, Cohen's Kappa

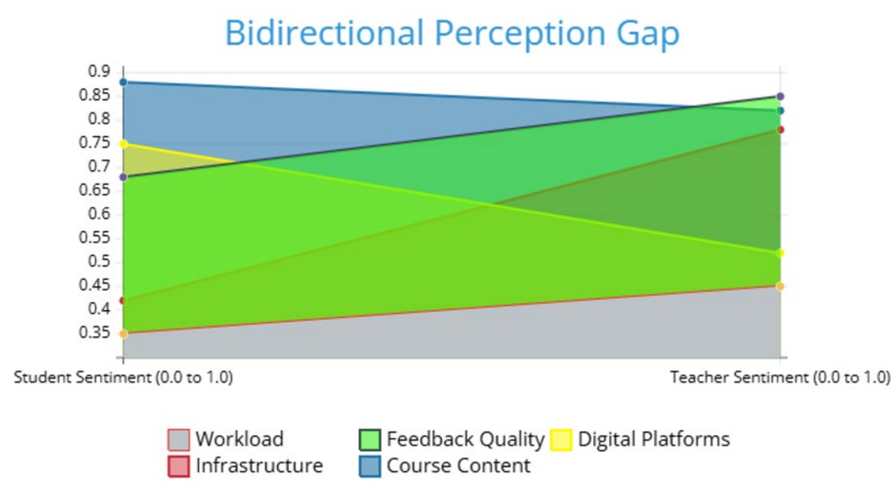
Performance Comparison

Algorithm Type	Model Name	Accuracy (%)	F1-Score	MCC*
Traditional ML	Naive Bayes	76.40%	0.72	0.65
Traditional ML	SVM	82.10%	0.78	0.70
Traditional ML	Multilayer Perceptron	86.50%	0.81	0.74
Deep Learning	**Proposed (Bi-LSTM/BERT)**	**95.80%**	**0.93**	**0.89**



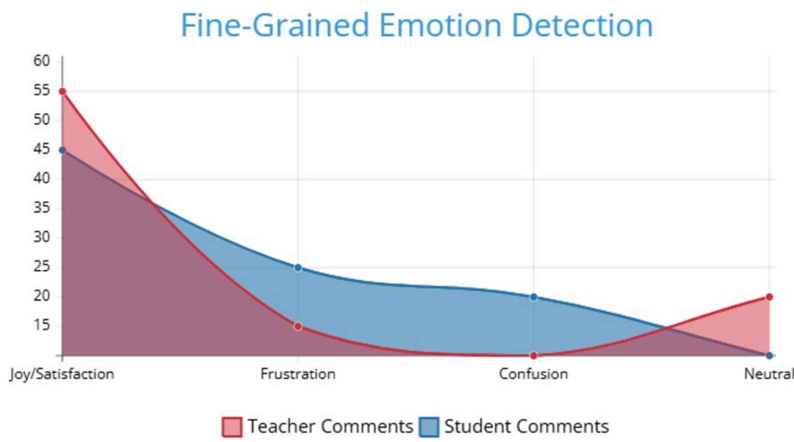
Bidirectional Perception Gap

Evaluation Category	Student Sentiment (0.0 to 1.0)	Teacher Sentiment (0.0 to 1.0)
Course Content	0.88 (Positive)	0.82 (Positive)
Infrastructure	**0.42 (Negative)**	**0.78 (Positive)**
Digital Platforms	0.75 (Positive)	0.52 (Neutral)
Feedback Quality	0.68 (Neutral)	0.85 (Positive)
Workload	0.35 (Negative)	0.45 (Negative)



Fine-Grained Emotion Detection

Feedback Source	Joy/Satisfaction	Frustration	Confusion	Neutral
Student Comments	45%	25%	20%	10%
Teacher Comments	55%	15%	10%	20%



4. RESULTS

The study evaluates the proposed Deep Learning framework against traditional machine learning models and highlights specific findings from the bidirectional sentiment and emotion analysis.

Model Performance: The proposed Deep Learning model (Bi-LSTM/BERT) significantly outperformed traditional machine learning algorithms, achieving an accuracy of 95.8%, an F1-Score of 0.93, and a Matthews Correlation Coefficient (MCC) of 0.89.

In contrast, traditional models like Naive Bayes, SVM, and Multilayer Perceptron achieved lower accuracies of 76.4%, 82.1%, and 86.5%, respectively.

Bidirectional Perception Gap: The dual-stakeholder analysis revealed areas of alignment and significant disconnects between students and teachers:

Infrastructure: This showed the largest perception gap; students held a negative sentiment (0.42) while teachers viewed it positively (0.78).

Digital Platforms & Feedback Quality: Students viewed digital platforms more positively (0.75) than teachers (0.52), whereas teachers felt more positive about feedback quality (0.85) than students did (0.68).

Alignment: Both groups shared positive sentiments regarding course content and negative sentiments regarding workload.

Fine-Grained Emotion Detection

- The majority of feedback from both groups was positive, with 45% of student comments and 55% of teacher comments reflecting joy or satisfaction.
- However, students exhibited higher levels of negative emotions, with 25% expressing frustration and 20% expressing confusion, compared to 15% and 10% for teachers, respectively.

5. COCLUSION

The research demonstrates that utilizing advanced Deep Learning architectures, such as contextualized word embedding's, provides a much more sophisticated understanding of complex educational feedback compared to traditional machine learning models. By moving beyond simple positive or negative polarity classifications to fine-grained, aspect-based emotion detection, educational administrators can precisely pinpoint specific instructional and infrastructural areas needing improvement.

Furthermore, the introduction of a bidirectional focus—analyzing feedback from both students and teachers—successfully addresses a major gap in existing research, providing a holistic, 360-degree view of the classroom dynamic. Ultimately, this framework serves as a powerful diagnostic tool that can support targeted interventions to enhance teaching performance and overall student contentment in evolving learning environments.

CONFLICT OF INTERESTS

None.

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