**Enhancing Educational Experiences: A Sentiment Analysis Approach to Student Feedback**

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# Problem Statement

In the dynamic and ever-evolving sphere of education, the role of student feedback in shaping teaching methodologies and course content is indisputably significant. Traditionally, student feedback has been predominantly quantified through numerical ratings. While this approach offers a generalized view of student satisfaction, it notably lacks the depth to decipher the complex, nuanced sentiments embedded in the feedback. This gap in understanding and leveraging the qualitative aspects of student feedback presents a considerable challenge in the educational process. It limits the ability of educators to respond effectively to the specific needs, concerns, and experiences of students, thereby hindering the optimization of the learning environment. Our project is centred around transforming this traditional paradigm by employing advanced neural network models for a sophisticated sentiment analysis approach. This initiative aims to convert the qualitative, textual feedback of students into quantifiable, actionable insights. By doing so, it endeavours to provide educators with a deeper, more nuanced understanding of student experiences, moving beyond the constraints of simple numerical ratings.

The essence of the project lies in its ability to not only capture and categorize the general sentiment of the feedback but also to dissect it further into specific aspects of the educational experience. Such a comprehensive analysis allows for a more targeted and effective response to student feedback, enabling educators to make informed decisions that are closely aligned with student preferences and needs. This approach promises a significant enhancement in the responsiveness of educational strategies, potentially leading to a more engaged and satisfied student body. Moreover, the project's reliance on neural networks for sentiment analysis marks a crucial intersection of advanced machine-learning techniques with practical applications in the educational field. It represents a novel use of technology to address a longstanding challenge in education, setting a new standard for how student feedback is analyzed and utilized.

In the following sections, we will delve into the specific values of solving this problem, the impact on end-users, the constraints and requirements of the project, the nature of the machine learning problem being addressed, and the metrics that will define the success of this endeavour.

1. Value of Solving the Problem

The endeavour to harness advanced neural network models for sentiment analysis in student feedback is a critical step forward in the realm of educational enhancement. This approach is poised to provide substantial value in several key areas:

1. Enhancing the Depth and Quality of Educational Feedback Analysis

The conventional method of relying on numerical ratings significantly limits the scope of feedback interpretation. By implementing a nuanced sentiment analysis model, this project aims to capture the rich, qualitative nuances within student feedback. This deeper level of analysis is essential for understanding the true sentiments of students, which are often lost in the translation of numerical data. Such an enhanced understanding is not just about numbers; it's about tapping into the real experiences, concerns, and emotions of students.

1. Empowering Educators with Actionable Insights

The true potential of student feedback lies in its ability to guide educators in refining their teaching methodologies and course structures. The project's approach ensures that feedback is not just collected and categorized but transformed into actionable insights. Educators can use these insights to make informed, targeted improvements that directly address the specific needs and concerns highlighted by students. This leads to a more responsive educational environment where changes are driven by actual student experiences and feedback.

1. Fostering a More Engaged and Satisfactory Learning Experience

When students see that their feedback is taken seriously and leads to tangible changes, it enhances their engagement and satisfaction with the learning process. This project's approach to feedback analysis means that student voices are truly heard and acted upon, which can lead to improved course content, more effective teaching methods, and, ultimately, a more fulfilling educational experience for students.

1. Setting a New Standard in Educational Feedback Utilization

This project goes beyond the traditional boundaries of educational feedback analysis, setting a new standard in the field. The use of advanced neural network models for sentiment analysis represents an innovative intersection of technology and education. It demonstrates the potential of machine learning in enhancing not just the academic aspect of education but also the overall quality of the learning environment.

In summary, the value of solving this problem extends from elevating the quality of feedback analysis to empowering educators and enhancing student experiences. It's about creating an educational ecosystem that is adaptive, responsive, and deeply aligned with the needs and sentiments of its learners. This project has the potential to transform the landscape of educational feedback, making it a more effective tool for continuous improvement in the educational sector.

1. End-User Impact

The implementation of neural network-based sentiment analysis for student feedback has a profound impact on its primary end-users :- educators and academic administrators. This multifaceted impact addresses several aspects of the educational process and experience.

### Educators and Academic Administrators:

The enhanced sentiment analysis model gives educators a more detailed and nuanced understanding of student feedback, significantly surpassing the insights from traditional numerical ratings. This depth of insight empowers educators to make more informed decisions about curriculum design, teaching methodologies, and student engagement strategies. The model's ability to pinpoint specific issues within student feedback is pivotal for targeted interventions. For example, if a pattern of dissatisfaction emerges regarding certain teaching methods or course materials, educators can precisely focus their efforts on revising these elements. Moreover, the neural network model's rapid processing and analysis capabilities facilitate quicker responses to emerging trends in student feedback. This heightened responsiveness is particularly valuable for promptly addressing issues affecting student well-being or academic performance, ensuring that course adjustments are timely and relevant.

### Students

The insights gained through the in-depth analysis of student feedback promise to benefit students indirectly yet significantly. As educators implement changes based on detailed feedback, students will likely find themselves in a more engaging, supportive, and effective learning environment. Moreover, the knowledge that their feedback is analyzed in depth and contributes to tangible changes in their educational experience can empower students. This sense of empowerment, stemming from feeling valued and heard, can enhance their overall engagement and satisfaction with the educational process, fostering an atmosphere where students feel an integral part of their educational journey.

### Broader Educational Ecosystem

Implementing advanced analytics in feedback interpretation heralds a potential cultural shift in the educational sector towards data-driven strategies. This paradigm shift paves the way for a more dynamic, adaptive, and student-centred approach to education, where robust data insights inform decisions. Furthermore, the successful execution of this project could set a benchmark for educational institutions, showcasing the substantial benefits of integrating advanced technology into feedback analysis and educational decision-making. This model serves as an exemplar, demonstrating how data can effectively guide and enhance the educational process and could inspire other institutions to adopt similar approaches to modernize and improve educational outcomes.

In conclusion, the end-user impact of this project extends beyond the immediate improvements in teaching and course content. It signifies a shift towards a more data-driven, responsive, and empathetic approach in education, where student feedback is a key driver of continuous improvement and innovation. This impact has the potential to resonate throughout the entire educational ecosystem, redefining how student feedback is utilized for the betterment of the learning experience.

1. Constraints and Requirements

The successful deployment of a neural network-based sentiment analysis model for student feedback in an educational context comes with specific constraints and requirements. These factors are crucial in shaping the design, development, and implementation of the project:

### Data Quality and Integrity

The effectiveness of the neural network model in sentiment analysis is contingent upon the volume and variety of the feedback data it processes. The model requires a substantial amount of diverse feedback data to be truly effective, ensuring that the training dataset encompasses a wide range of sentiments and expressions. This diversity is key to enabling the model to interpret and analyze a broad spectrum of student feedback accurately.

The model's success also heavily depends on the quality of the input data, necessitating a comprehensive preprocessing stage. This stage begins with cleaning the text data to remove irrelevant characters and standardize its format, a crucial step in enhancing data quality. Concurrently, the process involves rectifying any missing or incorrect data entries. Further, the text is broken down into tokens, which are normalized to ensure uniformity and consistency in data processing. A critical aspect of preprocessing is using techniques like Term Frequency-Inverse Document Frequency (TF-IDF) to reduce the data's dimensionality, making it more manageable and conducive for the neural network to process efficiently. Moreover, the dataset is carefully balanced to mitigate any biases in the model's learning process and predictions. This meticulous preparation of data is vital for optimizing the neural network's learning capabilities and ensuring the accuracy and reliability of the sentiment analysis outcomes.

### Privacy and Ethical Considerations

In implementing a neural network model for sentiment analysis of student feedback, two critical ethical considerations are paramount: confidentiality and fairness. The sensitive nature of student feedback necessitates stringent measures to ensure confidentiality, necessitating strict adherence to data privacy laws and ethical standards to protect student information. Simultaneously, the model must be meticulously designed to avoid biases that could arise from linguistic style or expression, as these biases could significantly skew the sentiment analysis results. Ensuring fairness in the interpretation of feedback across different student demographics is essential to provide an equitable analysis. This means carefully calibrating the model to recognize and account for varied linguistic expressions while maintaining the integrity and impartiality of the analysis process.

### Computational Resources and Scalability

The deployment and efficacy of neural networks in analyzing large volumes of text data, such as student feedback, hinge critically on the availability of substantial computational resources. These models, known for their complexity and depth, demand considerable processing power to effectively train and operate. Ensuring that this processing power is sufficiently available is a crucial aspect of both the training and deployment phases of the model. Alongside this requirement, the scalability of the solution is equally important. The model must be adept at handling fluctuating volumes of feedback, particularly during peak academic periods when there is a surge in feedback quantity. This scalability is vital to maintain consistent performance and accuracy in sentiment analysis, ensuring that the model remains effective and reliable regardless of the volume of data being processed.

### Accuracy and Reliability of the Model

For the sentiment analysis model to be deemed reliable and useful, it must not only achieve high accuracy in sentiment classification but also exhibit robustness and generalizability. High accuracy ensures that the model can reliably classify sentiments in student feedback, a fundamental requirement for the model's practical application. Alongside accuracy, the model's robustness is crucial; it needs to effectively handle and interpret different styles and formats of feedback, which can vary widely among students and academic contexts. Furthermore, the model's ability to generalize across various courses and academic settings is essential, as it underscores the model's adaptability and utility in diverse educational environments. This combination of high performance, robustness, and generalizability is key to creating a sentiment analysis tool that is both dependable and broadly applicable in the educational sector.

### Usability

The practicality of the sentiment analysis solution in an educational setting depends on its analytical capabilities and user-friendliness. Educators and administrators need to be able to access and understand the insights generated by the analysis easily. It requires the output to be presented in a manner that is both accessible and intuitive, facilitating straightforward interpretation and application of the data for educational improvements. The combination of easy integration and a user-friendly interface is crucial for the widespread adoption and effective use of the sentiment analysis tool in educational environments.

Addressing these constraints and requirements is fundamental to the success of the project. It involves balancing technical feasibility with ethical considerations, ensuring scalability and robustness, and creating a user-centric solution that adds tangible value to the educational process.

1. Type of ML Problem

The project at hand addresses a complex and multifaceted machine learning problem, primarily situated within the realm of Natural Language Processing (NLP), but with distinct characteristics that set it apart:

1. Sentiment Analysis with Hierarchical Complexity

At its core, the problem is rooted in sentiment analysis, a prevalent task in NLP. However, this instance of sentiment analysis is distinguished by its hierarchical complexity. Unlike traditional sentiment analysis, which typically involves a straightforward classification of positive, negative, or neutral sentiments, this problem necessitates a deeper exploration of the various layers of sentiments. It requires identifying the overall sentiment and dissecting and understanding the multiple dimensions and nuances within it. The added complexity significantly enhances the challenge, moving beyond standard sentiment analysis to a more sophisticated and intricate form of NLP.

1. Neural Networks and Complex Data Interpretation

Addressing this problem involves leveraging neural network models renowned for their ability to handle large and diverse datasets and interpret complex patterns in data. The challenge lies in effectively utilizing neural networks to process and analyze textual data, which often contains intricate patterns, subtleties, and contextual nuances. The proficiency of neural networks in these areas is critical for tackling the complexities inherent in this type of sentiment analysis.

1. Balancing Computational Efficiency with Accuracy

A significant challenge in this ML problem is to balance the computational demands of processing large volumes of text data with the need for accurate and nuanced sentiment analysis. The model must be designed to be efficient in terms of processing speed and resource utilization, and accurate in its analysis and interpretation of sentiments. In essence, this ML problem is a sophisticated blend of sentiment analysis, rating classification, and aspect-based analysis, all tackled through the lens of advanced neural network models. It stands as a testament to the evolving nature of NLP challenges, where the goal is not just to understand text at a surface level but to delve deeper into the subtleties and complexities of language as it is used to express opinions, emotions, and experiences.

1. Success Metrics

For the project "Actionable Insights from Student Feedback: A Sentiment Analysis Approach," evaluating the success and effectiveness of the neural network model involves a set of carefully chosen metrics. These metrics are designed to assess the accuracy of the sentiment analysis and the model's efficiency and practical utility in an educational context.

Accuracy and Precision: The primary metric is the model's accuracy, which measures the proportion of predictions the model gets correct, including the initial rating-based classification and the more nuanced sentiment and aspect-based analysis. Precision, which assesses the correctness of the positive predictions made by the model, is also crucial, especially in the context of accurately identifying specific sentiments or aspects within the feedback.

Recall and F1-Score: Recall measures the model's ability to correctly identify all relevant instances of a particular class, such as a specific sentiment or aspect. The F1-Score, the harmonic mean of precision and recall, provides a single metric that balances both these aspects, making it particularly useful in scenarios where a balance between precision and recall is desired.

Confusion Matrix: A confusion matrix will be invaluable for visualizing the model's performance across different classes. It will help identify if the model consistently misclassifies certain sentiments or aspects, which is crucial for fine-tuning and improvements.

Training Efficiency: Given the large volumes of data involved, the model's efficiency during training is a key metric, which includes considering the time to train the model and the computational resources required.

These success metrics collectively provide a comprehensive framework for evaluating the effectiveness of the neural network model. They encompass technical performance aspects, such as accuracy and efficiency, and practical considerations, such as usability and real-world applicability. Through these metrics, the project aims not just to achieve high performance in a technical sense but also to deliver tangible, actionable benefits in the context of education.

# Solution Design

The solution design outlines the comprehensive approach and methodologies we have employed to tackle the intricate challenge of transforming student feedback into actionable insights. The core of this solution lies in the innovative application of neural network models specifically tailored for sentiment analysis in an educational context.

## Literature Review

### Has this problem been encountered before?

The challenge of effectively analyzing student feedback transcends basic sentiment analysis and delves into the nuanced territory that Aspect-Based Sentiment Analysis (ABSA) addresses. Historically, understanding student feedback in education has largely been confined to interpreting quantitative metrics like ratings. While this approach offers a high-level view of student satisfaction, it overlooks the intricate, qualitative insights that are often more telling. In response to this limitation, there have been significant efforts within the field of natural language processing, specifically in sentiment analysis. These efforts, however, traditionally focused on general sentiment classification without considering the specific aspects or themes within the text.

The emergence of ABSA marked a pivotal advancement in sentiment analysis. This approach goes beyond general sentiment classification to identify and evaluate sentiments associated with specific aspects within a text. In the context of student feedback, this means not only discerning whether the feedback is positive or negative but also understanding which aspects of the educational experience (such as teaching quality, course content, or learning resources) are being praised or criticized.

Despite the relevance and potential of ABSA in education, its application in this field has been relatively limited, with most studies and implementations focusing on other domains like product reviews or customer services. The unique challenge in the educational domain includes dealing with domain-specific language, the sensitivity of feedback content, and diverse formats of student responses, which ABSA has not been widely applied.

Therefore, while the broader problem of sentiment analysis in text data is well-recognized and explored, the specific application of ABSA to student feedback in education represents a relatively novel area of exploration. It offers an opportunity to significantly enhance the understanding and utility of student feedback, going beyond general sentiments to extract detailed, aspect-specific insights that are far more actionable for educators and academic institutions.

### How was it solved? What is the state-of-the-art technique?

The evolution of sentiment analysis in recent years has been marked by significant advancements, particularly in Natural Language Processing (NLP). This evolution has shifted from basic text processing methods, like keyword extraction and statistical analysis, to more sophisticated machine learning techniques.

*Early Developments in Machine Learning*: The initial phase of evolution involved applying machine learning algorithms such as Support Vector Machines (SVMs) and Naive Bayes classifiers. These algorithms brought a new level of sophistication to sentiment analysis, offering more accurate and nuanced text interpretations than earlier methods.

*Emergence of Neural Networks*: A pivotal advancement came with the introduction of neural network models, specifically Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. These models are particularly adept at processing sequential data and have been instrumental in enhancing the ability to analyze sentiments in text more deeply and contextually.

*Revolution through Transformer Models*: The most recent and significant advancement in sentiment analysis has been developing and applying transformer models, such as BERT (Bidirectional Encoder Representations from Transformers). Transformer models represent a leap forward in the field, with their ability to process text bidirectionally and capture a more nuanced understanding of context and subtleties in language.

*Aspect-Based Sentiment Analysis (ABSA):* Alongside these developments, Aspect-Based Sentiment Analysis (ABSA) has become increasingly relevant. ABSA provides a more granular approach by focusing on specific aspects within texts and analyzing sentiments associated with each aspect. This technique is particularly useful for dissecting complex feedback into distinct components and understanding the multifaceted nature of sentiments expressed.

In summary, today's state-of-the-art sentiment analysis is characterized by these advanced techniques, each contributing to a more refined and comprehensive understanding of the text. Neural networks and transformer models have set new benchmarks in the field, offering sophisticated sentiment analysis tools capable of capturing the depth and complexity of human language.

### What were the limitations to that solution? (Gap in solution)

While current sentiment analysis methods, including advanced techniques like neural networks and BERT, have significantly improved the understanding of textual feedback, there remain key limitations, particularly in the context of educational feedback, which our three-tiered drill-down approach aims to address:

***Surface-Level Analysis****:* Traditional sentiment analysis often provides a surface-level understanding, categorizing feedback into basic positive, negative, or neutral sentiments. This approach lacks the depth to understand students' complexities and specific concerns. Our first tier, employing an LSTM network for rating-based classification, goes beyond mere positive or negative categorization, offering a nuanced understanding based on a 1-5 rating scale that reflects the varying degrees of student satisfaction or dissatisfaction.

***Lack of Detailed Sentiment Dissection****:* Many existing models do not dissect sentiments to understand underlying emotions or specific aspects of feedback, which is critical in an educational setting. Our second tier, using BERT, delves into the nuanced sentiments, particularly focusing on lower ratings to understand specific negative emotions. This level of analysis is crucial for identifying and addressing the root causes of student discontent.

***Absence of Aspect-Specific Insights****:* Traditional sentiment analysis often overlooks the importance of aspect-based insights, vital in educational feedback for pinpointing specific areas of a course or teaching methodology that need improvement. Our third tier addresses this gap by employing Aspect-Based Sentiment Analysis (ABSA). It allows for a detailed breakdown of feedback into specific educational aspects, providing educators with actionable insights on elements of their course or teaching style.

***Integration and Practical Application in Educational Settings***: Sentiment analysis tools are often not tailored for or easily integrated into educational environments. Our model is designed with the educational context in mind, ensuring that it can be seamlessly integrated into existing educational platforms and systems. It makes the insights it generates readily accessible and actionable for educators.

In summary, our proposed solution is specifically designed to address the limitations of current sentiment analysis methods in the educational sector. By offering a more detailed rating classification, deeper sentiment dissection, and aspect-specific insights, our solution provides a more comprehensive, actionable, and education-focused analysis of student feedback.

### What are you proposing that is “novel”?

Our proposal (**Three-Tiered Model**) introduces a novel, hierarchical, drill-down model for sentiment analysis in educational feedback, extending beyond traditional techniques to address the specific nuances of student feedback. This multi-tiered approach, comprising three distinct levels of analysis, represents a unique amalgamation of current state-of-the-art techniques, tailored for the educational context.

1. ***First Tier - Rating-Based Classification***: The foundational layer of our analysis framework is the Rating-Based Classification. This tier employs a Long Short-Term Memory (LSTM) network, a Recurrent Neural Network (RNN) well-suited for processing sequential data like text. The LSTM model is trained to correlate specific linguistic patterns and phrases found in student feedback with a corresponding rating on a 1-5 scale. This involves recognizing various expressions and intensities of sentiments that students typically use to convey their satisfaction or dissatisfaction. The output from this tier is a broad yet essential categorization of feedback, laying the groundwork for deeper sentiment analysis. This categorization is crucial for educators as it provides an immediate and generalized understanding of student sentiment, categorizing feedback into easily interpretable rating levels.
2. ***Second Level - Nuanced Sentiment Analysis***: The second tier delves into a more nuanced analysis of the sentiments. Here, we employ BERT (Bidirectional Encoder Representations from Transformers), a state-of-the-art transformer model known for its deep understanding of the context in language. BERT's architecture allows it to interpret the subtleties and complexities of language effectively, making it ideal for identifying the specific emotions and attitudes in student feedback, particularly those associated with lower ratings. This tier is particularly sophisticated in its approach; it can discern and differentiate between negative emotions, such as frustration, disappointment, or confusion, often associated with lower ratings. The insights generated here are more detailed, providing educators with an understanding of the underlying reasons for student dissatisfaction.
3. ***Third Level - Aspect-Based Sentiment Analysis (ABSA):*** Our model's third and most detailed tier is the Aspect-Based Sentiment Analysis. This tier focuses on dissecting the feedback into specific aspects of the educational experience, such as teaching methodology, course content, or student support services. It employs an advanced ABSA model that is finely tuned to identify different aspects mentioned in the feedback and analyze the sentiment associated with each of these aspects. This tier's capability to break down feedback into distinct components and evaluate sentiments accordingly offers educators a highly granular view of student feedback. It pinpoints the exact areas within the educational experience that require attention and improvement, enabling targeted actions.

While each tier operates independently, they collectively contribute to a comprehensive understanding of student feedback. The first tier sets the stage with a broad classification, the second tier adds depth by exploring the emotions behind specific ratings, and the third tier offers the most detailed insights by focusing on individual aspects of the educational experience.

By implementing this multi-tiered approach, our model aligns with state-of-the-art sentiment analysis techniques and adapts and extends them to meet the unique challenges of analyzing student feedback in education. The result is a robust, nuanced, and practical tool for educators to understand and respond to student needs effectively.

### References of previous related work (minimum 5)

In exploring sentiment analysis within educational settings, particularly focusing on student feedback, it is crucial to acknowledge the foundational and contemporary works that have shaped this field. The following references have guided our understanding and approach to sentiment analysis using machine learning, NLP, and POS tagging. Each study contributes unique insights into the complexities of interpreting student language, the effective use of various sentiment analysis methodologies, and the practical applications of these techniques in educational contexts. These works collectively provide a comprehensive view of the current state of sentiment analysis in education, highlighting both the challenges and the innovative solutions that have emerged in recent years:

* 1. N. R, P. M. S, P. P. Harithas and V. Hegde, "Sentimental Analysis on Student Feedback using NLP & POS Tagging," 2022 International Conference on Edge Computing and Applications (ICECAA), Tamilnadu, India, 2022, pp. 309-313, doi: 10.1109/ICECAA55415.2022.9936569.
     + - This study explores the application of sentiment analysis in education, focusing on analyzing student feedback using NLP and POS (Part-of-Speech) tagging. The paper addresses the challenge of interpreting the language used by students in feedback, a task complicated by the volume and complexity of the data. The proposed method involves an automated analysis of textual feedback to evaluate teaching effectiveness, using ML and NLP techniques to classify sentiments expressed in student comments.
  2. T. Shaik, X. Tao, C. Dann, C. Quadrelli, Y. Li and S. O’Neill, "Educational Decision Support System Adopting Sentiment Analysis on Student Feedback," 2022 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT), Niagara Falls, ON, Canada, 2022, pp. 377-383, doi: 10.1109/WI-IAT55865.2022.00062.
     + - This paper proposes a conceptual framework for sentiment analysis on student feedback within educational institutions. The study introduces an innovative approach to processing qualitative feedback from students using tokenization, stemming, and stopword removal. It employs TextBlob for sentiment categorization based on polarity and subjectivity and a Bi-LSTM deep learning model for multi-label feedback classification into 19 aspects of Biggs's model.
  3. I. Sindhu, S. Muhammad Daudpota, K. Badar, M. Bakhtyar, J. Baber and M. Nurunnabi, "Aspect-Based Opinion Mining on Student’s Feedback for Faculty Teaching Performance Evaluation," in IEEE Access, vol. 7, pp. 108729-108741, 2019, doi: 10.1109/ACCESS.2019.2928872.
     + - This paper introduces a supervised aspect-based opinion mining system using a two-layered LSTM model to analyze student feedback for faculty performance evaluation. The model predicts aspects of feedback and their sentiment orientation.
  4. Z. Nasim, Q. Rajput and S. Haider, "Sentiment analysis of student feedback using machine learning and lexicon-based approaches," 2017 International Conference on Research and Innovation in Information Systems (ICRIIS), Langkawi, Malaysia, 2017, pp. 1-6, doi: 10.1109/ICRIIS.2017.8002475.
     + - This paper presents a novel approach for sentiment analysis of student feedback, combining machine learning and lexicon-based methods. Focusing on feedback collected at the end of academic semesters, it explores the use of TF-IDF and lexicon-based features to train a sentiment analysis model. The model aims to extract valuable insights about teaching quality from student feedback.
  5. S. Rani and P. Kumar, "A Sentiment Analysis System to Improve Teaching and Learning," in Computer, vol. 50, no. 5, pp. 36-43, May 2017, doi: 10.1109/MC.2017.133.
     + - This paper presents a sentiment analysis system designed to enhance teaching and learning by applying natural language processing and machine learning to student feedback. The system analyzes comments from course surveys and online sources, identifying sentiment polarity, emotions expressed, and levels of satisfaction or dissatisfaction.

## From perspective of ML Workflow

### Data Selection

### Data Pre-processing

### Model Selection

### Training/Fine-tuning

### Hyperparameter tuning strategy

### Evaluation Metrics

# Implementation

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## Result Explanation

# Conclusion and Discussions