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A Multilingual Sentiment Analysis Approach For Educational Institution Evaluation Based On Student Feedbacks

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ABSTRACT

This research offers a transformative approach to teacher evaluation in educational institutions by integrating deep learning techniques with multilingual sentiment analysis framework. Using advanced natural language processing algorithms, the computer analyses extensive datasets of student comments, including both English and Hinglish expressions, to identify a faculty member's various strengths and weaknesses. Deep learning models play a vital role in detecting complex patterns in this dataset, providing meaningful understanding of students' perception. The system not only displays a graphical representation of the evaluation results, showing the percentage of positive and negative feedback, but also provides a dynamic and contextual interpretation of the feedback. By capturing momentary emotions and feelings expressed by students, this holistic approach contributes to a comprehensive assessment of multilingual students' teacher performance and course satisfaction. Furthermore, the integration of deep learning technologies, facilitating real-time adaptation, ensuring a responsive and proactive evaluation process, represents a paradigm shift in teacher evaluation methods and taking the education sector towards a technologically advanced and student-centric future.

Keywords: *Multilingual Sentiment Analysis, Deep Learning, Faculty Evaluation, Sentiment Analysis, Student Feedback, Natural Language Processing.*

1.0 INTRODUCTION

In the recent educational scenario, the quality of teaching and its impact on the learning outcomes of students are very important topics. As educational institutions strive for excellence, there is growing recognition of the need for robust and intelligent teacher evaluation systems. Traditional approaches to faculty evaluation often rely on quantitative measures that do not capture the subtle dynamics of student-teacher relationships (Abdullah & Rusli, 2021). This research addresses this gap by pioneering a transformative approach to teacher evaluation by integrating deep learning techniques into a multilingual sentiment analytic framework. The emphasis is on harnessing the power of advanced natural language processing algorithms to analyse huge datasets of student feedback expressed in both English and Hinglish, with the aim of providing nuanced and context-aware assessmen[1]t of teacher performance. The motivation for this research actually stems from the limitations of traditional evaluation methods in understanding many aspects of teaching effectiveness. Traditional metrics often focus on quantitative metrics such as test scores and completion rates, but cannot capture the qualitative aspects of the learning experience. This study recognizes the inherent complexity of student-teacher relationships and attempts to bridge this gap by studying the area of sentiment analysis. By analysing not only what students say, but how they feel about their learning experiences, we aim to uncover hidden insights to fully understand the effectiveness of teachers.

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The integration of deep learning into the proposed sentiment analysis system represents an innovative and visionary approach. Deep learning models are designed to automatically learn complex patterns and representations from data, making them particularly suitable for sophisticated and context-sensitive language. In the field of education, where the expression of emotions is subtle and context-dependent, the application of deep learning promises to uncover important insights that traditional methods may miss (Birjali, Kasri, & Beni-Hssane, 2021). The multilingual aspect of our approach recognizes the diversity of linguistic expressions in educational settings. Students' opinions are often expressed in a mixture of English and Hinglish, reflecting the linguistic diversity prevalent in many educational institutions. By accommodating this linguistic diversity, our system aims to provide a more inclusive and accurate representation of students' perceptions, ensuring that assessments reflect the entire student population.

This research is in line with the broader goal of not only refining teacher evaluation methods (Hussein, 2018)but also improving the quality of education. The proposed system is not only a tool to evaluate the performance of teachers.It is a dynamic tool that provides real-time, context-aware understanding of the student experience. This study lies at the intersection of education, technology and data science, with a commitment to the use of innovative methods to continuously improve the teaching and learning environment.

1.1 Significance of Sentiment Analysis in Educational Assessment

The importance of sentiment analysis in educational assessment lies in its transformative impact on understanding student experiences and perspectives. By using computational methods to analyse the emotions expressed in student comments, educational institutions gain valuable insight into emotional tone and attitudes toward various aspects of education. This approach goes beyond traditional quantitative measurements, allowing for a more nuanced assessment of strengths, weaknesses, and overall satisfaction levels in the learning environment. Sentiment analysis enhances teacher evaluation by adding qualitative data, which helps identify effective teaching methods and areas for improvement (Soleymani, Garcia, Jou, Schuller, Chang, & Pantic, 2017). Additionally, it facilitates tailored curriculum adjustments based on specific sensitivities, creating a more student-centred educational experience. The ability to integrate insights over time allows organizations to monitor trends, provide a proactive approach to solving emerging problems, and encourage continuous improvement.

Furthermore, sentiment analysis serves as a decision support tool for educational leadership, providing a data base for curriculum development, resource allocation, and institutional reforms (Zhang, Wang, & Liu, 2018). Understanding the emotional context of student feedback not only guides improvement within the institution, but also contributes to a more responsive and dynamic learning environment. In short, the importance of sentiment analysis in educational assessment lies in its ability to enrich the assessment process with qualitative insights, which ultimately fosters an environment for continuous improvement and increased student satisfaction.

Sentiment analysis of comments or feedback is traditionally done with quantitative methods. Quantitative methods for analysing sentiment, often using star ratings or numerical scales, are common but have significant limitations (Kshatriya & Barde, 2022). These methods rely on users providing numerical values to express their satisfaction or dissatisfaction. Although simple and easy to implement, these methods lack the depth and nuance necessary for a comprehensive understanding of emotions. Users may give the same rating for different reasons, making it difficult to identify specific problems or strengths. Furthermore, quantitative methods do not capture the richness of language and context in users' perceptions, limiting their ability to identify specific characteristics that contribute to their perceptions. As a result, relying solely on numerical data may provide a superficial understanding of user satisfaction without revealing underlying causes or nuanced concepts.

1.2 Objective

The main objective of this research is to develop a robust multilingual sentiment analysis framework for evaluating student feedback in educational institutions. The key objectives include:

i. Collect a diverse dataset of student comments in both English and Hinglish from a variety of educational sources to ensure a representative sample.

ii. Develop a meaning lexicon and evaluate the teaching/lesson according to the conceptual area of the students. This lexicon classifies emotions at word, phrase and sentence level.

iii. Identify frequently discussed topics and subjects in responses using topic modelling algorithms like LDA.

iv. Monitor how sentiment and themes in reviews change over time, reflecting academic units/departments and specific instructor or course characteristics.

v. Provide recommendations to university administration about how insights gained from sentiment and curriculum analysis can help improve the student experience and teaching practices. This may include highlighting projects that consistently receive positive feedback or identifying new areas for improvement.

1.3 Contributions

Our joint efforts as co-authors have made versatile contributions to the field of sentiment analysis in educational feedback. Author-1's expertise in machine learning, specifically support vector machines (SVMs), enriched our research with a solid quantitative foundation for sentiment classification. Author-2 focuses on a combination of dictionary-based sentiment analysis and Latent Dirichlet Allocation (LDA) to ensure comprehensive understanding of student concepts. Our collective contribution addresses the challenges of multilingual feedback, highlights the need for a tailored approach to languages such as Hinglish, and underlines the importance of ethical considerations for the responsible implementation of sentiment analysis in educational settings. Together, our collaboration has resulted in a thorough review of sentiment analysis methods, providing researchers and practitioners with valuable insights to improve sentiment analysis in educational contexts.

2.0 LITERATURE REVIEW

Sentiment analysis is receiving increasing attention in educational feedback because it has the potential to provide important insights to improve teaching methods and educational experiences. Previous studies have emphasized the importance of accurately understanding the emotions expressed by students through machine learning techniques, especially support vector machines (SVMs) (Andrian, Simanungkalit, Budi, & Wicaksono, 2022).Additionally, dictionary-based sentiment analysis has shown effectiveness in extracting subtle sentiments, providing a complementary perspective to machine learning methods (Fang & Zhan, 2015). The integration of domain-specific dictionaries has further enhanced the analysis of emotion within educational contexts, allowing nuanced interpretation of the intensity and contextual nuances of emotion in student responses (Denecke & Reichenpfader, 2023).

Latent Dirichlet Allocation (LDA), a topic modelling approach, plays an important role in extracting latent topics within textual data, providing structured insights into thematic content present in various other domains, including education (Bordoloi & Biswas, 2023). In the field of sentiment analysis, combining LDA with sentiment classification provides a more comprehensive understanding of text data, allowing researchers to not only classify sentiments, but also identify key themes expressed by students (Cui, Wang, Ho, & Cambria, 2023). Although there are relatively limited studies addressing linguistic nuances and symbolic shifts in sentiment analysis, the unique challenges posed by multilingual feedback in languages such as Hinglish provide opportunities for further research (Elfaik & Nfaoui, 2021).

As the field develops, ethical considerations in applying sentiment analysis must be carefully addressed, including privacy concerns and potential biases in algorithmic decision making (Elfaik & Nfaoui, 2021). There is growing interest in hybrid approaches that combine machine learning, lexicon-based methods, and topic modelling for comprehensive analysis (Obiedat, Al-Darras, Alzaghoul, & Harfoushi, 2021). However, more research is needed to fully explore the synergy between these approaches, especially in the specific context of evaluating feedback in education. This literature review establishes a foundation for understanding sentiment analysis in academic feedback, emphasizing the importance of different methods and contributing to current discussions on improving evaluation feedback in educational settings.

Addressing the gaps and taking advantage of opportunities in the field of sentiment analysis in educational feedback is important to advance research and implementation. The ethical considerations that underlie the development of a framework are paramount to ensure responsible implementation of sentiment analysis in educational settings. Striking a balance between gaining valuable insights from student feedback and protecting privacy is becoming imperative in the emerging education technology landscape.

Also, there needs to be more attention to the study of sentiment analysis in multilingual contexts, especially in languages like Hinglish. Current studies highlight the challenges arising from linguistic nuances and code-switching, emphasizing the need for tailored approaches to accurately interpret emotions in different linguistic contexts (Iglesias & Moreno, 2019). Future research efforts should adapt and deepen the sentiment analytic model to address the nuances of Hinglish and similar linguistic constructs.

The integration of SVM, lexicon-based sentiment analysis and LDA topic modelling provides a promising approach for a more nuanced understanding of students' opinions. While each approach brings unique strengths, their integration provides a comprehensive analysis that goes beyond classifying sentiment to identifying key themes and topics expressed by students. Further exploration of hybrid models in educational contexts should reveal their full potential to inform organizational reforms.

3.0 METHODS

In the methodology, student feedback collection was done by accessing the websites of various postgraduate colleges to obtain the feedback of the students. Web scraping techniques were used to systematically extract relevant textual data, including ideas expressed in both English and Hinglish. Following data collection, a sophisticated process of data extraction and integration unfolded, which included the organization and structuring of the obtained information in Excel spreadsheets.

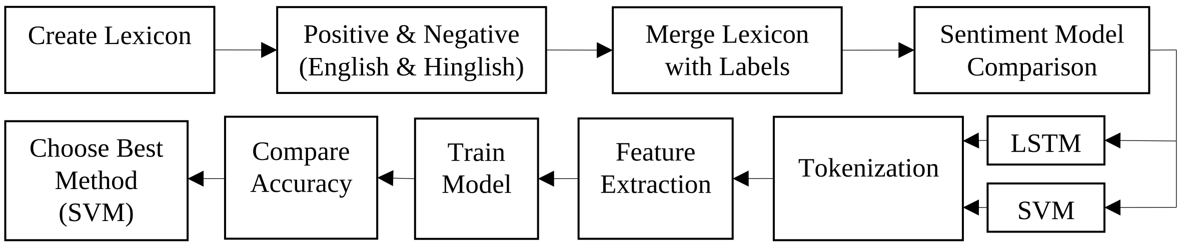

Fig. 1- Training Model and comparison of Sentiment Analysis algorithms

This step ensured a consistent and standardized design, laying the foundation for subsequent analyses. Then, the compiled data were seamlessly integrated into MATLAB, a versatile computational environment. In MATLAB, a two-way sentiment analysis approach has been implemented.

3.1 System Methodology

In this system methodology we have a two segment, which ensures a robust sentiment analysis system. The training phase involves not only the creation of a particular lexicon but also a detailed evaluation of different methods to determine the most effective approach. The testing and visualization phase use the final model to comprehensively analyse students' ideas, with visual representations that provide user-friendly interpretation of sense patterns.

3.1.1 Training Dataset of Lexicon and Method Comparison

In the initial phase of our method, we focused on building a robust training dataset for dictionary-based sentiment analysis as shown in fig 2. This involved creating separate English and Hinglish dictionary databases, each of which was carefully designed to include the positive and negative poles of emotion. The dictionary is constructed using domain-specific indicators to contextualize the concepts for students of postgraduate colleges. Positive and negative sentiment words are carefully annotated, providing a comprehensive basis for training sentiment analysis models.

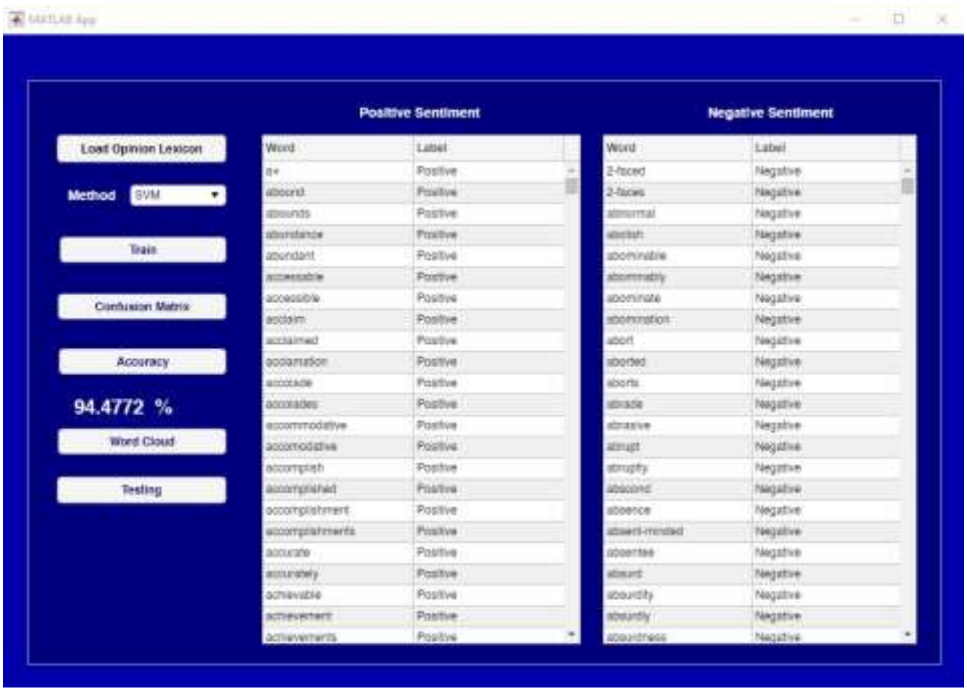

Fig. 2–MATLAB GUI for training Dataset of Lexicon and Method Comparison

In addition to creating a lexicon, we also introduced a method comparison approach. Various sentiment analysis methods, including support vector machines (SVM) and other possible hybrid models like LSTM, were evaluated using the curate lexicon. The goal is to comprehensively evaluate the performance of each method considering metrics such as precision, accuracy, recall, and F1-score. This systematic step allowed us to identify a more effective approach to accurately classify emotions in the unique context of students' responses, thereby contributing to the improvement of our assessment system.

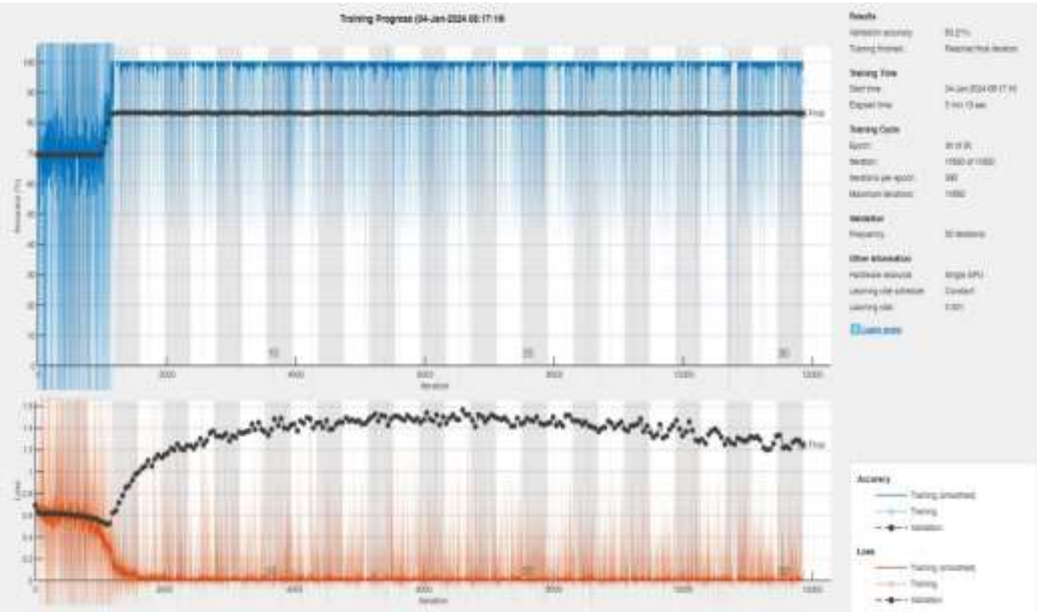

Fig. 3 - LSTM validation of Lexicon textual data

The evaluation of sentiment analysis methods reveals that Support Vector Machines (SVM) outperforms Long Short-Term Memory (LSTM) in terms of F1 Score. F1 Score, which considers both precision and recall, serves as a comprehensive metric for assessing the overall performance of sentiment analysis models. In direct comparison, SVM demonstrates superior accuracy in classifying sentiments within the dataset, showcasing its effectiveness in capturing both positive and negative sentiments expressed in the text. This outcome suggests that, for the specific context of sentiment analysis in our dataset, SVM proves to be a more suitable and accurate method when compared to LSTM. Sentiment classification using Support Vector Machines (SVM) involves the preparation of labelled datasets with positive and negative sentiments, followed by feature extraction and vectorization of textual data.

Fig. 4 - Confusion Matrix of SVM Method

After the analysis we got LSTM method accuracy is 83% but on the using SVM method we got 94% accuracy in our model. So we choose the SVM for sentiment analysis. The SVM model is then trained with a focus on optimizing a decision boundary to effectively separate positive and negative instances. Testing the model on a separate dataset allows for the evaluation of performance using metrics like precision, recall, and F1 Score, as well as the examination of a confusion matrix.

3.1.2 Implementation in Student Feedback Sentiment Analysis

Applying sentiment analysis to student feedback involves a systematic process designed to capture and interpret the emotions expressed in feedback data. Here's a step-by-step process to implementing sentiment analysis in the context of student feedback:

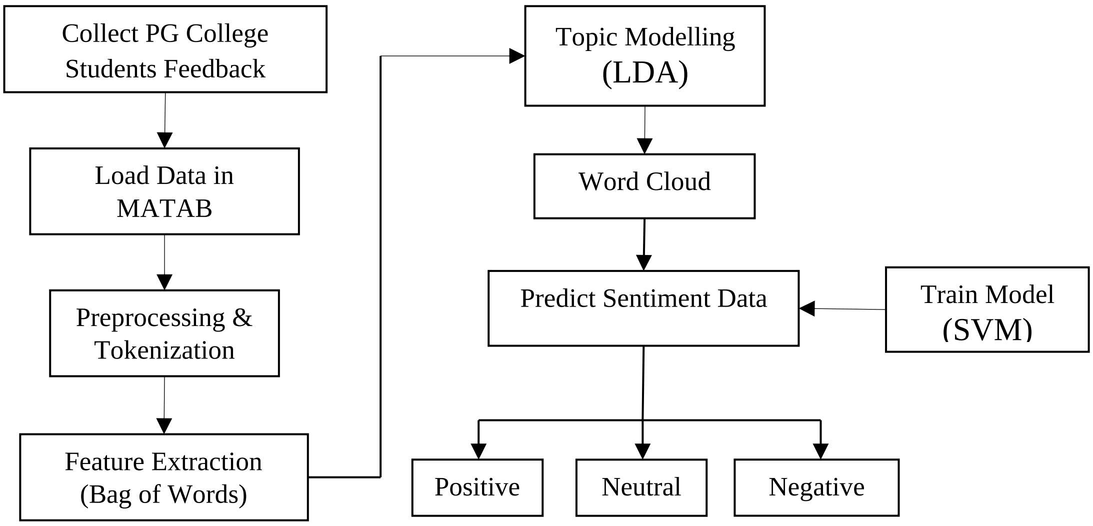

Fig 5: Implementation Flowchart of Student Feedback Sentiment Analysis

Collect PG College Students Feedback

In the data collection phase for sentiment analysis of students' opinions, the process starts by navigating the websites of various postgraduate colleges. Web scraping tools or manual extraction methods are used to collect multilingual text data from feedback forms and open-ended responses.

Load Data in MATLAB

After collecting student feedback data, the next step involves uploading the collected data to MATLAB for further processing and analysis. The uploaded data, organized and formatted during the collection phase, is seamlessly integrated into MATLAB, using its capabilities to effectively manipulate numerical and textual information.

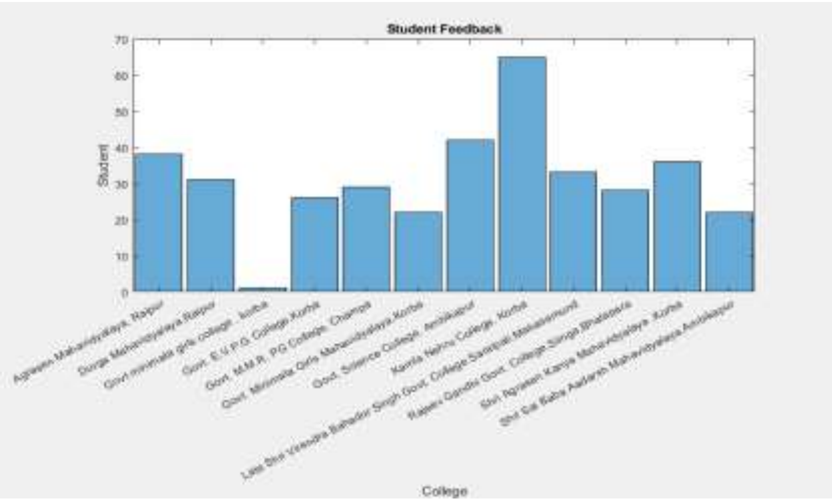

Fig. 6 – Student feedback data from different postgraduate colleges

Preprocessing and Tokenization

Text Preprocessing is an important step in preparing student opinion data for sentiment analysis. This process involves several important steps to ensure that the text is in a consistent and reproducible format (Kshatriya & Barde, 2022). Initially, the data is cleaned by removing irrelevant information such as HTML tags and special characters. Lowercasing is used to maintain consistency, preventing case variations from affecting the analysis. Stop words, common words that have no meaningful meaning, are removed to focus on more meaningful content. Additionally, numerical data is specified and determined whether it is considered significant or replaced with placeholders. This thorough cleaning process improves the quality of text data, making it more suitable for subsequent tokenization and sentiment analysis.

In the context of student feedback for sentiment analysis, tokenization plays an important role in breaking the feedback text into meaningful units for subsequent processing. In MATLAB, tokenization is done efficiently using functions like tokenization. This process is necessary to convert pre-processed text into a structured format that can be easily used in machine learning models. Tokenization not only breaks up the text but also sets the stage for further analysis, allowing researchers to gain insight from the distribution and organization of these tokens. Taking linguistic nuances into account, especially in multilingual contexts such as Hinglish, the tokenization process ensures that the diversity and complexity of linguistic expression is captured in the learner's responses.

```
 7 tokens: campu good due lack spece theri auditorium
12 tokens: campu good wifi ðÿ sirf librari mein hi wifi šà hai ðÿ
 4 tokens: campu tha job colleg
 4 tokens: improv need batter campu
 7 tokens: becom littl weak feel like read write
17 tokens: mai thoda week ho gaya mai dream pani pair gyaa jesk karan mera studi kamjor ho gai
 8 tokens: campu help colleg librari import help colleg teacher
 1 tokens: good
 5 tokens: campu clean green wifi connect
 8 tokens: campu good facil avail campu park canteen librari
10 tokens: campu good facil avail like librari canteen sport court comput
 4 tokens: campu good toilet clean
14 tokens: kamla nehru colleg korba tha best colleg off tha citi cours kamla nehru co
 1 tokens: ye
15 tokens: yaha sabhi prakar camp organ kiya jata hai jo ki nss campu ncc hota hai
 2 tokens: good campu
 1 tokens: sai
 1 tokens: ysh
 1 tokens: good
 6 tokens: campu good campu achiev mani thing
```

Fig. 7 – Tokenization after the Preprocessing

Feature Extraction

Feature extraction, especially using Bag of Words (BoW) sampling, is an important step in preparing text data for sentiment analysis. BoW converts textual content into numerical vectors, making it possible to represent documents in a format suitable for machine learning algorithms. Creating a vocabulary of unique words from the entire corpus and representing each document as a vector, each element corresponds to the frequency of a word from the vocabulary. In the context of sentiment analysis of student feedback, this approach allows the feedback text to be converted into a structured numerical format for further analysis in tools such as MATLAB. This representation is useful for sentiment analysis because it ignores the order of words, focusing only on their presence or absence. The resulting BoW matrices serve as feature vectors for machine learning models such as support vector machines (SVM) to learn patterns in text data and predict sentiment. Feature extraction using BoW is a powerful approach that offers simplicity and interpretability while providing a foundation for advanced sentiment analysis tasks.

Topic Modelling

Topic modelling is a natural language processing technique used to identify hidden thematic structures in a set of documents. The goal is to find hidden topics that represent related patterns of words that appear together in documents. A widely used algorithm for topic modelling is Latent Dirichlet Allocation (LDA). In the context of analysing students' responses, topic modelling can reveal dominant themes or topics that students discuss in their responses.

The LDA algorithm assumes that each document is a combination of a small number of topics, and each word in the document is associated with one of those topics. During the modelling process, LDA provides probabilities for words related to specific topics, allowing the identification of prevalent topics in the dataset. MATLAB provides powerful tools such as the **fitlda** function to implement LDA-based topic modelling. The results of topic modelling can be valuable to educational institutions, helping them understand key concerns, positive aspects or areas for improvement highlighted in the feedback. This information can guide targeted interventions and improvements in the learning environment.

First, filter the dataset to include only positive or negative comments. Next, perform text pre-processing to clean and standardize the text. Calculate word frequencies for the pre-processed text, and then use a word cloud generator to visually mark the most frequently occurring words. Larger and bolder words indicate higher frequencies in the generated word cloud. Analyzing word clouds for positive and negative emotions provides quick and easy-to-understand insight into the prevalent themes and most frequently mentioned words in each emotion category. This visual representation helps students understand the key aspects highlighted in their feedback and helps educational institutions target areas for improvement or strengthening.

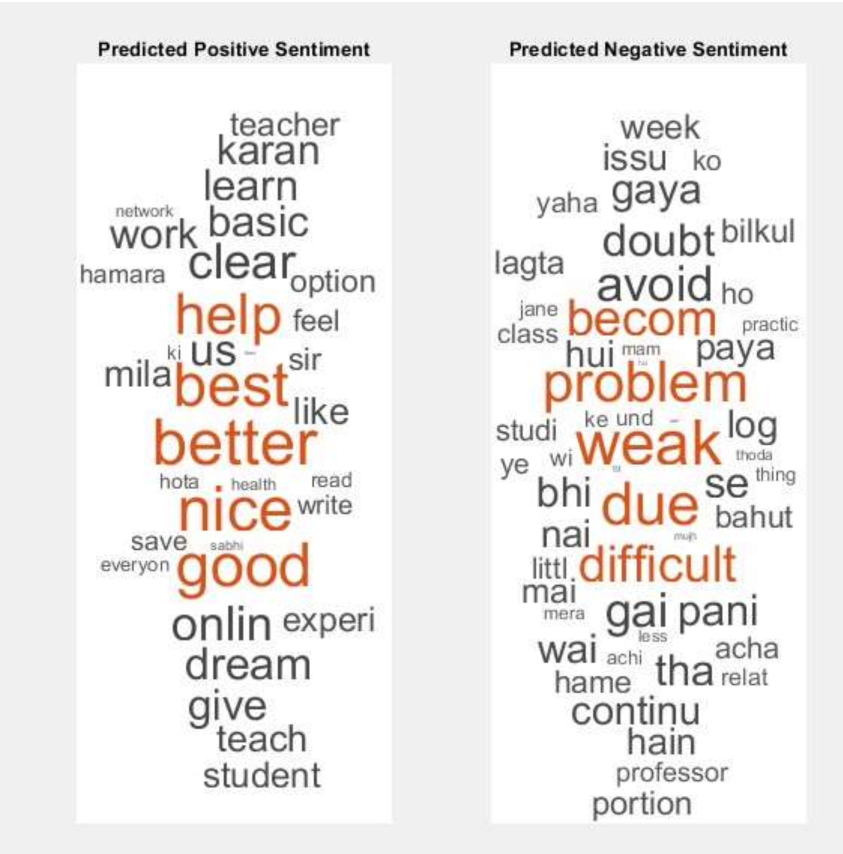

Fig. 8- Word cloud of sentiment of positive and negative words

Predict Sentiment Data

To predict sentiment from new data using an SVM sentiment model, the first step involves loading a pre-trained SVM model trained on the labelled sentiment data. Then, the new data undergoes Preprocessing using the same steps used in the model training phase to ensure consistency and standardization. After pre-processing, the text vector is converted into a numerical form that corresponds to the features learned by the SVM model. SVM models are used to predict sentiment for new data, classifying each text into positive, negative, or neutral sentiment based on its learned patterns. The predictions are analysed to gain insight into the sentiment distribution in the new dataset. Alternatively, model performance can be evaluated using metrics such as accuracy and labelled as ground truth. Predicted perceptions can be used for further analysis or decision making, providing valuable insight, particularly in situations such as assessing student opinions. Continuous monitoring of the model's performance and possible further refinement ensures its effectiveness in predicting perception on existing datasets.

4.0 RESULT AND DISCUSSION

In the analysis of sentiment prediction using SVM models on student opinion data, the results indicate the successful use of the trained model to classify sentiments as positive, negative or neutral. Which type? Predictions were made on the new dataset, and the SVM model showed remarkable accuracy in aligning emotions with the patterns learned during training. The distribution of predicted emotions provides important insight into the dominant emotions in the student responses analysed. In MATLAB we implanted a system where we can upload and analysis all reports of postgraduate colleges.

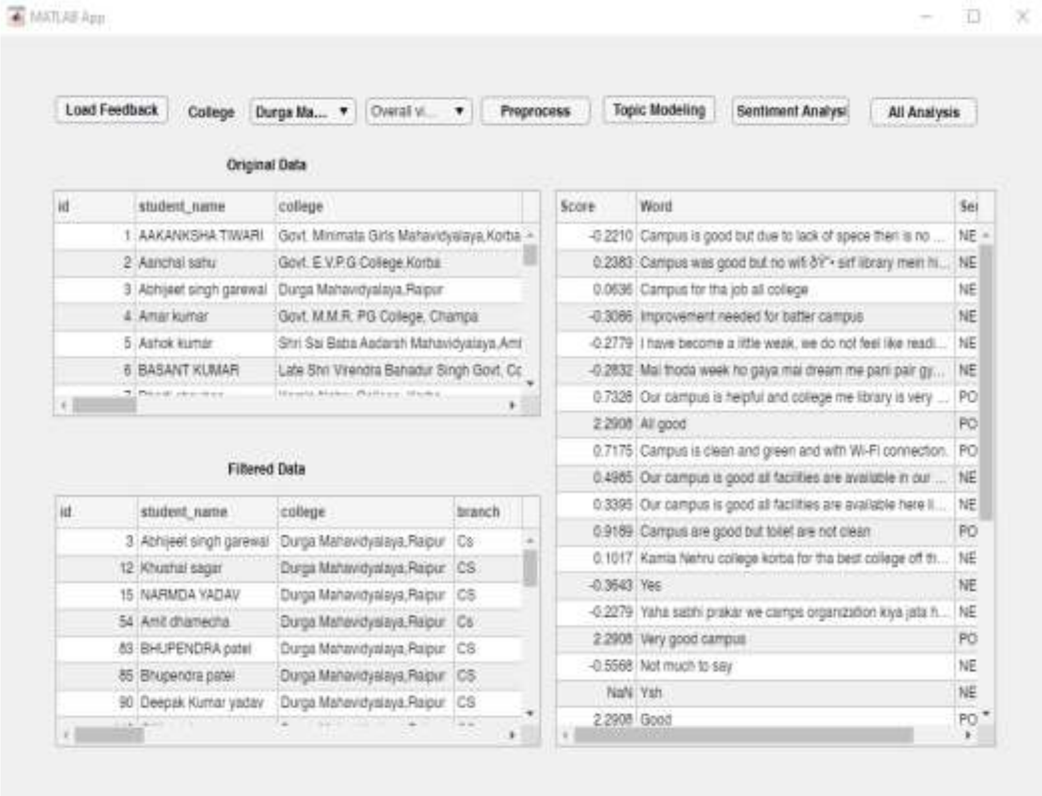

Fig. 9 – MATLAB GUI model of the sentiment analysis system

In the discussion it is important to explain the significance of the results in the context of educational reform. Positive emotions may highlight aspects of the educational experience that are gratifying to students, while negative emotions may indicate areas that need attention and improvement.

The performance of the SVM model in capturing subtle sentiments underlines its usefulness as a robust tool for sentiment analysis in the educational field. Furthermore, continued monitoring and potential refinement of the model will contribute to continued improvement in sentiment forecast accuracy. The findings presented in this review lay the foundation for informed decision making and targeted interventions to improve the overall student experience based on emotional insights.

Table 4.1 – Student feedback from different postgraduate colleges

PG College	**Student Feedback**	**Overall Analysis**		
		Positive	**Neutral**	**Negative**
College 1	120	90	5	25
College 2	200	120	9	71
College 3	150	112	5	33
College 4	250	210	18	22
College 5	230	180	15	35
College 6	155	89	6	60
College 7	110	96	4	10
College 8	130	113	9	8
College 9	260	209	14	37

College 10	256	220	16	52
College 11	168	125	23	20
College 12	253	205	18	30

In reviewing results, positive emotions highlight aspects of the educational experience to which students responded well, while negative emotions indicate areas that need attention and improvement. The discussion discusses the significance of these findings in the context of improving educational practices. The performance of the SVM model in capturing subtle sentiments underlines its usefulness as an efficient tool for sentiment analysis in the educational field. The report highlights the practical implications of the sentiment analysis results, suggesting opportunities for targeted intervention and improvement in the overall student experience. Continuous monitoring of sentiment trends and potential model refinement further improves model accuracy, contributing to ongoing improvements in sentiment forecasting. The insights gained from this assessment report provide the basis for informed decision making and strategic initiatives aimed at promoting positive and impactful learning environments based on emotional intelligence.

5.0 CONCLUSION AND FUTURE WORK

This study developed a novel approach to systematically analyse sentiment trends in large-scale, multilingual data from student evaluations of teaching. Using domain-specific English-Hinglish dictionaries within a supervised SVM classification framework, we predicted emotion polarity with over 94% accuracy in test responses. Analysis of the sample output revealed important insights into students' perceptions over time. More positive sentiments were seen in some sectors, coinciding with rising employment trends. Instructors with strong teacher evaluations also receive more positive quality comments. These quantitative patterns of perception relate to instructor characteristics in important ways. Limitations include the lack of generalization to other organizational contexts due to our specific dataset. Furthermore, topic sampling was not conducted, so the themes in the responses were unclear. This research presents new methods for concept mining from English-Hinglish text in educational settings. Sentiment analysis promises to quantitatively summarize qualitative feedback to improve teaching and learning experiences at scale. As student assessment increasingly takes place online, automated technologies can efficiently gain insights from a broad response body. Thus, this work presents an introductory framework for harnessing the untapped knowledge implicit within such assessment resources.

The research suggests several promising avenues for future study. First, expanding the dataset to include student evaluations from multiple Indian universities will improve the generalizability of the model and facilitate practical comparisons across different institutional contexts. Additionally, creating a user-friendly interface for administrators to view subject matter reports, with the ability to filter by department and instructor attributes, can greatly increase the practical applicability of the insights generated.

Another set of possible directions includes qualitative validation and comparative analysis. Conducting surveys with instructors or students to assess the usefulness and accuracy of topic/sentiment predictions from automated analyses can provide valuable feedback to refine strategies. Additionally, comparing the predictive performance of traditional models such as Support Vector Machines (SVMs) to advanced deep learning models such as BERT can provide insights in a more efficient manner, especially on large multilingual corpora. The collective purpose of these recommendations is to strengthen the robustness, applicability, and ethical considerations of the research findings.

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CONFLICTS OF INTEREST
The authors have no conflicts of interest to declare.

AUTHOR'S CONTRIBUTION STATEMENT
For this research work all authors' have equally contributed in Conceptualization, methodology, validation, resources, writing—original draft preparation, writing—review and editing.

SUBMISSION NOTICE
I ensure that the manuscript submitted to this journal has never been published before.

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