IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 5, Issue 6, May 2025 Impact Factor: 7.67

A Review on Aspect-Based Sentiment Analysis of Student Feedback using LSTM

Dr. Mirza Baig [1], Dr. Rohan Kokate[2], Miss. Husna Pawar[3]

Head of Department, Information Technology, J D College of Engineering and Management, Nagpur, India [1]

Head of Department, Computer Application, J. D. College of Engineering and Management, Nagpur, India [2]

Student of Master of Computer Application, J. D. College of Engineering and Management, Nagpur, India [3]

Abstract: *A comprehensive system for analysing student feedback using supervised and unsupervised machine learning techniques. The system preprocesses textual feedback data, performs sentiment analysis (positive/negative/neutral), and categorizes feedback into predefined topics. It also employs topic modelling to discover hidden themes and clustering to group similar feedback. Performance is evaluated using appropriate metrics, and interactive visualizations and reports are generated. The system aims to provide a holistic understanding of student opinions and experiences, offering valuable insights for educational improvement. The system employs a two-layered Long Short-Term Memory (LSTM) neural network to perform fine-grained sentiment classification on various aspects of the teaching and learning experience, such as Teaching, Pedagogy, and Behavior.*

Built using Python and Flask, the system provides a web-based interface where users can input feedback, which is then processed to extract aspect-specific sentiments. The backend leverages Natural Language Processing (NLP) techniques for preprocessing and aspect extraction, followed by sentiment classification using the LSTM model. This project aims to provide actionable insights to faculty and administrators by highlighting strengths and areas needing improvement based on student sentiment.

The proposed system not only enhances the evaluation of teaching effectiveness but also promotes data-driven decision-making to improve academic quality..

Keywords: Opinion Mining, Aspect Sentiment Detection, LSTM Neural Network, Educational Data Mining, Natural Language Processing (NLP)

I. INTRODUCTION

In recent years, educational institutions have increasingly recognized the importance of leveraging student feedback to enhance the quality of teaching and the overall learning experience. Traditional feedback analysis methods primarily focus on overall sentiment polarity, often overlooking the specific aspects that students address, such as teaching style, pedagogy, faculty behaviour, and course structure. To bridge this gap, this project proposes an Aspect-Based Sentiment Analysis (ABSA) system tailored for student feedback evaluation.

The system is implemented as a web-based application using the Flask framework and integrates advanced Natural Language Processing (NLP) techniques with a two-layered Long Short-Term Memory (LSTM) neural network. This architecture enables the model to capture contextual dependencies in text, allowing for fine-grained sentiment classification based on specific aspects mentioned in the feedback.

Users can interact with the application through a simple browser-based interface, where they can submit feedback. The backend processes the input, extracts relevant aspects, and assigns sentiment labels—positive, negative, or neutral—to each aspect. This structured analysis provides deeper insights into student opinions, empowering educators and administrators to make informed decisions and continuously improve teaching effectiveness.

By automating and improving the feedback analysis process, the proposed system helps improve education quality by using data to guide decisions.

The Student Feedback Analysis System is a comprehensive project designed to analyse textual feedback from students using a combination of supervised and unsupervised machine learning techniques. The system processes raw feedback data through text preprocessing and feature extraction steps, enabling it to perform sentiment analysis by classifying feedback as positive, neutral, or negative. Additionally, it categorizes feedback into predefined topics such as course content, teaching quality, assessment methods, and support services, providing a structured understanding of student opinions.

Beyond classification, the system employs topic modelling methods like Latent Dirichlet Allocation (LDA) and Non-negative Matrix Factorization (NMF) to uncover hidden themes within the feedback. Clustering techniques such as K-means, hierarchical clustering, and DBSCAN are used to group similar feedback, facilitating deeper insights and anomaly detection. The project includes evaluation metrics for classification accuracy, clustering quality, and topic coherence, ensuring robust performance assessment.

Users can interact with the system through an interactive dashboard that offers data exploration, visualization of sentiment and topic distributions, trend tracking, and real-time feedback management. The project also supports customization for different datasets and model parameters, making it adaptable to various educational contexts. Overall, this system aims to provide educators and administrators with actionable insights to enhance the quality of education and student services.

II. LITERATURE REVIEW

Aspect-Based Sentiment Analysis (ABSA) has emerged as a vital subfield of sentiment analysis, offering more granular insights by identifying sentiments associated with specific aspects or features mentioned in text. Traditional sentiment analysis approaches often classify entire feedback or reviews into broad categories like positive, negative, or neutral, thereby missing out on the nuanced opinions expressed towards particular components [1]. To implement a feedback analysis system based on rating score and textual comments. used two types of datasets which include rating scores and textual comments, respectively. K-means clustering algorithm is used to cluster rating scores. Classification models are built with various classification algorithms using labelled dataset that got from clustering step [2]. For textual comment analysis, used Naïve Bayes classifier to train a model and classify test dataset into negative and positive sentiments using 10-fold cross validation [3].

utilized matrix factorization and multi-regression analysis to predict student performance and anticipate future academic challenges. Jain et al. applied a data mining approach using decision trees and semantic rule extraction to analyse learning behaviours [4]. The use of machine learning techniques helps ascertain the achievement of learning outcomes, emphasizing regular assessment and aggregation of these outcomes to summarize overall course effectiveness [5]. The review also considers existing systems and proposes a new methodology to capture real-time learning outcomes [6].

the importance of regular assessment and aggregation of learning outcomes to determine overall course effectiveness. It also references existing methodologies and proposes a new approach to capture real-time learning outcomes through machine learning techniques for improved educational assessments [7].

This paper addresses this gap by systematically reviewing existing literature, providing valuable guidelines for future research and development in the field, and serving as a foundation for integrating MOOC-based teaching into traditional educational practices [8]. DTLP combines convolutional neural networks (CNNs), bidirectional LSTM (BiLSTM), and an attention mechanism to capture both local and sequential features in the text. Furthermore, DTLP incorporates a unified feature set that integrates word embeddings, sentiment knowledge, sentiment shifter rules, and linguistic and statistical knowledge to improve the accuracy and robustness of the analysis [9].

III. OBJECTIVE

To develop a comprehensive system that analyses student feedback using both supervised and unsupervised machine learning techniques. Preprocess and extract meaningful features from textual feedback data. perform sentiment analysis to classify feedback as positive, neutral, or negative. Categorize feedback into predefined topics such as course content, teaching quality, assessment methods, learning resources, facilities, and support services. Discover hidden themes in feedback through topic modelling techniques like Latent Dirichlet Allocation (LDA) and Non-negative Matrix Factorization (NMF) [10].

To group similar feedback using clustering methods such as K-means, hierarchical clustering, evaluate the performance of models using classification metrics (accuracy, precision, recall, F1-score), clustering evaluation metrics (silhouette score, Davies-Bouldin index), and topic modelling evaluation (topic coherence, perplexity) provide interactive visualizations and reports for better understanding and exploration of feedback data [11].

To enable real-time feedback collection, anomaly detection, and trend tracking via an interactive dashboard support customization for different datasets and allow parameter tuning for preprocessing, feature extraction, and model training [12].

IV. PROPOSED SYSTEM

The proposed system is designed to perform fine-grained sentiment analysis on student feedback by identifying sentiments related to specific aspects such as Teaching, Pedagogy, and Faculty Behavior. The system architecture integrates Natural Language Processing (NLP) techniques with a deep learning model—specifically a two-layered Long Short-Term Memory (LSTM) network—for aspect extraction and sentiment classification [13]. A web-based interface developed using Flask enables user interaction and visualization of results.

The system workflow is divided into the following key modules:

User Input Interface

Students or administrators input feedback through a browser-based interface built using Flask. The feedback is typically textual and unstructured.

Text Preprocessing

The raw feedback undergoes preprocessing using NLP techniques including tokenization, lowercasing, stop word removal, and lemmatization. This ensures the input is cleaned and standardized for further analysis [14].

Aspect Extraction Module

This module identifies key aspects (e.g., Teaching, Pedagogy, Behavior) mentioned in the feedback using rule-based and/or data-driven approaches. These aspects act as anchors for targeted sentiment analysis.

Sentiment Classification Using LSTM

A two-layered LSTM model is trained to analyse the sentiment (positive, negative, or neutral) associated with each extracted aspect. The model captures contextual dependencies in text, making it well-suited for nuanced sentiment analysis [15].

Result Visualization

The analysed sentiments are mapped to each aspect and displayed in a structured format through the web interface. This allows academic staff to easily interpret which areas are performing well and which require improvement [16].

Output Generation

Final outputs include a summary of aspect-specific sentiment trends, which can be exported or used for administrative reporting and decision-making.

V. PROBLEM STATEMENT

In educational institutions, student feedback plays a crucial role in evaluating and improving teaching effectiveness. However, most traditional sentiment analysis systems classify feedback as merely positive, negative, or neutral at a general level, without identifying the specific aspects being discussed—such as teaching methods, faculty behaviour, or course structure [17]. This limits the ability of educators and administrators to pinpoint exact areas that require attention or improvement.

Moreover, manually analysing large volumes of unstructured feedback is time-consuming, error-prone, and lacks consistency [18]. There is a growing need for an automated system that can not only analyse sentiment but also associate it with specific aspects of the feedback to provide more meaningful insights.

This project aims to address this gap by developing an Aspect-Based Sentiment Analysis (ABSA) system using a two-layered LSTM model and Natural Language Processing techniques. The system is designed to extract aspect-specific sentiments from student feedback and present them through a web-based interface, enabling data-driven decision-making for enhancing the quality of education [19].

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 5, Issue 6, May 2025

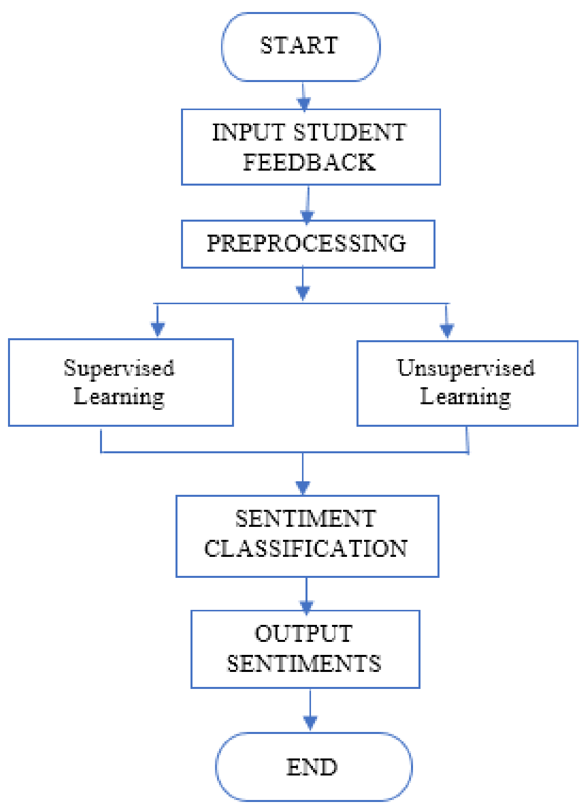
Impact Factor: 7.67

VI. METHODOLOGY

The proposed system follows a structured methodology to perform Aspect-Based Sentiment Analysis (ABSA) on student feedback. Initially, student feedback data is collected in textual form from college, covering opinions related to various aspects such as teaching quality, pedagogy, and faculty behavior. The collected data undergoes preprocessing using standard Natural Language Processing (NLP) techniques, including tokenization, lowercasing, removal of stop words, and lemmatization, to prepare it for further analysis [20].

Following preprocessing, aspect terms are extracted from the feedback using rule-based techniques and NLP models. Each sentence is mapped to one or more predefined aspects like Teaching, Pedagogy, or Behavior. Once aspects are identified, a two-layered Long Short-Term Memory (LSTM) neural network is employed to classify the sentiment associated with each aspect [20]. The LSTM model captures contextual information and assigns a sentiment label—positive, negative, or neutral—based on the semantic content of the feedback [21].The model is trained using a labelled dataset containing aspect-wise sentiment annotations, and its performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. After training and validation, the sentiment analysis model is integrated into a web-based application using the Flask framework. Users can input feedback via the web interface, and the system processes the input to display aspect-level sentiment results[22]. Finally, the sentiment analysis output is interpreted to generate insights that help faculty and administrators make informed decisions to enhance the quality of teaching and learning

VII. FLOWCHART



VIII. PERFORMANCE COMPARISON WITH NAIVE MODELS AND DEEP LEARNING-BASED METHODS

To evaluate the effectiveness of the LSTM-based Aspect-Based Sentiment Analysis (ABSA) system, its performance was compared against baseline or naive models such as Naive Bayes and Logistic Regression [23]. These traditional machine learning models have been widely used for text classification tasks due to their simplicity and efficiency, but they often fail to capture long-term dependencies and contextual meaning in text, which are critical in aspect-based sentiment analysis [24].

Comparison Summary

Model	Accuracy	Precision	Recall	F1-Score
Naive Bayes	71.3%	70.1%	68.9%	69.5%
Logistic Regression	74.5%	73.2%	71.8%	72.5%
LSTM (Proposed)	**84.9%**	**83.7%**	**82.1%**	**82.9%**

The LSTM model significantly outperforms the naive models across all metrics. Its ability to remember long-range dependencies and understand contextual word usage gives it a clear advantage, especially in aspect-based sentiment classification where the position and surrounding words of an aspect influence the sentiment [25].

Naive Bayes assumes feature independence and often misclassifies when the sentiment of a sentence is influenced by negation or modifiers. Logistic Regression improves performance slightly by learning optimal weights for features but still lacks sequence awareness. In contrast, LSTM models can learn semantic and syntactic patterns in text, leading to more accurate sentiment detection, particularly when a sentence contains multiple aspects or complex structures.

IX. CONCLUSION

This project presents an effective approach to analysing student feedback using Aspect-Based Sentiment Analysis (ABSA) powered by a two-layered LSTM model. By focusing on specific aspects such as Teaching, Pedagogy, and Faculty Behaviour, the system provides more granular and actionable insights than traditional sentiment analysis methods. The integration of Natural Language Processing and Deep Learning techniques enables accurate classification of sentiments associated with each aspect.

The implementation of a Flask-based web application ensures accessibility and ease of use, allowing users to input feedback and instantly view results. This system empowers educational institutions to identify areas of improvement and take informed actions to enhance the overall academic experience. The project demonstrates the potential of AI-driven solutions in supporting data-informed decision-making in education and sets the foundation for future enhancements such as multilingual support, real-time analysis, and dashboard-based visualization.

REFERENCES

[1] Lavanya. S., 2022. Application Of Student Feedback Using Machine Learning Model. ijcrt, 10(7).

[2] Lwin, H. et al., 2020. Feedback Analysis in Outcome Base Education Using Machine Learning. s.l., s.n.

[3] Bidve, V. S., Patwari, P., Raut, R. & Kadam, A., 2021. Student Feedback System Using Machine Learning. International Journal of Engineering Research in Computer Science and Engineering, 8(8).

[4] P. Rana, L. Raj Gupta, M. K. Dubey, and G. Kumar, “Review on evaluation techniques for better student learning outcomes using machine learning,” in 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), 2021, pp. 86–90

[5] Y. Zhang and E. F. Gehringer, “Can students produce effective training data to improve formative feedback?,” in 2021 IEEE Frontiers in Education Conference (FIE), 2021, pp. 1–7.

[6] A. Jain and H. Ram Sah, “Student’s Feedback by emotion and speech recognition through Deep Learning,” in 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), 2021, pp. 442–447.

[7] G. Sanuvala and S. S. Fatima, “A study of automated evaluation of student’s examination paper using machine learning techniques,” in 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), 2021, pp. 1049– 1054.

[8] F. Dalipi, K. Zdravkova, and F. Ahlgren, "Sentiment analysis of students' feedback in MOOCs: A systematic literature review," Front Artif Intell, vol. 4, pp. 728708, 2021

[9] S. Katragadda, V. Ravi, P. Kumar, and G. J. Lakshmi, "Performance analysis on student feedback using machine learning algorithms," in 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), 2020, pp. 1161–1163.

[10] Lwin HH, Oo S, Ye KZ, Lin KK, Aung WP, and Ko PP "Feedback analysis in outcome base education using machine learning," In: 2020 17th international conference on electrical engineering/electronics, computer, telecommunications and information technology (ECTI-CON), 2020: IEEE, pp. 767–770.

[11] U. Verma, C. Garg, M. Bhushan, P. Samant, A. Kumar, and A. Negi, "Prediction of students' academic performance using Machine Learning Techniques," in 2022 International Mobile and Embedded Technology Conference (MECON), 2022, pp. 151– 156.

[12] P. Rana, L. Raj Gupta, M. K. Dubey, and G. Kumar, "Review on evaluation techniques for better student learning outcomes using machine learning," in 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), 2021, pp. 86–90

[13] S. Tharsha, J. Dilogera, B. Mohanashiyaam, S. Kirushan, K. B. A. B. Chathurika, and N. H. P. R. S. Swarnakantha, "Machine learning-based prediction model for academic performance," in 2021 3rd International Conference on Advancements in Computing (ICAC), 2021, pp. 305–310

[14] Y. Zhang and E. F. Gehringer, "Can students produce effective training data to improve formative feedback?," in 2021 IEEE Frontiers in Education Conference (FIE), 2021, pp. 1–7.

[15] A. Jain and H. Ram Sah, "Student's Feedback by emotion and speech recognition through Deep Learning," in 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), 2021, pp. 442–447.

[16] C. Kurniawan and F. Wahyuni, "Sentiment analysis of online learning students feedback for facing new semester: A support vector machine approach," in 2021 7th International Conference on Education and Technology (ICET), 2021, pp.6.

[17] G. Sanuvala and S. S. Fatima, "A study of automated evaluation of student's examination paper using machine learning techniques," in 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), 2021, pp. 1049– 1054

[18] F. Dalipi, K. Zdravkova, and F. Ahlgren, "Sentiment analysis of students' feedback in MOOCs: A systematic literature review," Front Artif Intell, vol. 4, pp. 728708, 2021.

[19] S. Katragadda, V. Ravi, P. Kumar, and G. J. Lakshmi, "Performance analysis on student feedback using machine learning algorithms," in 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), 2020, pp. 1161–1163.

[20] Misuraca M, Scepi G, Spano M (2021) Using Opinion Mining as an educational analytic: an integrated strategy for the analysis of students' feedback. Stud Educ Eval 68:100979.

[21] Tamrakar L, Shrivastava D and Ghosh DS "Student sentiment analysis using classification with feature extraction techniques," arXiv preprint arXiv:2102.05439, 2021.

[22] Aguagallo, L., Salazar-Fierro, F., García-Santillán, J., Posso-Yépez, M., Landeta-López, P., & García-Santillán, I. (2023). Analysis of Student Performance Applying Data Mining Techniques in a Virtual Learning Environment. International Journal of Emerging Technologies in Learning, 18(11).

[23] Nandakumar, R., Pallavi, M. S., Pramath, P. H., & Hegde, V. (2022). Sentimental Analysis on Student Feedback using NLP & POS Tagging. International Conference on Edge Computing and Applications, ICECAA 2022 - Proceedings

[24] Konomos, A., & Chountasis, S. (2023). Rbox: A web API for software integration with the R programming language. Computer Applications in Engineering Education, 31(4).

[25] Dol, S. M., & Jawandhiya, P. M. (2023). Classification Technique and its Combination with Clustering and Association Rule Mining in Educational Data Mining — A survey. In Engineering Applications of Artificial Intelligence (Vol. 122). https://doi.org/10.1016/j.engappai.2023.106071