INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

ORIGINAL ARTICLE

Sentiment Analysis in Social Networks: A Case Study on Student Feedback

Manoj Kumar Srivastav[1]*, Somsubhra Gupta[1], Subhranil Som[2]

1 School of Computer Science, Swami Vivekananda University, Barrackpore, India
2 Department of Computer Science, Bhairab Ganguly College, Kolkata, India

OPEN ACCESS

Received: 21/11/2025

Accepted: 13/01/2026

Published: 24/01/2026

Citation: Srivastav MK, Gupta S, Som S (2026) Sentiment Analysis in Social Networks: A Case Study on Student Feedback. Indian Journal of Science and Technology 19(3): 157-168. https://doi.org/10.17485/IJST/v19i3.1877

* **Corresponding author**.

mksrivastav2015@gmail.com

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Abstract

Objectives: Social network applications such as Facebook, LinkedIn, Twitter, and WhatsApp are becoming an important part of daily communication. These platforms help users to share opinions, information, and feedback with others. Sentiment analysis of such content provides insights into users' views, emotions, and engagement levels. This paper analyzes student feedback data collected from Kaggle to identify sentiment patterns in social networks. The study also aims to examine whether hybrid models can provide a balanced and interpretable alternative to deep learning models and transformer-based methods. **Methods:** This study uses several sentiment analysis approaches, including Support Vector Machine (SVM) along with TF-IDF features, Long Short-Term Memory (LSTM) networks, a hybrid TF-IDF–LSTM model, and transformer-based models like BERT and RoBERTa. The analysis is performed on a student feedback dataset consisting of 5,200 cases. The dataset is divided into training and testing sets using 80:20 ratios. Performance is measured using accuracy, precision, recall, F1-score, and a confusion matrix. The models are tested on student feedback data and compared under a unified experimental framework. **Findings:** In the LSTM model highest accuracy of 0.881 is found whereas in BERT and RoBERTa achieved accuracies of 0.880 each, while TF-IDF with SVM reached 0.865. LSTM and transformer-based models performs better than traditional methods in classification accuracy. In these results it is found that deep learning and transformer-based models give higher accuracy in sentiment classification. The hybrid TF-IDF and LSTM approach shows stable and competitive performance. It also needs less computational resources. So there can be a practical option for sentiment analysis of student feedback on social networks. **Novelty:** A hybrid sentiment analysis method combining TF-IDF and LSTM is presented. It combines frequency-driven statistical feature extraction and representation of sequential data for sentiment classification. The hybrid model is not designed to perform better than transformer models. The study tried to show hybrid models can be applicable in sentiment analysis of student feedback in social networks.

Keywords: Sentiment Analysis; Social Networks; Student Feedback; LSTM; BERT; TF-IDF

1 Introduction

Social networks are now a major part of everyday life; helping people stays connected and communicate with one another [1]. Users make many decisions on these platforms, such as joining a network, sending or accepting friend requests, sharing posts, or responding to others. Simple actions can also shape interactions, like posting more photos after receiving many likes, connecting with others to gain followers, or sharing popular content. These choices help users like, comment on, and share posts. This process is showing users' interests, opinions, and emotions. Over time, a large amount of unstructured text data is created.

All such large-scale user-generated data analysis has evolved into an important research problem since it gives very valuable insights about user behavior, satisfaction, and engagement patterns over social networks. Sentiment analysis can be used to classify user opinions based on textual feedback and to understand expressed emotions and perceptions.

Rule-based approaches are used initially to help in opinion classification. Rule-based methods are first applied for polarity detection. Data-driven and language-based techniques are used afterward to achieve better results. SVM classifiers with TF-IDF features give good results. LSTM models understand the sequence and surrounding meaning of words in text. Models like BERT and RoBERTa improve text classification by capturing deeper semantic associations between words.

Srivastav et al. (2024) [2] analyzed engagement of students on social networking sites using sentiment analysis with VADER and BERT models. The results showed that the highest level of engagement was observed in the postings expressing neutral sentiment, which was helpful in determining how people react to various postings of sentiments. Even though the work was helpful in obtaining descriptive results, it lacked a comparative analysis among various sentiment analysis models. Therefore, the relative performance of traditional approaches and neural network–based approaches remains unclear.

The study in [3] reviews how sentiment analysis has developed.. In this paper it is discussed from rule-based methods to deep learning and transformer models. It also points out difficulties such as identifying sarcasm, dealing with data from different fields, and analyzing sentiment across more than one language.

The Amazon Fine Food Reviews dataset is also applicable for sentiment classification [4]. Both machine learning and deep learning methods are useful in this. These methods show good performance. Despite these results, the dataset represents structured product reviews rather than informal social network content. Consequently, issues such as informal language, emojis, short text length, and context-dependent expressions common in social media are not thoroughly considered. The study does not explore how the method works in other domains. It also does not use transformer-based architectures. This limits its usefulness for sentiment analysis in social networks.

The survey in [5] studies two methods for opinion classification on Twitter. These methods include lexicon-based approaches and machine learning approaches. The opinions are classified into positive, negative, or neutral. Studies also discuss problems caused by noisy and unstructured text. However, recent deep learning and transformer-based models are not included. This creates a gap in understanding modern sentiment classification on social network data.

The study in [6] examines different methods of sentiment analysis for student feedback. It uses lexicon-based and machine learning approaches on open-ended student comments. The results show that machine learning models give higher accuracy than lexicon-based methods. However, the study uses only two machine learning models, Artificial Neural Network and Random Forest. It also uses only one lexicon-based method, VADER. Because of this, the study does not cover the full range of available sentiment analysis methods.

From the limits of earlier studies, a clear research gap is identified. Many previous studies use only a few models. Some do not compare models in a systematic way. Others do not study student feedback taken from social networks. From the limitations of earlier studies, a clear research gap is identified. Many previous studies have looked at traditional methods. However, only a few models are used, and comparisons are not done systematically. Informal social network data is also relied upon. Most studies do not consider hybrid approaches that use both frequency-based statistical features and sequential learning models to improve accuracy while keeping computation manageable. This study fills these gaps by examining traditional (SVM), deep learning (LSTM), and transformer-based (BERT/RoBERTa) models under a unified framework using a specific student feedback dataset.

This study compares different sentiment analysis methods in a clear and systematic manner. It includes traditional machine learning methods such as TF-IDF with SVM. It also includes deep learning methods such as LSTM. In addition, transformer-based models like BERT and RoBERTa are examined on the same dataset. This helps identify the most effective sentiment analysis model. The study also explains why a hybrid TF-IDF and LSTM approach performs well.

This work examines student feedback from social networks through sentiment analysis. This dataset is taken directly from Kaggle and contains 5,200 text samples having binary sentiment labels. The value 0 represents negative sentiment, and the value 1 represents positive sentiment. The study applies traditional machine learning using TF-IDF with SVM, deep learning using LSTM, and models like BERT and RoBERTa. All models are evaluated under the same experimental conditions to enable

Table 1. Related Works in Sentiment Analysis

	Dataset / Domain	Methods Used	Key Findings
	Student engagement on social networks	VADER, BERT	Neutral sentiment posts received higher engagement
	Survey (multiple domains)	Rule-based, ML, Deep Learning, Transformers	Comprehensive overview of sentiment analysis evolution
	Amazon Fine Food Reviews	ML and Deep Learning models	Both approaches achieved good classification performance
	Twitter data	Lexicon-based and ML methods	Highlighted challenges of noisy and unstructured text
Proposed study	Student feedback from social networks (Kaggle)	TF-IDF + SVM, LSTM, BERT, RoBERTa, Hybrid TF-IDF + LSTM	LSTM achieved highest accuracy; transformers performed competitively

fair comparison. The study examines sentiment classification models and evaluates the performance of a hybrid TF-IDF and LSTM-based approach.

2 Methodology

This research studies student feedback collected from social networks. The data comes from a publicly available dataset on Kaggle[7]. It followed the methodological framework: preparation of the dataset, cleaning and organization of the text, training of the models, and performance checking by approach of machine learning, deep learning, and transformer techniques.

2.1 Methodological Framework

The methodological framework included dataset preparation, organizing the text, building models, and measuring performance using traditional machine learning[7] and transformer-based approaches.

2.1.1. Dataset Preparation

The dataset includes student feedback text with sentiment labels, either positive or negative. The sentiment labels are converted to integers (0 = negative, 1 = positive) for use with classification algorithms. The dataset is divided into two parts, with 80% allocated for training and 20% for testing. Sampling is done to maintain a balanced number of positive and negative sentiments.

2.1.2. LSTM-Based Deep Learning Model

A Long Short-Term Memory network is applied in text data to learn sequential patterns, using neural network methods for sentiment analysis[8].

- Tokenization and Padding: The training data uses the 10,000 most common words. These words are used to break the text into tokens. Each sentence is changed into a sequence of numbers for the words.The sentences are made 100 tokens long by adding extra tokens or cutting extra words.
- Model Architecture: The LSTM model starts with an embedding layer of 128 dimensions. It has two bidirectional LSTM layers with 64 and 32 units. Dropout is added to prevent overfitting. A dense layer with ReLU activation is connected to a sigmoid output layer for classifying two classes.
- Training: The model is trained for five epochs with a batch size of 32. An adaptive optimizer and a binary loss function are used during training.
- Evaluation: The model's performance is measured using accuracy, precision, recall, and F1 score. A confusion matrix is also used to check the results.

2.1.3. Traditional Machine Learning with TF-IDF + SVM

A classical machine learning pipeline is used as the baseline model:

- Feature Representation: Text data converted into numerical form using TF-IDF with up to 10,000 features, including bi-grams. English stop words are removed.
- Model Training: A linear Support Vector Machine (SVM) with balanced class weights is trained for classification.
- Evaluation: Testing is done using new data and accuracy and other classification measures are reported.

2.1.4. Transformer-Based Models: BERT and RoBERTa

Pre-trained transformer models are used[9]. Fine-tuning helps the models learn from the text data.

2.1.4.1. BERT Fine-Tuning.

- The text is tokenized with the BERT base uncased tokenizer. Each sequence is adjusted to a maximum length of 128 tokens and padding or truncation are used in it.
- The Hugging Face Trainer API is used into fine-tune the BERT model. Training runs for two epochs and uses the batch size of 16.
- The Adam optimizer is run with a learning rate of 3e-5.

2.1.4.2. RoBERTa Fine-Tuning.

- The same process is applied using the roberta-base model and tokenizer.
- Training and evaluation followed identical hyperparameter settings as BERT for consistency.

Evaluation: Both models are assessed on the test dataset. Evaluation metrics cover accuracy, precision, recall, F1-score, and loss.

Machine learning and deep learning[10],[11] prove to be effective for sentiment classification of student feedback data from social networks[10],[11].

2.1.5. Comparative Analysis

By combining traditional (TF-IDF + SVM), deep learning (LSTM), and transformer-based (BERT and RoBERTa), this methodology allowed for a comprehensive comparison of sentiment classification methods.

2.1.6. Algorithm: TF-IDF + LSTM-Based Sentiment Classification

Algorithm: TF-IDF + LSTM-Based Sentiment Classification (Training Procedure)
Input: Student feedback text data with binary sentiment labels.
Output: Trained sentiment classification model.
Step 1: Load the student feedback dataset and verify data integrity.
Step 2: Convert text to lowercase and encode sentiment labels (Positive = 1, Negative = 0).
Step 3: Apply TF-IDF vectorization with a maximum of 10,000 features.
Step 4: Select the top-ranked TF-IDF features to form sequential inputs.
Step 5: The dataset is arranged with 80% for training and 20% for testing.
Step6: Construct LSTM network consisting embedding layer, bidirectional LSTM layers, dropout layers, sigmoid output layer.
Step 7: Set up the model with the Adam optimizer and binary cross-entropy loss**.**
Step 8: The model is trained for a fixed number of epochs using a defined batch size.
Step 9: Check the model's performance using standard classification measures, including accuracy, precision, recall, F1-score, and a confusion matrix.

3 Results and Discussion

Dataset source:

https://www.kaggle.com/datasets/chandusrujan/sentimental-analysis-on-student-feedback[7]

Dataset shape: (5200, 2)

The dataset contains two sentiment classes: negative and positive. Approximately 2,600 feedback instances are negative and 2,600 are positive**.** This nearly balanced distribution reduces bias and supports fair evaluation of the classification models.

The performance is illustrated using figure. Figure 1 illustrating the confusion matrix for the LSTM model, Figure 2 presents training and validation accuracy and loss curves for LSTM, and Figure 3 illustrates about comparative accuracy of LSTM, TF-IDF + SVM, BERT, and RoBERTa models. Figure 4 illustrates the training and validation loss for the LSTM model, Figure 5 presents the training and validation loss curves for the BERT and RoBERTa models, Figure 6 shows the comparative F1-scores

Table 2. Student Feedback Dataset – Text and Corresponding Sentiments

Index	Text	Sentiment
0	Display is excellent and camera is as good as ...	1
1	Battery life is also great!	1
2	Protects the phone on all sides.	1
—	——–	–
—	—	–
—	—-	—
—	—-	—
5200	Excellent but sometimes lack of books especially during exam times	0

of LSTM, TF-IDF + SVM, BERT, and RoBERTa models, Figure 7 depicts the model accuracy of the TF-IDF + LSTM-based sentiment classification approach, and Figure 8 presents the corresponding confusion matrix.

3.1 LSTM Model

The model gets better with each epoch. Training accuracy goes from 61.2% to 98.1%, and training loss falls from 0.63 to 0.07. Validation accuracy rises from 83.9% to 88.1%, and validation loss changes from 0.37 to 0.40.

Table 3. LSTM Model Training Results

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	0.6120	0.6283	0.8394	0.3656
2	0.8849	0.3122	0.8721	0.3218
3	0.9559	0.1511	0.8788	0.3560
4	0.9742	0.0978	0.8817	0.3860
5	0.9814	0.0695	0.8808	0.4034

The results show balanced performance for both classes. Precision, recall, and F1-score are close to 0.88 for negative and positive feedback. The overall accuracy of the model is 0.88, based on 1,040 samples.

Table 4. Classification Report

Class	Precision	Recall	F1-Score	Support
Negative	0.87	0.89	0.88	520
Positive	0.89	0.87	0.88	520
Accuracy	-	-	0.88	1040
Macro Avg	0.88	0.88	0.88	1040
Weighted Avg	0.88	0.88	0.88	1040

3.2 TF-IDF + SVM results

Table 5 presents the results of sentiment classification using TF-IDF and SVM. The performance is similar for negative and positive feedback. The overall accuracy of the model is 0.87 based on 1,040 samples.

3.3 BERT Fine-Tuning

In the Table 6 training and evaluation results are given for BERT Fine-Tuning

Model Evaluation (BERT):

- Accuracy: 0.88
- Evaluation Loss: 0.1666

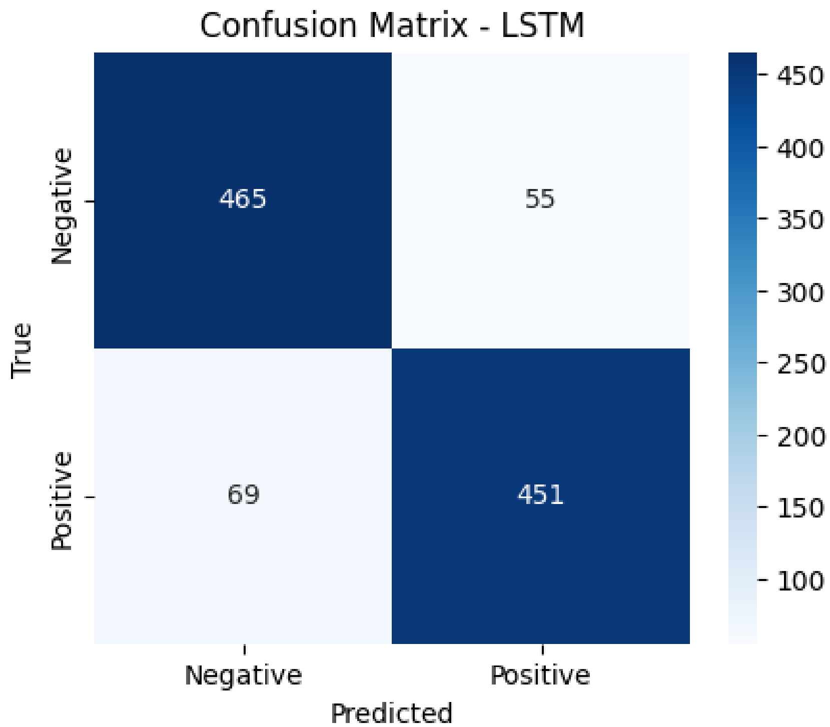

Fig 1. Confusion Matrix for LSTM

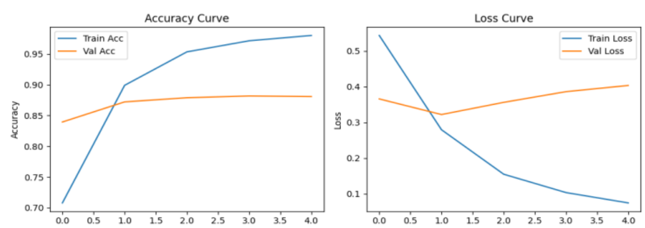

Fig 2. Accuracy Curve and loss curve for LSTM

Table 5. Performance evaluation of sentiment classification (TF-IDF + SVM Results)

Sentiment Type	Precision	Recall	F-score	Sample Count
Negative Feedback	0.86	0.87	0.87	520
Positive Feedback	0.87	0.86	0.86	520
Overall Accuracy			**0.87**	1040
Macro Mean	0.87	0.87	0.87	1040
Weighted Mean	0.87	0.87	0.87	1040

Table 6. BERT Fine-Tuning – Training and Evaluation Results

Epoch	Training Loss	Validation Loss
1	0.220700	0.168819
2	0.117800	0.166592

3.4 RoBERTa Fine-Tuning

In the Table 7 training and evaluation results are given in the RoBERTa Fine-Tuning

Table 7. RoBERTa Fine-Tuning: Training and Evaluation Results

Epoch	Training Loss	Validation Loss
1	0.295900	0.144814
2	0.153300	0.178934

RoBERTa Evaluation:
Accuracy: 0.88
Eval Loss: 0.1789

3.5 Comparative study of model accuracy

The comparative results are shown below

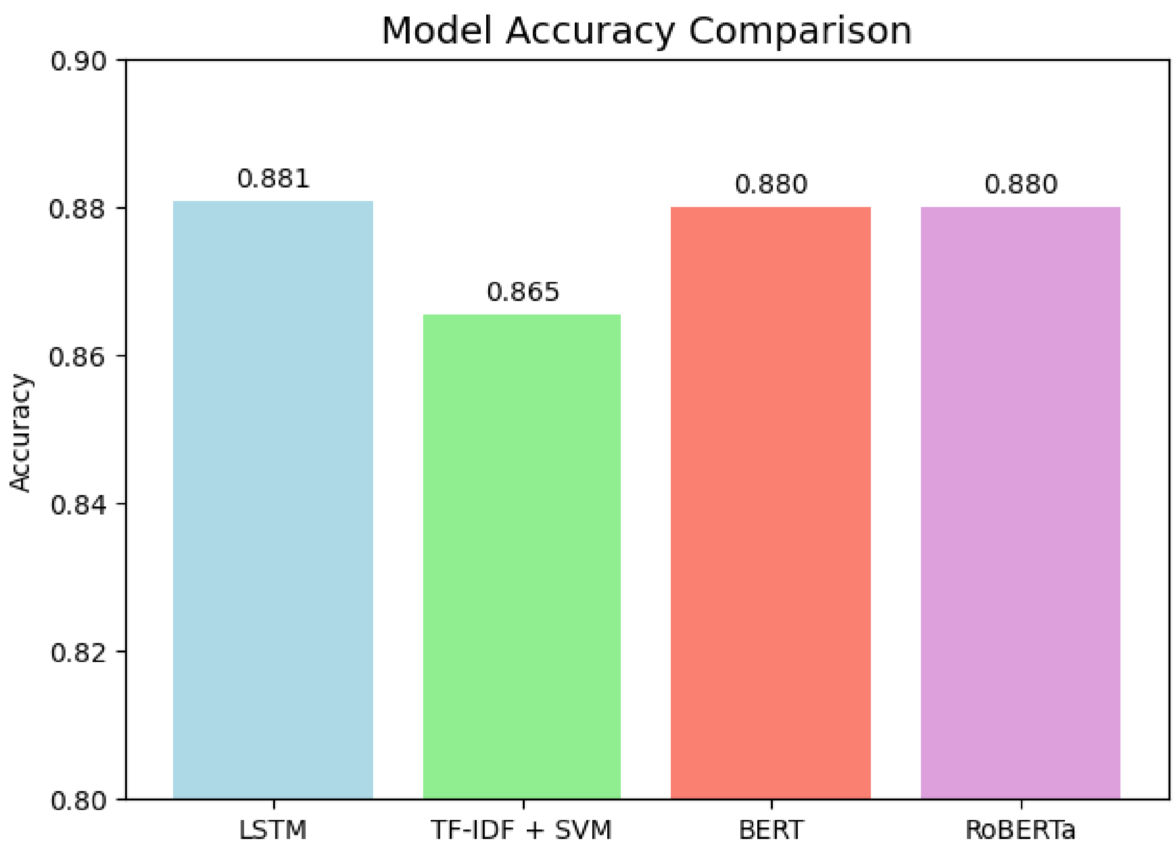

Fig 3. Comparative study of model accuracy

3.6 Results on Algorithm: TF-IDF + LSTM-Based Sentiment Classification

The sentiment analysis process starts by loading the feedback dataset

$$\mathrm{D} = (t_i, s_i) : i = 1, \ldots, n,$$

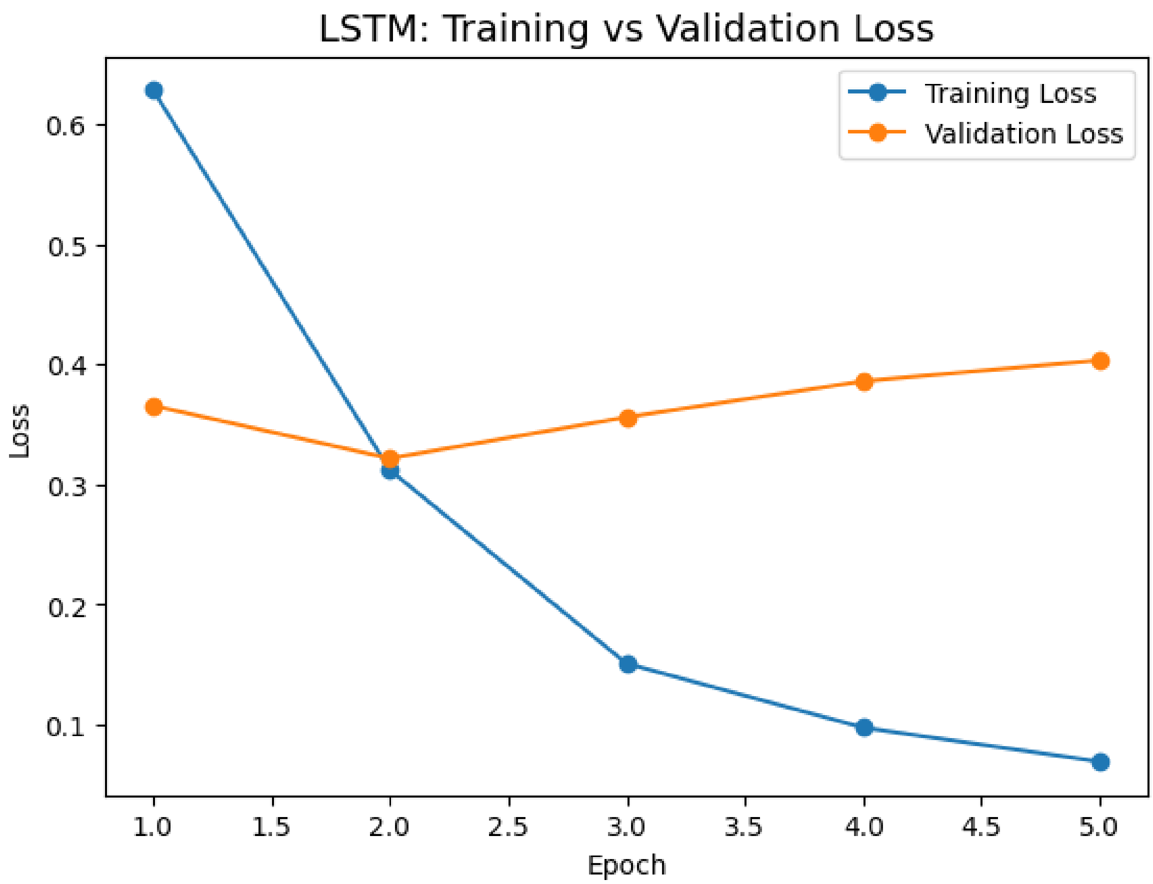

Fig 4. LSTM-Training vs Validation Loss

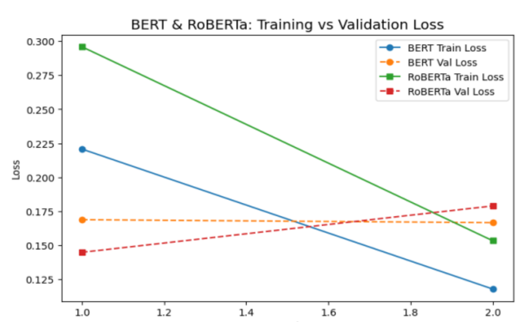

Fig 5. BERT &RoBERTa: Training vs Validation Loss

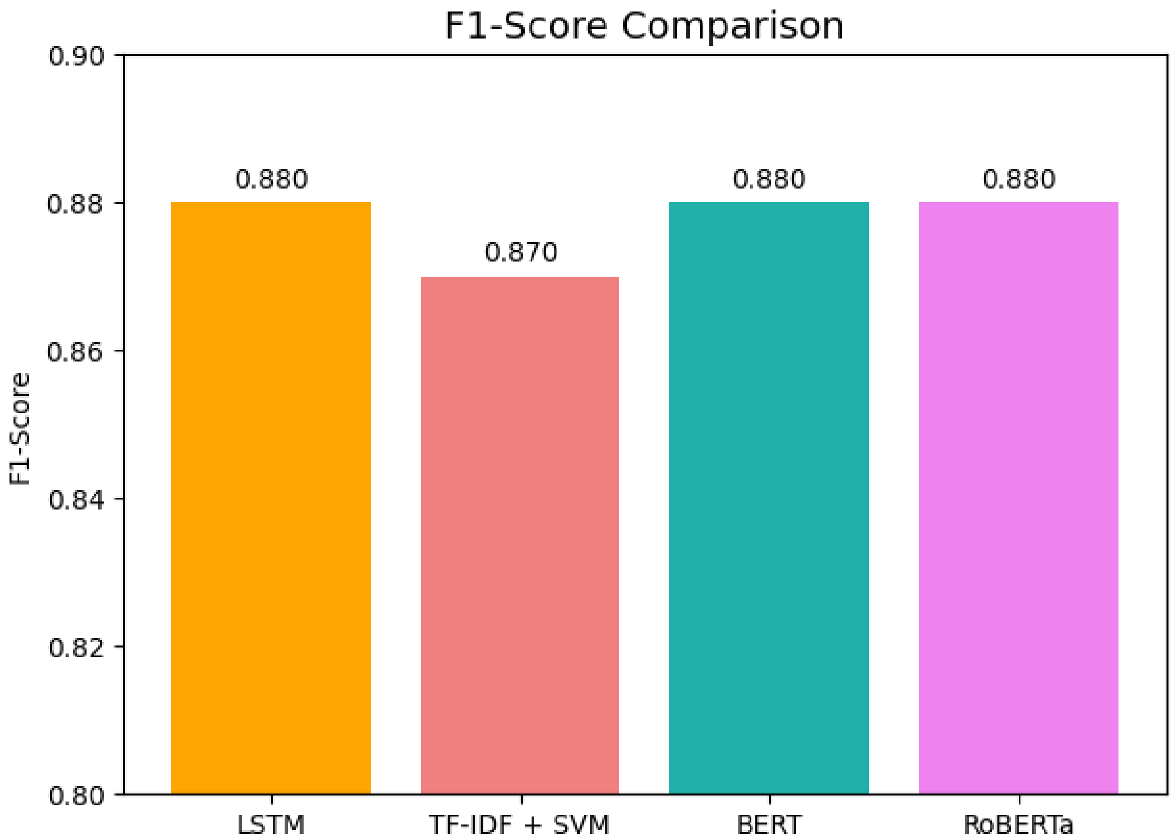

Fig 6. Comparative score of F1-score

Where, t_i denotes the i_{th} text instance and $s_i \in \{0,1\}$ represents the sentiment label.

Next, the text is converted to lowercase, and the sentiment labels are coded as numbers (Positive = 1, Negative = 0). The distribution of sentiment classes is checked to confirm balance. TF-IDF is then used to extract features by selecting the most frequent 10,000 terms and keeping 200 important features for each text entry.

The dataset is divided into two parts. Eighty percent is used for training, and twenty percent is used for testing. A fixed random value is used for consistency. An LSTM model is built in sequence. It starts with an embedding layer of size 128 using 10,000 input words. This is followed by a bidirectional LSTM layer with 64 units. A dropout layer with a rate of 0.3 is added. Another bidirectional LSTM layer with 32 units is included. A second dropout layer is applied. The final layer uses a sigmoid function for binary classification. The model is set up using the Adam optimizer with a learning rate of 0.001 and binary cross-entropy loss. Accuracy is used to measure performance. The model runs for five epochs with 32 samples at a time, and 20% of the data is used for validation. Training and validation accuracy and loss are recorded. The test data is used to check accuracy and to create a classification report and a confusion matrix. Visualization involves plotting training vs. validation accuracy and loss curves, a confusion matrix heatmap, and the sentiment distribution of the dataset. Finally, the trained model predicts the sentiment of new text samples. The results are checked using numbers and plots. These results show how well the model works for each class and overall. Table 8 shows the results for each epoch. Training accuracy increases with each epoch. Training loss decreases over time. Validation accuracy stays almost the same. Validation loss increases slightly at the end.

Test Accuracy: 0.8490

Table 9 shows that the TF-IDF + LSTM model achieves 0.85 accuracy with similar performance for both classes, meaning it performs equally well on positive and negative feedback.

Table 8. Epoch-wise Training and Validation Results

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	0.6405	0.6260	0.8630	0.3305
2	0.9449	0.1859	0.8738	0.3316
3	0.9672	0.1193	0.8630	0.3627
4	0.9755	0.0961	0.8618	0.4172
5	0.9847	0.0664	0.8522	0.4624

Table 9. TF-IDF + LSTM-Based Sentiment Classification

Class	Precision	Recall	F1-Score	Support
0	0.82	0.89	0.86	521
1	0.88	0.80	0.84	519
Accuracy			0.85	1040
Macro Avg	0.85	0.85	0.85	1040
Weighted Avg	0.85	0.85	0.85	1040

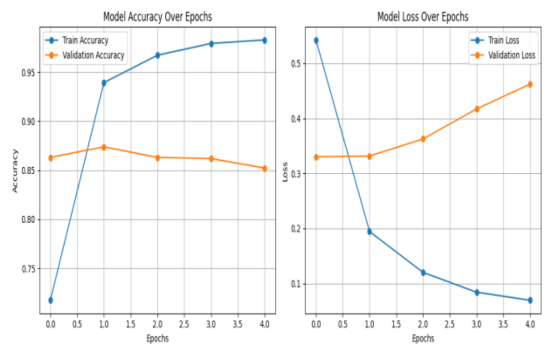

Fig 7. Model accuracy for TF-IDF + LSTM-Based Sentiment Classification

3.7 Experimental Results and Model Performance

It is seen that the LSTM model gives the highest accuracy. BERT and RoBERTa perform slightly lower but are close. The traditional TF-IDF with SVM also performs well. The hybrid TF-IDF and LSTM model does not beat the deep learning or transformer models. However, it gives stable and balanced classification results. This makes it useful for sentiment analysis when computational resources are limited.

3.8 Comparison with Previous Studies

The outcomes of this research agree with the findings of previous papers which emphasize the great effectiveness of deep learning and transformer models for sentiment analysis on various datasets [12], [13]. Most previous studies focused only on TF-IDF with SVM or on deep learning models. This paper compares conventional, deep learning and transformer-based models together. It uses the same student feedback dataset for all models. This allows a more systematic evaluation of their performance.

3.9 Hybrid TF-IDF + LSTM Model Contribution

A key contribution of this study is the hybrid TF-IDF + LSTM approach. It combines statistical feature representation with sequential learning. TF-IDF captures the importance of each term. LSTM models the order and dependencies of words in the text. This combination uses the strengths of both methods and overcomes the limits of using only one. The hybrid approach shows strong performance and provides a balanced representation of the text.

Novelty of the Study

- This study compares traditional, neural network, and transformer-based sentiment analysis methods using the same student feedback dataset.

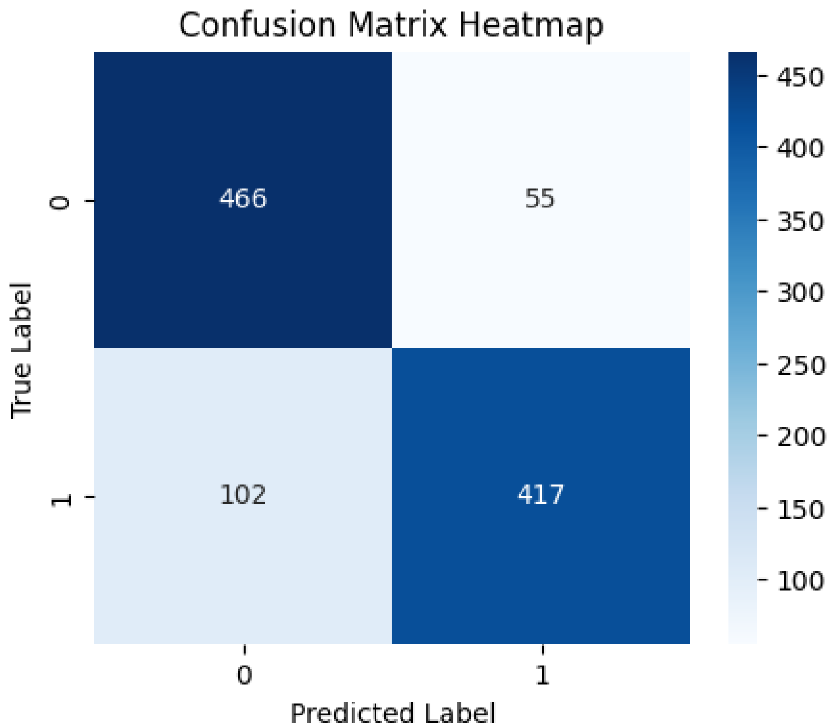

Fig 8. Confusion matrix for TF-IDF + LSTM-Based Sentiment Classification

- A hybrid model using TF-IDF and LSTM is introduced. It combines statistical feature representation with sequential learning.
- The study highlights that hybrid models can offer competitive and stable performance

Overall, the results show that hybrid and deep learning methods work well for analyzing student feedback on social networks. This study looks at different methods together. It also introduces a hybrid model. It shows the benefits of combining statistical and sequential text analysis.

4 Conclusion

This study examines different methods for sentiment analysis of student feedback from social networks. Traditional machine learning, using TF-IDF with SVM are working consistently well. Deep learning models, especially LSTM, did better by capturing the order and meaning of words.

Transformer models like BERT and RoBERTa gave the highest accuracy, about 88%, and understood user sentiments well. The hybrid TF-IDF and LSTM model was not the most accurate but gave steady results with less computing power. This shows hybrid methods can be useful when speed and simplicity matter.

To give a clear overview of the performance of different sentiment analysis approaches, a summary comparison of the models is shown in Table 10. It presents the performance levels of traditional machine learning, hybrid, and transformer-based models used in this study.

Table 10. Comparative outcome of different models studied

Model Type	Performance Level
Traditional Machine Learning (TF-IDF + SVM)	Moderate
Hybrid Model (TF-IDF + LSTM)	Balanced and Stable
Transformer Models (BERT, RoBERTa)	Highest

For future research, the following directions can improve accuracy and usefulness.

- Expanding sentiment categories to include neutral, mixed, or complex emotions can give a clearer view of user behavior.
- Using images, videos, and emojis with text can capture more emotions. This helps make sentiment detection more accurate.
- Transformer models can be trained for specific topics or fields. This helps them understand special terms or context better. It can improve prediction accuracy.
- Monitoring sentiment in real time on different social platforms can show trends and detect new topics or issues early.
- Combining sentiment analysis with social network analysis can reveal how users influence each other and share information.

Using these strategies, future studies can detect sentiment more accurately. Future studies can also better understand online behavior. This can give useful insights for businesses, policymakers, and researchers working with social network users.

References

1) Chakraborty T. Social Network Analysis. Wiley. 2021. Available from: https://www.wileyindia.com/social-network-analysis.html.
2) Srivastav MK, Gupta S, Som S. Sentiment analysis of student engagement on social networks. *GRENZE International Journal of Engineering and Technology*. 2025;11(1):2153–2160. Grenze ID: 01.GIJET.11.1.63.
3) Lalrinawma, Nunsanga MVL. Sentiment analysis review: methods and challenges. Silchar, India. 2025. 10.1109/ISACC65211.2025.10969235.
4) Alabdulkarim NA, Haq MA, Gyani J. Exploring Sentiment Analysis on Social Media Texts. *Engineering, Technology & Applied Science Research*. 2024;14(3):14442–14450. 10.48084/etasr.7238.
5) Kharde VA, Sonawane SS. Sentiment Analysis of Twitter Data: A Survey of Techniques. *International Journal of Computer Applications*. 2016;139(11):5–15. 10.5120/ijca2016908625.
6) Dervenis C, Kanakis G, Fitsilis P. Sentiment analysis of student feedback: A comparative study employing lexicon and machine learning techniques. *Studies in Educational Evaluation*. 2024;83:101406. 10.1016/j.stueduc.2024.101406.
7) Rujan. Sentimental Analysis on Student Feedback. *Kaggle*. 2025. Available from: https://www.kaggle.com/datasets/chandusrujan/sentimental-analysis-on-student-feedback.
8) Adelakun NO, Lasisi MA. Deep Learning-Based Sentiment Analysis Using Gated Recurrent Unit. *Andalasian International Journal of Applied Science, Engineering and Technology*. 2025;5(1):27–38. 10.25077/aijaset.v5i1.217.
9) Atandoh P, Zhang F, Al-Antari MA, Addo D, Gu YH. Scalable deep learning framework for sentiment analysis prediction for online movie reviews. *Heliyon*. 2024;10(10):e30756. 10.1016/j.heliyon.2024.e30756.
10) Shaik T, Tao X, Dann C, Xie H, Li Y, Galligan L. Sentiment analysis and opinion mining on educational data: A survey. *Natural Language Processing Journal*. 2023;2:100003. 10.1016/j.nlp.2022.100003.
11) Dhole M, Sahu N. Sentiment analysis of social media using machine learning approach. *International Journal of Creative Research Thoughts*. 2023;11(4). Available from: https://ijcrt.org/papers/IJCRT2304852.pdf.
12) Octava MQH, Putri DGP, Hilmy FM, Farooq U, Nurhaliza RA, Alfian G. Web-based Sentiment Analysis System Using SVM and TF-IDF with Statistical Feature. *2023 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)*. 2023;p. 9–14. 10.1109/3ICT60104.2023.10391734.
13) Lu J. Text vectorization in sentiment analysis: A comparative study of TF-IDF and Word2Vec from Amazon Fine Food Reviews. *ITM Web of Conferences*. 2025;70:03001. 10.1051/itmconf/20257003001.