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Integrating LSTM with Generative AI for Feedback Management

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Abstract

Institutions are becoming more aware of the importance of student input in improving learning experiences in the current educational environment. However, the intricate and complex patterns found in this feedback are frequently missed by conventional techniques like manual reviews and simple statistics. Our proposal suggests a novel method for analyzing student input and more accurately predicting sentiment by utilizing long short-term memory (LSTM) algorithms. We can learn more about student experiences and patterns because of LSTM's proficiency with sequential data. By transforming feedback analysis into a thorough, data-driven assessment tool, this novel approach seeks to enhance teaching methods. Furthermore, we use a generative pre-trained transformer (GPT) model to offer dynamic, customized recommendations for students' development. Our technology analyzes comments and provides practical recommendations by merging cutting-edge machine learning algorithms, creating a more encouraging and productive learning environment. This all-encompassing strategy seeks to improve institutional procedures as well as student outcomes

Keywords: Feedback analysis, sentiment analysis, LSTM algorithm, GPT model 1.0, customized recommendations

INTRODUCTION

Many educational institutions, including colleges and universities, rely on student feedback to enhance the overall quality of their education system, improve their curriculum, and foster student growth. With the rapid advancement of machine learning technologies, supervised learning algorithms have emerged as key players in the fields of sentiment analysis and opinion mining [1]. Algorithms such as the Naive Bayes Classifier and Support Vector Machine (SVM) Classifier have proven to be effective tools in predicting and analyzing the sentiments behind student feedback [2]. These techniques have opened new avenues for understanding and utilizing feedback data more comprehensively.

Traditionally, feedback systems have focused primarily on closed-ended questions, often neglecting the potential value of open-ended responses. While open-ended feedback provides unique and detailed insights into the opinions of students, traditional methods of analysis fail to fully utilize this rich qualitative data. This limitation has rendered much of this feedback underutilized, leading to a gap in the actionable information available to institutions. However, with the advent of modern machine learning algorithms and models, this gap can now be effectively addressed [3].

The supervised learning algorithms designed for sentiment analysis are increasingly being used to uncover valuable insights in areas where feedback

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is critical. For example, they have shown a significant impact in fields such as library systems, where understanding student sentiments can help improve services and address deficiencies.

Our study employs the long short-term memory (LSTM) algorithm to process the context and sentiment behind qualitative feedback more accurately and comprehensively. LSTM is known for its ability to handle sequential and time-dependent data; it is particularly well-suited for analyzing open-ended responses. Furthermore, our study goes beyond sentiment analysis by dynamically generating actionable suggestions based on feedback and its associated sentiment. This approach aims to provide institutions with meaningful and implementable insights, enabling them to make informed decisions.

LITERATURE REVIEW

The study by Shaik *et al.* investigated the analysis of qualitative student responses from open-ended surveys using machine learning (ML). Sorting feedback into great, good, and terrible sentiments was the main objective. 280 feedback examples from Level 100 students at the University of Education in Winneba, Ghana, were gathered for the study using Google Forms. Missing values were eliminated during data preprocessing, and 232 examples were used to build the model. Four algorithms were used: support vector machine (SVM), Random Forest, J48 Decision Tree, and Naive Bayes. Using 10-fold cross-validation, the SVM algorithm had the best accuracy of 63.79%. 92% of fresh test data were correctly predicted by the SVM model after training. This demonstrated how well SVM can categorize student input. The study demonstrated how sentiment analysis can improve instruction and learning and serves as a foundation for SMART campus designs [4].

Another study looked at analyzing student comments to predict teacher performance using machine learning (ML) and opinion mining. Predictive models such as Naive Bayes, KNN, and SVM were trained using pre-processed student feedback data. Based on teaching and learning criteria, the system employed AI and human language processing techniques to ascertain the polarity and mood of student feedback. Students were also able to submit criticism using the system, which officials could see. The study indicated that the Naive Bayes Classifier outperformed other algorithms, including SVM, Naive Bayes, and KNN. The solution solved the drawbacks of manual analysis systems, which are inaccurate and time-consuming. Clustering [5] and the addition of new parameters to improve model accuracy were future improvements [6].

This study used sentiment analysis of student feedback on library facilities, using natural language processing (NLP) and machine learning. The study aimed to classify student feedback as positive, negative, or neutral to gauge satisfaction with library resources. Data was collected from a North Indian institution, focusing on library facilities, including books, audio/video CDs, staff services, and computers. The study uses text-based classification methods with Naive Bayes Multinomial and support vector machine algorithms. Preprocessing techniques such as tokenization, lemmatization, and stemming were applied. TF-IDF was used for feature extraction. According to the findings, 13% of the comments were neutral, 17% were negative, and 70% were positive. SVM obtained 88% accuracy for positive prediction, compared to 92% for the Naive Bayes algorithm. Libraries should improve their resources, particularly e-materials, according to the report. Sentiment analysis aids organizations in analyzing input and reaching well-informed conclusions [7].

One study examined sentiment analysis and opinion mining in the classroom, describing how student input might be interpreted using Natural Language Processing (NLP) approaches to improve teaching methods. Document, sentence, entity, and aspect-based analysis were among the various levels of analysis that were examined; the last offered the most in-depth information. Along with the application of AI techniques, including machine learning, deep learning, and transformers, sentiment annotation techniques like lexicon-based and corpus-based approaches were also studied. It was highlighted how AI can process vast amounts of feedback. Improving evaluation, decision-making, and pedagogy were among the effects on education. Future directions included education-based annotation and knowledge bases, and issues like multi-polarity, polysemous terms, negation handling, and opinion spam were explored. In order for educational institutions to make educational decisions based on student input in both online and offline education, the study underlined how important it is to combine sentiment analysis with NLP and AI [8].

The importance of sentiment analysis of consumer feedback for airline services in the cutthroat airline sector was highlighted in research. The study classified customer evaluations as neutral, negative, or positive using machine learning (ML) approaches. Random Forest performed the best when traditional machine learning techniques like Naive Bayes, Support Vector Machine (SVM), and Decision Tree (DT) were used. However, BERT, a transformer-based model pre-trained on tasks including masked language modelling and sentence prediction, was also assessed. The accuracy of the BERT model was 83%, while Random Forest‘s was 77%, outperforming the other machine learning techniques. BERT‘s bidirectional context understanding, which enables it to better understand the subtleties of customer reviews, was credited with this improved performance. A dataset of airline reviews from Kaggle was employed in the study [9].

Another study looked into the use of machine learning (ML) to identify DoS/DDoS attacks in distributed systems, like social media networks and the internet, which are becoming more and more susceptible to these kinds of attacks. The study classified network traffic as either malicious or benign using an ensemble model, which integrates many machine learning approaches. This method uses techniques such as Linear SVC, Random Forest, and Naive Bayes to train a hybrid model. A created dataset was used in the first methodology, while the NSL-KDD dataset was used in the second. The ensemble model detected DoS/DDoS assaults with 99% accuracy. The results showed that, out of the two approaches, the hybrid model offers the best accuracy. In order to generate a dataset for the study, streaming network packet traffic was captured using tools like Wireshark and the WinPcap Tool. Future research, according to the authors, will examine the application of deep learning (DL) algorithms to improve detection capabilities by identifying intricate patterns in network data [10].

METHODOLOGY

The proposed system aimed to enhance educational outcomes by analyzing student feedback and generating actionable suggestions for teachers. The system comprises several interconnected components, including a student module for feedback submission, a sentiment analysis module using an LSTM model, a suggestion generation module powered by Hugging Face Hub API, and a teacher module to review feedback and suggestions. A feedback loop ensures continuous improvement by notifying both students and teachers to provide and implement follow-up actions [11].

To prepare the dataset, student feedback was collected through Kaggle and other sources where students have submitted feedback for teachers. A dataset consisting of 3000 rows was created and used for training. Feedback comments were manually labelled as positive, neutral, or negative to create a labelled dataset for training the sentiment analysis model. The system has an eligibility check where students can provide feedback based on their academic performances, such as marks and attendance. This made it clear that students with low attendance and marks were not allowed to submit feedback.

We developed an LSTM-based model to classify feedback into three sentiment categories: positive, neutral, and negative. One kind of recurrent neural network (RNN) is the long short-term memory (LSTM) algorithm. Because LSTMs can recognize long-term connections between time steps of data, they are primarily employed for learning, processing, and classifying sequential data, which makes them appropriate for long sentence analysis. Gates in this algorithm regulate the information flow. Three gates are present:

1. *Forget gate:* The information that is no longer required is removed from this gate.

$$f_n = \sigma_g\left(W_f[h_{n-1}, x_n] + b_f\right)$$

2. *Input gate:* The useful information is added to the cell state with the help of the input gate.
   $i_n = \sigma_g(W_i \cdot [h_{n-1}, x_n] + b_i)$
3. *Output gate:* The extraction of useful information from the cell state in the form of output is given by the output gate.
   $o_t = \sigma_g(W_o \cdot [h_{n-1}, x_n] + b_o)$

Current cell state: The cell state shows the network's memory, which retains information about previous inputs. This state is updated at each step of the process, and the network relies on it to generate predictions based on the current input.

$$C_n = f_n * \left[C_{n-1} + i_n * \tilde{C}_n\right]$$

Temporary cell state: This refers to a short-lived version of the cell state that is updated during each time step. It carries information from previous time steps but can be modified or reset based on the current input and the network's internal gates (input, forget, and output gates).

$$\tilde{C}_n = \sigma_n(W_c \cdot [h_{n-1}, x_n] + b_c)$$

Hidden state: The hidden state is a vector that holds the output of the network at a particular time step. It represents the network's "current memory" and is used to make predictions or inform decisions based on the input and past information.

$$h_n = o_t * \sigma_h(C_n)$$

where,

- σ_g (sigmoid) and σ_h(tanh): Activation function,
- W_f, W_i, W_o, W_c: Linear transformation matrix, and
- $b_f,\ b_i,\ b_o,\ b_c$: Bias.

These equations were found in earlier studies [12].

The text was pre-processed through tokenization, padding, and the removal of stop words and special characters. The LSTM model utilized pre-trained word embeddings for input representation, followed by sequential layers to capture dependencies in the feedback. Metrics, including accuracy, precision, recall, and F1-score, were used to assess the model's 80% test accuracy. The dataset was divided into training (80%), validation (10%), and testing (10%) subsets.

The suggestion generation module dynamically creates prompts for the Huggin Face hub API, incorporating feedback and sentiment predictions. The API generates actionable suggestions, which are stored in the database and displayed to teachers. The suggestions are reviewed by educators to evaluate relevance and applicability, with metrics focusing on relevance and perceived usefulness. The model used for generating suggestions is GPT-NEO-2.7B.

The system's backend is built using Python's Flask framework. It includes a relational database for storing student data, feedback, sentiment predictions, and suggestions. Key database tables include students' details, which store profiles and eligibility details; feedback, which store feedback and related metadata; and suggestions, which store GPT-generated outputs, shown in Figure 1. A notification system was implemented to inform students and teachers about follow-up actions. Students are notified to resubmit feedback after suggestions are implemented, while teachers receive periodic notifications summarizing feedback and suggestions [13].

A feedback loop ensured that implemented suggestions led to measurable improvements. Teachers reviewed feedback and adjusted their teaching strategies accordingly, while students provided follow-up feedback to validate the impact of these changes.

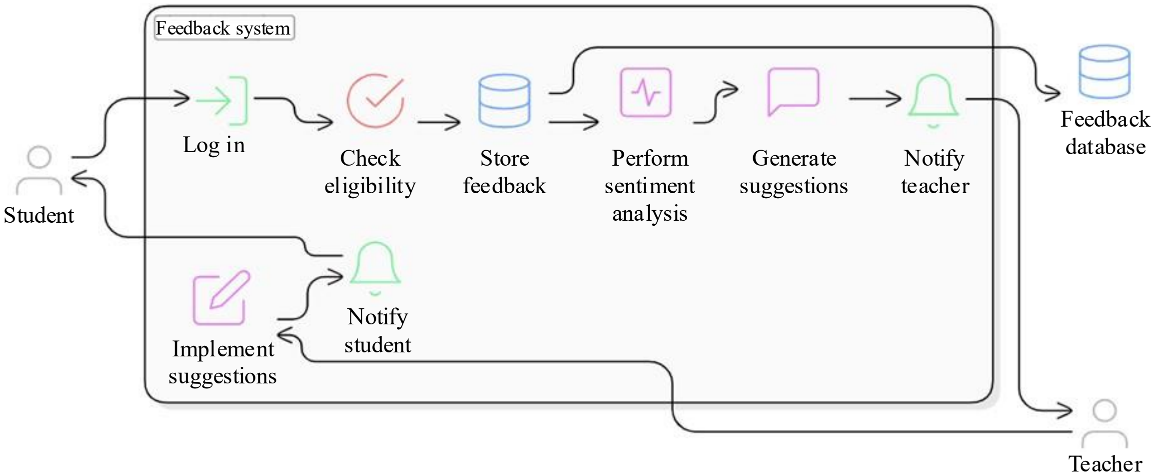

Figure 1. System architecture.

RESULTS AND DISCUSSION

Results

This student feedback system demonstrates the efficiency of combining sentiment analysis with GPT-based suggestion generation to enhance the feedback analysis. Using an LSTM model for sentiment prediction, the system achieved an overall accuracy of 83%, while the 10-k-fold accuracy was, highlighting its robustness in classifying feedback into positive, negative, and neutral sentiments shown in Figures 2 and 3. This accuracy ensured that the subsequent suggestions generated by GPT were contextually relevant and actionable. The addition of eligibility checks ensured that only authorized and relevant feedback was accepted, leading to improved quality and reducing noise in the feedback dataset.

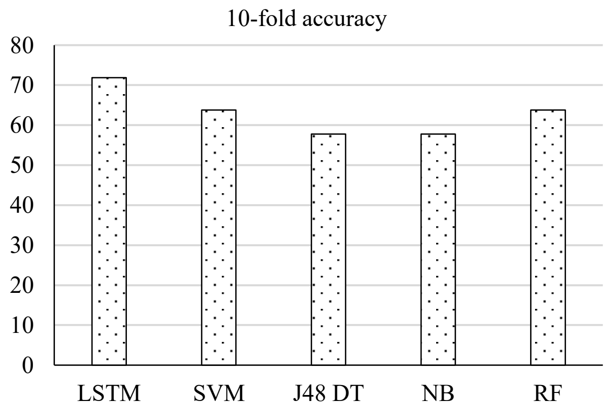

Figure 2. Accuracy of various classifiers on 10 k-folds [1].

	precision	recall	f1-score	support
0	0.78	0.87	0.82	216
1	0.86	0.77	0.81	196
2	0.84	0.81	0.82	188
accuracy			0.82	600
macro avg	0.82	0.82	0.82	600
weighted avg	0.82	0.82	0.82	600

Figure 3. Classification report for the LSTM algorithm.

DISCUSSION

The findings highlight how important it is to incorporate natural language processing and machine learning methods into student feedback systems. The use of LSTM for sentiment analysis ensured high accuracy in predicting feedback sentiment, while GPT-generated suggestions will add value by providing actionable insights to educators. The eligibility checks and notification features contribute to maintaining the integrity of feedback collection and accountability in the system. Compared to traditional manual feedback analysis methods, this system demonstrates clear advantages in terms of efficiency, automation, and scalability. The approach lays the foundation for expanding similar systems to other domains, such as employee performance reviews or customer feedback, while maintaining adaptability and reliability.

CONCLUSION

In this study, we explored sentiment analysis on qualitative textual feedback by employing the LSTM (long-short term memory) algorithm. The GPT helped in providing dynamic suggestions based on the sentiment and the feedback. The suggestions suggested by the model aim to improve the teaching content and overall student performance. The system allows only eligible students to submit feedback, ensuring the feedback is relevant and fair, with an improvement in feedback quality. The notification system will ensure transparency and fairness by consulting with teachers and students about feedback and suggestions. The system will provide automated reminders for immediate actions and regular updates.

The system provides real-time notifications, improved student engagement and data driven decision-making. The system can be expanded to analyze multilingual feedback, collecting from various stakeholders including parents and alumni, which can further increase its inclusivity and impact. The system can also find application in employee feedback system to gather feedback on workplace culture, leadership and policies as well as for customer feedback in various businesses, showing its potential in various fields.

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