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# Emotion Recognition for Short Text in AI-Assisted Vocational Education Teaching Process

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Abstract. *The development of artificial intelligence assisted emotion identification technology offers fresh opportunities for enhancing vocational education instructional approaches and learning environments. With an emphasis on analysing how to identify students's emotional states using natural language processing (NLP) and long short-term memory networks (LSTM), this paper investigates the application of AI assisted short text emotion detection technology in vocational education. Teachers can get real-time understanding of students' learning situation and emotional requirements using sentiment analysis on brief texts created by students on online learning environments, including comments and feedback. This real-time feedback system helps teachers improve their techniques and provide customised direction while also increasing student involvement and interaction. Research shows that in vocational education, the ability for emotional awareness has great importance since it helps to maximise the teaching process, enhances the learning opportunities, and supports professional growth of the students.*
**Keywords:** vocational education; emotion recognition; NLP; LSTM

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1. **Introduction.** As information technology develops quickly, vocational education is changing towards a more digital and intelligent form. Using online learning tools not only gives students more freedom in their education but also gives teachers comprehensive information on student performance and instructional results. This data-driven educational strategy creates chances for tailored assistance, individualised training, and continuous improvement of teaching efficacy. But in this data-centric world, properly evaluating and using the data produced by students—especially their emotional states—has become a crucial problem in improving the quality of instruction and the general learning process.

Through face-to-face interactions and the study of nonverbal signals like facial expressions and body language, teachers in conventional classroom environments can evaluate students' emotional responses and learning development. By use of this emotional feedback, teachers can modify their pace, topic, and teaching strategies such that they better meet the needs of their students. In an online learning environment, however, teachers find it challenging to naturally record students' emotional comments without direct engagement. This lack of emotional data could hinder prompt identification and resolution of pupils' learning difficulties, therefore compromising their academic achievement. Finding efficient means to gather and evaluate students' emotional information in the online learning environment of vocational education has thus become a critical issue.

AI technology—especially in NLP and deep learning—have lately offered encouraging answers to this problem [1, 2]. For teachers, emotion identification technology—which can automatically detect emotional states by examining student-generated text data including discussion postings and comments—offers insightful analysis. Knowing students' emotional states improves online education systems in using tailored recommendations, intelligent tutoring, and adaptive training as well as in monitoring student involvement and emotional changes by means of feedback.

This paper intends to investigate the use of artificial intelligence-assisted emotional recognition in vocational education, more especially by means of an analysis of emotional data included in student short essays. Vocational education aims to develop students' professional abilities and vocational skills, so its teaching strategies and materials are more specialised and practice-oriented than in conventional education. Therefore, in vocational education especially knowledge of students' emotional states and learning experiences is of great relevance. While negative emotions such as irritation or worry can impede learning and may even drive pupils to withdraw from the learning process, positive emotional states can boost motivation and result in improved learning results [3, 4].

This work focusses on the detection of emotions in students' brief texts, including discussion posts and assignment feedback, using NLP techniques together with LSTM models. Sentiment analysis is a fundamental task in natural language processing that uses semantic interpretation to automatically ascertain the emotional tone (e.g., positive, negative, neutral) inside a document. Using LSTM models—a kind of RNNs—the work seeks to increase the accuracy of emotion recognition and capture contextual connections inside brief sentences. Sentiment analysis of both long and short texts is appropriate for LSTM models, especially made to solve the problem of vanishing gradients in conventional RNNs processing long sequences.

In this work, we build an emotion classification model by aggregating and annotating brief text data produced in online learning environments by graduates of vocational school. The model uses LSTM to classify emotional states and word-vector-based NLP methods for text preparation. We show the accuracy and efficacy of the model in emotional detection tasks by means of experimental evaluation, therefore investigating its pragmatic uses in learning environments.

Moreover, the application of emotion recognition technology not only helps teachers in monitoring students' learning progress in real time but also performs a fundamental part in teaching management and learning analytics. Online platforms might, for example, change the difficulty level of course materials depending on students' emotional states, offer customised learning tools, or send early warnings about possible learning challenges. Emotion identification also helps teachers to identify emotional stress pupils could go through in particular areas, thereby enabling more focused direction and support.

1.1. **Related work.** The fast digital revolution of vocational education in recent years has attracted more academics' attention on the application of emotion recognition technology inside AI-assisted learning. Integration of artificial intelligence to improve students' learning experiences and maximise teaching methodologies has been a major study focus in vocational education as online learning platforms and digital educational materials become more common. By analysing their emotional states, emotional recognition technology helps teachers to acquire better understanding of their demands, therefore improving the relevance and efficiency of teaching strategies. The pertinent literature on artificial intelligence technology in vocational education in recent years and emotional recognition will be reviewed in the following text together with their motivation for the research in this article.

Shaik et al. [5] systematically examined the use of sentiment analysis in educational data mining, stressing the important part sentiment recognition performs in improving learning results and teaching quality. They pointed out that teachers can quickly modify their approaches to better fit individual student needs by tracking students' emotional states over the course of instruction. This study is a valuable source for this paper since it emphasises the crucial part of emotional recognition technology in improving the data mining-based teaching efficacy in vocational education. Examining the use of deep learning methods in sentiment analysis, Ain et al. [6] focused especially on their efficiency in learning environments. Examining numerous popular deep learning models—including CNN, RNN, and their variations LSTM networks—they discussed the strengths of these models across many educational settings. This offers a theoretical framework for the investigation in this paper, particularly the possible use of deep learning models in short text sentiment analysis, which directly supports the research design of applying LSTM models for sentiment detection in occupational education environments. Fu et al. [7] carried out an extensive investigation on the use of deep learning technology in sentiment analysis, focusing on the evolution of sentiment recognition technology and its prospects in the field of education. Their research explores the prospects of sentiment analysis using multiple data types methods, including sentiment analysis of multiple data sources such as audio, text, and video. This inspires the research in this article not to be limited to a single text data, but to provide exploration directions for multimodal emotion recognition for future work. In online learning environments, Dalipi et al. [8] conducted a systematic review to explore how to use emotional data to improve learning experiences and teaching strategies. This study particularly emphasizes the role of real-time analysis and feedback of emotional data in enhancing students' learning motivation. This provides important inspiration for this article, that is, in the online learning environment of vocational education, real-time feedback through emotion recognition technology can significantly improve teachers' understanding of students' emotional states and dynamically adjust teaching strategies.

Ezaldeen et al. [9] focused on user evaluation sentiment analysis in online learning, exploring how educators can use this data to optimize course design. Their research results show that teachers can get timely comments on course content and instructional strategies by means of emotional analysis of student assessments. To improve curriculum design and raise teaching efficacy, this paper proposes using emotion recognition technology to the emotional analysis of student feedback in vocational education. Emphasising the success of several sentiment identification techniques, Grimalt lvaro et al. [10] conducted a thorough assessment of the application of sentiment analysis in the field of education. They underlined by comparing several sentiment analysis methods that choosing the suitable model is crucial for precisely understanding students' demands. This offers technical reference for the study in this paper, which drives the acceptance of the emotion recognition model best appropriate for vocational education environments, therefore enhancing the teaching efficiency. Using machine learning techniques, Osmanoğlu et al. [11] investigated how sentiment analysis of instructional materials might assist teachers in choosing their tools. Their research results show that sentiment analysis can be used for teaching material screening and optimisation as well as for student comments. This inspires the research idea of this article, that is, emotion recognition technology can assist teachers in selecting appropriate teaching materials in vocational education to further improve students' learning experience. Imani and Montazer [12] reviewed emotion detection technology in online education, analyzed the effectiveness of current methods, and pointed out possible directions for future development. They are particularly concerned about the limitations of current emotion recognition technology, such as insufficient accuracy or inability to capture complex emotions. This study prompts this article to consider how to optimize existing emotion recognition technologies to better adapt to complex situations in vocational education. Dang et al. [13] introduced a hybrid deep learning model to analyze emotions in educational text data, demonstrating that the model effectively captures students' emotional shifts. Their research provides technical references for this article, especially in the model design of short text emotion recognition, which provides inspiration for this study. Shen et al. [14] explored sentiment analysis in online learning platforms through case studies and pointed out that sentiment analysis can significantly improve students' learning experience. This study further indicates that emotion recognition technology can not only be used for emotional feedback, but also for predicting students' learning behavior. This enlightens the research in this article that the application of sentiment analysis technology in vocational education is not only to identify emotions, but also to predict students' learning progress through sentiment data, thereby providing more personalized teaching support.

In summary, these related works provide various inspirations for the research in this article, especially in the process of AI assisted vocational education teaching, how to use emotion recognition methods to boost instructional effectiveness and student learning experience, which provides important references. This study is not only based on existing emotion recognition theories and models, but also combined with the practical needs of vocational education, aiming to optimize the teaching process and enhance students' career development abilities through emotion recognition technology.

### 1.2. **Contribution.**

(1) Developed a short text emotion recognition model: Based on the LSTM network, this paper performs emotion recognition on short texts (such as discussion comments and feedback) in vocational education teaching, providing teachers with an effective tool to help them understand students' emotional states and learning needs in real time.

(2) Improved personalized teaching support: This article demonstrates that through sentiment analysis, instructors can modify their teaching approaches according to students' emotional responses, provide more personalized tutoring and support, thereby enhancing students' learning experience and classroom participation.

(3) Improved Real-Time Feedback Mechanism in the Teaching Process: Emotion recognition technology enables educators to promptly detect fluctuations in students' emotional states during learning. This capability fosters increased interaction and communication between teachers and students, ultimately enhancing teaching effectiveness.

(4) Provision of Practical Foundation and Empirical Support: This article empirically evaluates the efficacy of short text emotion recognition technology in vocational education through experimental studies, demonstrating its practical value in optimizing teaching management and enhancing student learning outcomes.

## 2. **Theoretical analysis.**

**2.1. Natural language processing.** NLP is a significant area within artificial intelligence focused on the analysis, understanding, and generation of natural language using computational methods. It integrates concepts from linguistics, computer science, and statistics to process and analyze substantial volumes of textual data. In vocational education, NLP technologies serve as valuable tools for analyzing student feedback, identifying emotional states, and performing various related tasks [15, 16]. Below are key theories and mathematical frameworks associated with NLP.

1) **Text Representation: Bag of Words (BoW) Model:**
The Bag of Words model is a foundational approach to text representation that disregards the order of words while focusing solely on their frequency of occurrence. For a given document $d$, it can be represented as a vector $v_d$ where each dimension corresponds to a unique word in the vocabulary, and the value indicates the frequency of that word within the document:
$$v_d = [f_1, f_2, \ldots, f_n] \tag{1}$$
where $f_i$ indicates how often the $i$-th word appears in document $d$, and $n$ is the size of the vocabulary.
2) **TF-IDF (Term Frequency-Inverse Document Frequency):**
Advanced word representation method TF-IDF considers not only word frequency but also word relevance in relation to the whole document corpus. This approach uses IDF to reduce the weight of often occurring words across the corpus whereas TF counts the frequency of a word inside a given document [17]. TF can be calculated with this equation:
$$TF(t, d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} \tag{2}$$
where $f_{t,d}$ indicates the frequency of word $t$ in document $d$, with the denominator representing the total occurrences of all words in the document. The calculation equation for IDF is:
$$IDF(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|} \tag{3}$$
where $N$ represents the total count of documents in the document set $D$, while the denominator indicates how many documents include the word $t$. The final TF-IDF representation is:
$$TF - IDF(t, d, D) = TF(t, d) \times IDF(t, D) \tag{4}$$
TF-IDF can better identify words with significant meaning in documents.
3) **Word Embedding:**
In deep learning, word embedding is a frequently used method for word representation that maps words into a low-dimensional continuous vector space while preserving their semantic links. Popular methods for word embedding include Word2Vec and GloVe. Each word $w$ in the vocabulary is represented as a $d$-dimensional vector $v_w$:
$$v_w \in R^d \tag{5}$$
These vectors are generated through training, with the objective of positioning semantically similar words closer together in the vector space. Popular training techniques include the Skip Gram and CBOW (Continuous Bag of Words) models. The primary aim of the Skip Gram model is to predict the context surrounding a specific word. The loss function is:
$$L = -\sum_{(w,c) \in D} \log P(c|w) \tag{6}$$
where $P(c|w)$ is the probability of predicting the contextual word $c$ through the central word $w$, and $D$ is all word pairs in the document set.

4) **Sequence models: RNN and LSTM:**
In natural language processing tasks, text can be viewed as a sequence of data. RNNs and LSTMs are commonly used models for processing sequential data. They capture the relevant information before and after in the sequence through the cyclic structure of hidden layers. The basic equation of RNN is as follows:

$$h_t = \sigma(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \tag{7}$$

where $h_t$ is the hidden state of time step $t$, $x_t$ is the input, $W_{xh}$ and $W_{hh}$ are the weight matrices input to the hidden layer and hidden layer to hidden layer, $b_h$ is the bias term, and $\sigma$ is the activation function.

5) **Text classification and sentiment analysis:**
Text classification is a crucial task in natural language processing. In sentiment analysis, texts are categorized as positive, negative, or neutral. In neural network models, the loss function for text classification is usually cross entropy loss:

$$L = -\sum_{i=1}^{N} y_i \log \hat{y}_i \tag{8}$$

where $y_i$ is the actual label, $\hat{y}_i$ is the probability distribution predicted by the model, $N$ denotes the total number of samples.

2.2. **LSTM.** Designed to solve the difficulties of gradient vanishing and exploding that are often experienced when processing long sequences of data, LSTM networks are a specialised variation of RNNs [19, 20]. Because LSTMs effectively capture long-term dependencies in sequential data, they are increasingly used in several fields including natural language processing, speech recognition, and time series forecasting. Three gating mechanisms—the forget gate, the input gate, and the output gate—link "memory cells" that form the basic unit of an LSTM. Every gate has a different purpose and together controls data storage and transfer [21].

The forget gate decides which data should be thrown away at any one instant. Indicating which knowledge is no longer relevant, it produces an output depending on the present input and the past concealed state. This method lets the LSTM avoid the accumulation of superfluous data therefore enabling it to concentrate on the most relevant facts.

The input gate controls how fresh data finds their way into the memory cell. It first determines which fresh data should be updated then creates candidate values for inclusion. Crucially for guiding later learning processes, this adaptability lets the LSTM incorporate fresh emotional states or learning feedback.

The hidden state to be generated at the current time step—which will be used as input for either final predictions or the next time step—is decided by the output gate. LSTMs efficiently translate data kept in memory cells into useable outputs by using the output gate, therefore supplying necessary data for applications including sentiment categorisation.

LSTMs' design helps them to keep performance in jobs requiring long-term dependence. Whereas LSTMs keep and update information through their memory cells and gating systems, therefore enabling the acquisition of important contextual features during the learning process, traditional RNNs generally struggle to retain information over extended periods [22]. Every memory cell in an LSTM not only stores current information but also dynamically changes depending on past data, hence improving the capacity of the model to control both long- and short-term dependencies in time series data.

LSTMs show remarkable performance in many domains, including natural language processing, audio recognition, and video analysis, thanks to their ability to manage challenging temporal data. LSTMs can quite detect emotional changes in text in sentiment analysis. LSTMs give real-time assessments of emotional states for teachers by means of analysis of comments and discussion material produced by students on learning platforms, therefore allowing them to modify their teaching plans and enhance the results of instruction. All things considered, LSTMs are a strong modelling method that overcomes the constraints of conventional RNNs by their special design and mechanisms, therefore placing them as essential instruments for processing time series data and doing sentiment analysis. Their performance on several applications emphasises how well LSTMs capture dynamic information and long-term dependencies, thereby providing efficient solutions in sectors including business, education, and healthcare.

3. **Emotion recognition model for short text.** In order to achieve AI assisted teaching in the field of vocational education, this study combines natural language processing and long short-term memory networks to identify students' short text emotional states generated on online learning platforms. Emotion analysis helps teachers understand students' emotional needs and learning status in real time by processing text in discussions, comments, and feedback, thereby adjusting teaching strategies personalized and improving teaching quality. Figure 1 illustrates the model's framework diagram:

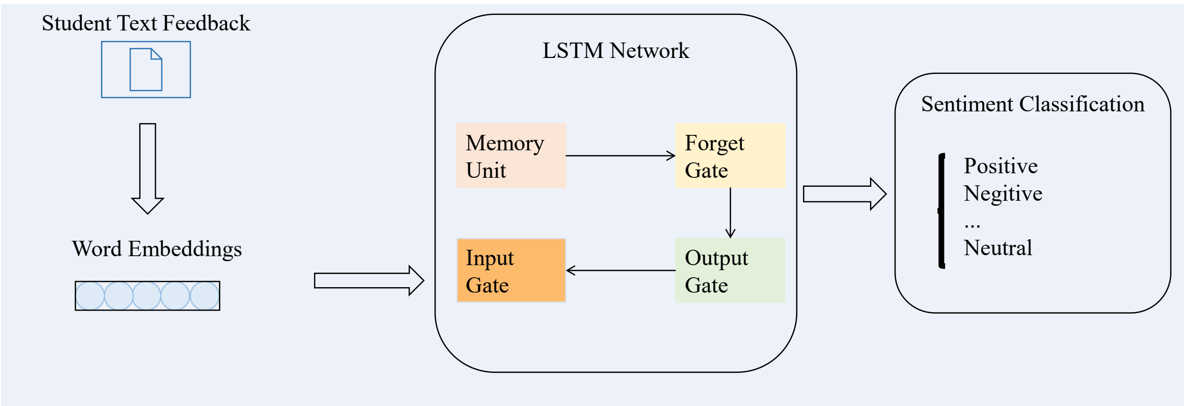


Figure 1. Model framework diagram

Firstly, data preprocessing and feature extraction are performed. In NLP tasks, the text data generated by students is preprocessed first. The preprocessing steps include:

1) Text cleaning: Remove noisy data (such as punctuation, HTML tags, extra spaces, etc.).
2) Vocabulary standardization: Convert all words in the text to lowercase, remove stop words, and perform morphological reduction or stem extraction.
3) Word embedding representation: In order to input text data into an LSTM model, the text must be converted into numerical representations. We use pre trained word embedding models (such as Word2Vec or GloVe) for representing each word as a fixed dimensional vector.

Assuming that the student's comments or feedback text on the platform is:

$$T = \{t_1, t_2, \ldots, t_n\} \tag{9}$$

where $t_i$ represents the $i$-th word, and through a pre trained word embedding model, each word $t_i$ is mapped to a word vector $x_i \in R^d$.

Therefore, students' short texts can be represented as vector sequences as inputs for LSTM:

$$X = \{x_1, x_2, \ldots, x_n\} \tag{10}$$

In the context of teaching, LSTM, through its unique gating mechanism, can capture the dynamic changes in students' emotional states throughout the entire learning process. This ability is particularly suitable for handling short text data such as feedback and discussions in vocational education. The LSTM model processes text data and extracts emotional information through the following steps:

1) **Forgotten Gate:** Used to determine whether certain information in the current learning process needs to be forgotten, especially when students' feedback contains some emotional fluctuations. The model can ignore unimportant parts and only retain key information related to emotions:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{11}$$

where $h_{t-1}$ is the hidden state of the previous time step, representing the emotional information retained by the previously processed text, $x_t$ is the current input text vector, and $W_f$ and $b_f$ are model parameters. The output produced by the forget gate $f_t$ determines which input information in the current time step needs to be retained and which needs to be discarded.

2) **Input Gate:** Used to introduce information about the emotional changes of students at the current moment. If students express new emotional states (such as dissatisfaction or satisfaction) in their feedback or discussion, LSTM will store this information in the model's memory through the input gate. The equation is:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{12}$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \tag{13}$$

where $i_t$ decides the extent of new emotional information that will be stored in the memory unit, while $\tilde{C}_t$ is the emotional information extracted by the input gate. $W_i$ and $W_C$ are weight matrices, $b_i$ and $b_C$ represent bias terms, while the hyperbolic tangent activation function is denoted as tanh.

3) **Memory unit update:** In AI assisted teaching scenarios in vocational education, students' emotional states change over time, and LSTM stores these emotional changes by updating memory units. The update equation for memory units is:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{14}$$

where $C_t$ is the current memory unit state, $C_{t-1}$ is the previous memory unit state, and the symbol $*$ represents element wise multiplication.

Through this mechanism, the model can dynamically update the state of students' memory units based on their emotional feedback, retain useful emotional information, and discard irrelevant information [23, 24].

4) **Output Gate:** The output gate decides the final judgment of LSTM on the emotional state of students at the present time step. It generates emotional output at the present time based on the state of memory units, which can be used by teachers to adjust teaching strategies [25]. The equation is:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{15}$$

$$h_t = o_t * \tanh(C_t) \tag{16}$$

where $o_t$ represents the output of the output gate, and $h_t$ denotes the hidden state at the present time. Hide state $h_t$ as the output of this time step and pass it on to the next time step.

On vocational education platforms, this step outputs the current emotional state of students. Combined with previous learning feedback, LSTM can help teachers determine whether a student's learning state is positive, negative, or neutral, and take corresponding personalized measures.

The last hidden state $h_n$ of the LSTM network (i.e., the hidden state after processing all words) is input to the dense layer for sentiment classification. The dense layer outputs a class probability distribution $y$, which is calculated using the softmax function:

$$y = \text{softmax}(W_y \cdot h_n + b_y) \tag{17}$$

where $W_y$ and $b_y$ represent the weights and biases of the fully connected layer, and $y$ is the predicted emotion category. The emotional category can be positive, neutral, or negative. By using the softmax function, the model can output the probability distribution of students' emotions, thereby helping teachers understand their specific emotional states.

In online learning platforms for vocational education, students generate a large amount of short text data through discussions, homework feedback, course evaluations, and other forms. Through the method described in this article, teachers can analyze students' emotional states in real-time, such as whether they understand the course content, whether they feel confused or anxious about the teaching content. The results of emotion recognition are transmitted to teachers through a feedback system, so that teachers can dynamically adjust course content or teaching pace. For instance, teachers can offer focused advice or rewards to help students keep a good learning attitude when the system senses that they are depressed or expressing irritation during conversations.

## 4. **Experiment.**

### 4.1. **Data set.** In this work, we performed sentiment recognition in short texts using the following datasets, namely with an eye towards student comments in online learning environments:

1. **Students' Feedback Dataset**: Comprising many courses and disciplines, this dataset consists of comments and feedback sent by students on several online learning systems. To help sentiment analysis, every piece of comments is classified as good, negative, or neutral.
2. **Online Course Review Database**: Acquired from numerous online course sites, this dataset comprises user comments and evaluations of the courses. The comments fall into several emotional groups including "satisfied," "dissatisfied," and others.
3. **Twitter Student Feedback Dataset**: Which gathers from Twitter tweets pertaining to educational experiences of students. These tweets can capture students' emotional responses towards several learning settings, courses, and instructional activities. Positive, negative, and neutral tweets are labelled.
4. **MOOC Reviews Dataset**: Which includes reviews on Massive Open Online Courses (MOOCs) covering student feedback from multiple courses. Each comment is labeled with an emotional category.
5. **Sentiment140 Dataset**: Is a large sentiment dataset for tweets, containing 160,000 annotated tweets. Although it is not specifically designed for the field of education, it can be used to train models to recognize general emotions and can be fine tuned to adapt to specific scenarios in vocational education.

### 4.2. **Experimental results and analysis.** Table 1 shows the performance results of the model on different datasets to demonstrate the generalization ability of the proposed combined NLP and LSTM model. We will conduct experiments using multiple datasets

and compare the precision, recall, and F1 score of the model on each dataset. Figure 2 is a visual representation of the experiment.

Table 1. Performance results of models on different datasets

| Data set | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|
| Students' Feedback Dataset | 0.92 | 0.89 | 0.90 |
| Online Course Reviews Dataset | 0.91 | 0.88 | 0.89 |
| Twitter Student Feedback Dataset | 0.87 | 0.85 | 0.86 |
| MOOC Reviews Dataset | 0.90 | 0.87 | 0.88 |
| Sentiment140 Dataset | 0.93 | 0.90 | 0.91 |

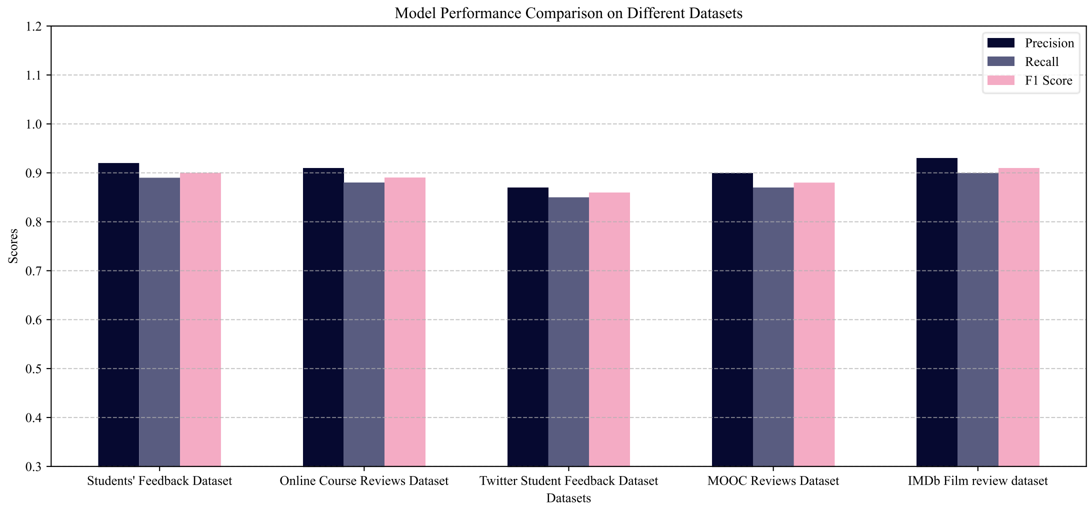


Figure 2. Experimental graphs of model performance on different datasets

With an accuracy of 0.92, a recall of 0.89, and an F1 score of 0.90 the Students' Feedback Dataset produced favourable findings. These measures imply that the model is good in spotting students' emotional states. With accuracy and recall rates of 0.90, the model also showed great performance for the Online Course Reviews Dataset, therefore stressing its dependability in evaluating online courses. With accuracy and recall levels of 0.87 and 0.85 respectively, the Twitter Student Feedback Dataset showed rather poorer performance. The heterogeneity in linguistic styles and emotional expressions found in tweets could help to explain this drop and hence challenge the recognising capacity of the model. With an F1 score of 0.88, the model kept performing well on the MOOC Reviews Dataset, therefore confirming its flexibility over a larger range of online learning environments.

At last, although the Sentiment140 Dataset is not especially suited for vocational education, the model nonetheless scored high accuracy (0.93) and recall (0.90), so indicating its general relevance in emotional recognition tasks. The above experimental findings show that the model combining NLP and LSTM has significant generalisation capacity and can keep good performance on several datasets. This suggests that the model is not just relevant to particular vocational education domains but may also be efficiently applied to tasks involving emotional detection in other allied sectors. By means of more experimentation and optimisation, the model can become more relevant in several contexts.

Table 2 and Figure 3 show the comparative experimental results of the proposed combination of NLP and LSTM network model with several other commonly used sentiment analysis models.

Table 2. Emotion analysis model comparison experiment results

| **Model** | **Precision (%)** | **Recall (%)** | **F1 Score (%)** |
|---|---|---|---|
| NLP+LSTM | 0.92 | 0.89 | 0.90 |
| Naive Bayes | 0.85 | 0.82 | 0.83 |
| SVM | 0.88 | 0.87 | 0.87 |
| RNN | 0.90 | 0.85 | 0.87 |
| CNN | 0.89 | 0.86 | 0.87 |
| BiLSTM | 0.91 | 0.88 | 0.89 |

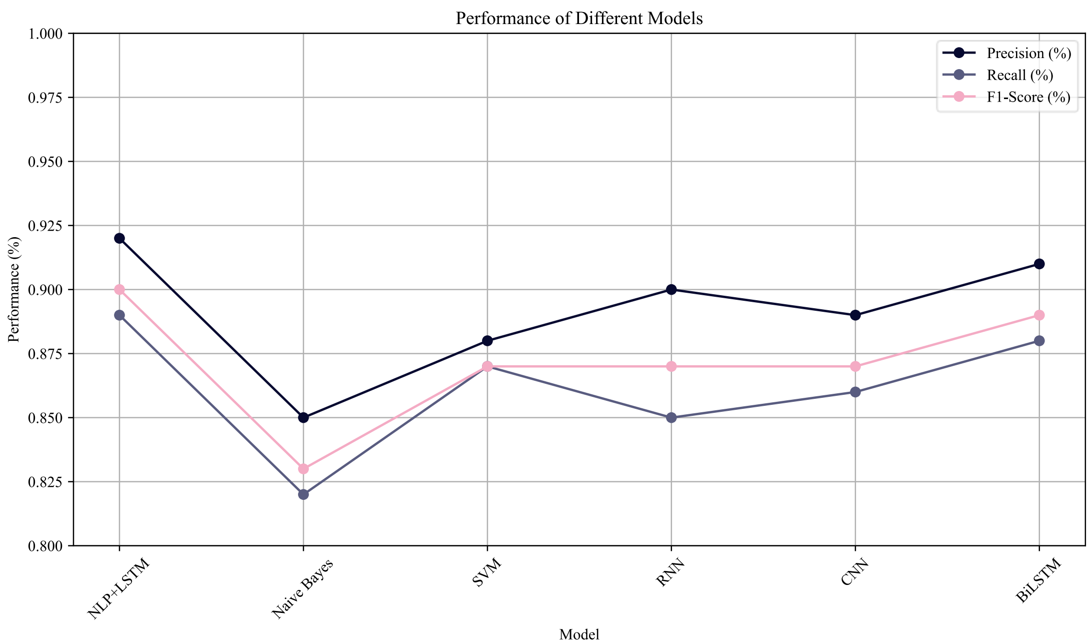


Figure 3. Comparison diagram of emotion analysis models

The model proposed in this article (NLP+LSTM) performs well in accuracy, recall, and F1 score, demonstrating its effectiveness in short text sentiment recognition. The Naive Bayes model performs relatively poorly, despite its high computational efficiency, but is limited by its assumption independence in sentiment analysis tasks. SVM performs well and is suitable for high-dimensional data, but the training time is relatively long. RNNs and CNNs have shown effectiveness in various sentiment analysis tasks; however, their capacity to manage long sequences is somewhat restricted. While the BiLSTM performs well, it remains slightly less effective than the model presented in this study. Comparative experiments indicate that the overall performance of our model surpasses that of other common models, particularly regarding accuracy and recall in capturing emotional information. These results underscore the effectiveness and advantages of integrating NLP techniques with LSTM architectures.

5. **Conclusion.** With an eye towards the use of NLP and LSTM models to evaluate students' emotional states, this paper investigates the application of AI-assisted emotion recognition technologies for short texts inside vocational education. Through the analysis of short texts created by students on online learning environments—such as comments and feedback—the study shows how teachers could get real-time understanding of students' learning statuses and emotional needs. Building an emotion detection model helps teachers to quickly modify their approaches during the learning process, therefore providing individualised direction and support that improves students' engagement and learning experiences. Based on sentiment analysis, this feedback system not only enhances teacher-student interaction but also motivates active student involvement, thereby improving the learning results.

The results of this study emphasise the great worth of emotional recognition technology for occupational training. It helps teachers to better grasp the needs of their pupils and lets them maximise their teaching materials and strategies by means of data-driven techniques. Sentiment analysis helps teachers to customise their lesson strategies based on the emotional states of every student, therefore improving the effectiveness of their education. To further enhance students' learning experiences, future studies could investigate the combination of other technologies as adaptive learning systems and recommendation systems. Furthermore, this work highlights the need of dataset diversity and model generalisation in the performance of emotion identification, thereby offering fresh directions for next research. Finally, artificial intelligence-assisted short text emotion detection technology offers fresh chances for vocational education since it shows how sophisticated technology approaches may maximise the teaching process, improve educational quality, and help students' career growth.

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