***Original Research Article***

**A Hybrid PhoBERT-CNN-LSTM Model for Sentiment Analysis of Vietnamese Student Feedback**

# ABSTRACT

Student feedback plays a crucial role in improving educational quality and creating an effective learning environment. This study applies sentiment analysis to Vietnamese student feedback to extract and classify emotions into positive, negative, and neutral categories, providing valuable insights to support teaching improvements. We propose a method that utilizes the PhoBERT model for semantic feature extraction, followed by a CNN-LSTM architecture to capture both local features and sequential relationships in feedback data. Experimental results on the UIT-VSFC dataset demonstrate that the proposed PhoBERT-based CNN-LSTM model achieves an accuracy and F1-score of up to 92.92%, surpassing several advanced methods. These findings confirm the effectiveness of the model in extracting and classifying sentiments from student feedback while proposing a practical approach for analyzing Vietnamese educational data, contributing to teaching quality enhancement.

*Keywords: Sentiment analysis, Machine learning, Deep learning, PhoBERT, Vietnamese natural language processing.*

# 1. INTRODUCTION

In student evaluation of teaching (SET), which plays a growing role in learner-centered education, gathering and analyzing student feedback has become common both on online learning platforms and at higher education institutions. The primary objective is to enhance teaching quality and refine pedagogical approaches (Giang et al, 2020). In the past, closed-ended Likert-scale questions were popular because they were easy to collect and analyze. Open-ended questions now stand out for their ability to better reflect emotions and provide more detailed information (Stupans et al, 2016). At the same time, analyzing feedback from Vietnamese students is challenging, especially when using the UIT-VSFC dataset. These challenges include slang, spelling errors, emoticons, and data imbalance, with neutral labels accounting for only approximately 4% of the dataset (Nguyen et al, 2018). Similar challenges have been documented in other studies (Kastrati et al, 2021) (Chebolu et al, 2022), including small sample sizes, the lack of publicly available datasets, and data imbalance when performing sentiment classification on user comments or feedback. Overcoming these challenges calls for models with a strong grasp of language and context. Pre-trained language models stand out in this regard, as their large-scale training enables them to effectively understand text, context, and vocabulary. Transformer-based architectures such as BERT have achieved state-of-the-art performance in various sentiment classification tasks across different domains (Devlin et al, 2018). Research by Sharma and Si highlights BERT as the leading model, surpassing LSTM and CNN. Its advantage comes from its ability to understand context, learn from large datasets, handle unfamiliar words, and accurately recognize subtle emotional expressions (Kaur and Sharma, 2023) (Si, 2025).

This research proposes a novel model for sentiment classification of feedback from Vietnamese students by integrating a custom Transformer architecture. The model classifies sentiments into three categories: positive, negative, and neutral while incorporating a semantic attention mechanism. A key contribution of this study is the evaluation and comparison of the pre-trained PhoBERT model with previous approaches, highlighting its effectiveness in enhancing sentiment classification performance.

The rest of the paper is structured as follows. Section 2 reviews key studies on sentiment polarity classification based on learner feedback. Section 3 details the datasets used in the research and describes the research methodology applied. Section 4 presents the experimental results and detailed analysis. Finally, we draw a conclusion in Section 5.

# 2. METHODOLOGY

The model development process follows a structured framework as illustrated in Figure 1. The first step involves preprocessing student feedback data, which includes handling missing values, removing punctuation, stop words, and numbers, as well as performing normalization and tokenization to prepare the data for training. After preprocessing, the sentiment analysis model is developed through sequential stages: model training, evaluation, and hyperparameter tuning to optimize performance. The model is then assessed using multiple metrics to ensure accuracy and reliability. Upon deployment, it can process user queries and classify sentiments (positive, negative, neutral), enabling educational institutions to extract valuable insights for enhancing teaching quality.

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**Figure 1: Sentiment Classification Processs**

## 2.1 Dataset

For this study, we utilized the UIT-VSFC dataset (Nguyen et al, 2018), which was published in 2018 and consists of student responses collected from end-of-term surveys at a Vietnamese university between 2013 and 2016. The dataset contains over 16,000 Vietnamese sentences. Table 1 provides sample sentences from the UIT-VSFC dataset, each labeled with different sentiment categories: positive, neutral, and negative

**Table 1.** Examples of Samples from the UIT-VSFC Dataset

|  |  |  |
| --- | --- | --- |
| **No.** | **Sentence** | **Sentiment** |
| 1 | Thầy rất tận tình và đi dạy rất đúng giờ.(The teacher is very dedicated and always punctual.) | Positive |
| 2 | Tạo ra sự cạnh tranh trong mỗi buổi thực hành.(Creates competition in each practice session.) | Neutral |
| 3 | Không có gì đặc biệt.(Nothing special.) | Neutral |
| 4 | Thời lượng môn học quá dài, sinh viên cảm thấy mệt mỏi.( The course duration is too long, students feel tired.) | Negative |

The dataset exhibits a significant class imbalance, with over 90% of the data belonging to the positive and negative sentiment labels, while the neutral label comprises only approximately 4% of the total data. Table 2 illustrates this disproportionate distribution of the dataset, including 7,440 positive sentences (46%), 8,037 negative sentences (50%), and 698 neutral sentences (4%).

**Table 2.** Sentiment statistics in UIT-VSFC

|  |  |
| --- | --- |
| **Sentiment Type** | **Number of Sentences** |
| Positive | 7,440 |
| Negative | 8,037 |
| Neutral | 698 |
| Total | 16,175 |

To ensure rigorous training and objective evaluation of the model, the dataset is systematically divided into three subsets: Train set, Test set, and Validation set, with the detailed distribution presented in Table 3. This proportional partitioning not only provides a sufficiently large dataset for effective model learning but also establishes independent evaluation sets, ensuring unbiased performance assessment.

**Table 3.** Sentiment distribution statistics of UIT-VSFC Dataset

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dataset** | **Total reviews** | **Positive** | **Neutral** | **Negative** |
| **Train** | 11,426 | 5,643 | 458 | 5,325 |
| **Validation** | 1,583 | 705 | 73 | 805 |
| **Test** | 3,166 | 1,589 | 167 | 1,410 |

To classify the sentiment of learner responses, the raw data must pass through a structured processing pipeline. This pipeline consists of two primary stages: data cleaning and data preprocessing, as depicted in Figure 2. During the data cleaning phase, punctuation removal standardizes the text, Unicode normalization ensures character consistency, and abbreviation handling reduces noise, enhancing model performance. The preprocessing stage further refines the data through word segmentation for accurate sentence structure recognition, lowercase conversion to improve uniformity, and stopword removal to filter out low-value terms. This comprehensive data processing workflow ensures consistency in input data while emphasizing the most relevant information for analysis.



**Figure 2: Data Preprocessing Steps in Sentiment Classification**

## 2.2 Feature extraction

In our study utilizing machine learning techniques, we experimented with various text classification models, incorporating features such as TF-IDF, bi-grams, and Word2Vec. The TF-IDF (Term Frequency-Inverse Document Frequency) method quantifies the importance of individual words within a given response by balancing their frequency in a specific document against their rarity across the entire dataset (Sparck Jones, 1972). This approach effectively highlights key terms with strong discriminative power.

N-grams, a probabilistic model, predict the likelihood of a word appearing based on the preceding N-1 words. By analyzing the frequency of consecutive word sequences within the corpus, N-grams capture linguistic patterns and sequential dependencies.

In contrast, Word2Vec, a deep learning-based technique, generates word embeddings by mapping words into a multi-dimensional vector space. This method places words with similar contextual and semantic properties in close proximity within the vector space, allowing the model to identify semantic relationships and significantly improve performance in natural language processing tasks (Mikolov et al, 2013).

## 2.3 Deep learning method based on Transformer architecture

Our proposed model integrates Word2Vec for word representation, LSTM for capturing long-term contextual dependencies, CNN for extracting local features, and Multi-Head Attention to enhance focus capabilities, thereby optimizing performance in natural language processing tasks.).

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**Figure 3:** **The CNN-LSTM architecture combined with Attention.**

The Multi-Head Attention mechanism, a pivotal component of our model, also serves as the foundation of the Transformer architecture, as introduced in the seminal paper "Attention Is All You Need" (Vaswani et al, 2017). As depicted in Figure 3, within the feature extraction phase, the input sequence, with a maximum length of 130 tokens, is preprocessed and passed through Word2Vec to derive sentence-level features, resulting in a 300-dimensional word vector. These vectors form an embedding matrix with dimensions of (130 × 300). The initial two layers of the encoder region consist of 1D convolutional layers. Different channels are convolved independently using the same kernel, with a kernel size of 3. The resulting local features are then normalized using LayerNormalization, subjected to nonlinear activation via ReLU, and mitigated for overfitting through a Dropout layer. To leverage sequential information from the data, the model employs two bidirectional LSTM (Bi-LSTM) layers with MaxPool1D and LayerNormalization, enabling the extraction of bidirectional features while preserving long-term dependencies. Following processing through the Bi-LSTM layers, the output consists of a sequence of context vectors corresponding to each time step. Rather than uniformly utilizing all these vectors, the Multi-Head Attention mechanism allows the model to selectively focus on and learn from the most salient information within the sequence.

The input to Multi-Head Attention consists of three matrices: Q (query), K (key), and V (value). These matrices are projected into lower-dimensional spaces through the learnable weight matrices $W\_{i}^{Q}$, $W\_{i}^{K}$, $W\_{i}^{V}$corresponding to each attention head. For each attention head, the attention mechanism is computed as follows:

$$head\_{i}=Attention\left(QW\_{i}^{Q},KW\_{i}^{K},VW\_{i}^{V}\right)$$

Where the attention function is defined as:

$$Attention\_{i}\left(Q,K,V\right)=Softmax\left(\frac{QW\_{i}^{Q}\left(KW\_{i}^{K}\right)^{T}}{\sqrt{d\_{k}}}\right)VW\_{i}^{V}$$

After that, the outputs from all heads are combined and projected through a weight matrix W0

$$Z=Concat\left(head\_{1},head\_{2},…,head\_{h}\right)W^{O}$$

The features obtained from the convolutional branch and the attention layer are processed through *GlobalMaxPooling1D*, then concatenated and normalized using *LayerNormalization*. Next, the data is passed through a series of Dense layers with 256, 128, and 64 units, respectively, using the ReLU activation function. Finally, the output layer consists of 3 units and applies the softmax function for classification. The model is trained with a learning rate of 1e-4, a batch size of 32, and the loss function used is categorical cross-entropy.

## 2.4 Fine-Tuning the pretrained model for sentiment classification

The proposed model is based on the Transformer architecture, specifically fine-tuned PhoBERT for sentiment classification. It combines the encoder of PhoBERT, with hidden sizes of 768. The encoder block (PhoBERT) handles deep semantic encoding, while the CNN-LSTM focuses on capturing sequential context and extracting local features. The CNN block consists of a 1D convolutional layer (256 channels, kernel size 3), followed by LayerNorm and GELU activation. The BiLSTM block, with 128 hidden units in each direction, processes bidirectional information in the data sequence. In the decoder block, a Fully Connected layer with 256 units is used, and the output consists of 3 units, corresponding to the predicted labels. GELU is applied as the activation function after the Fully Connected layer. The architecture of the proposed model is shown in Figure 4.



**Figure 4: The architecture of the PhoBERT + CNN-LSTM model**

During the fine-tuning process, the warm-up technique is used to minimize instability and convergence issues (Kalra and Barkeshli, 2024). The experiments on the PhoBERT models were conducted using the AdamW optimizer with warm-up. Both the PhoBERT + feed-forward model and the PhoBERT with CNN-LSTM model were configured with a learning rate of 2e-5, a batch size of 64, with the loss function being cross-entropy.

# 3. RESULT AND DISCUSSION

## 3.1 Result analysis

The experimental results indicate that Transformer-based models, particularly PhoBERT, outperform traditional machine learning methods and certain deep learning approaches. Among them, PhoBERT-v2 (Base) + CNN-LSTM achieved the highest performance with an F1-score of 92.92%. The LSTM-CNN model with an Attention mechanism achieved an F1-score of 90.63% on the original dataset, demonstrating its effectiveness in feature extraction for text classification. Among traditional machine learning models, Linear SVM achieved the highest accuracy of 88.91%, while Logistic Regression and XGBoost delivered a comparable performance with an accuracy of 88.31%. The experiments were conducted on the UIT-VSFC dataset, with detailed results presented in Table 4.

**Table 4. Evaluation of Machine Learning and Deep Learning Models for Sentiment Analysis (%).**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Accuracy** | **F1-Score** | **Recall** | **Precision** |
| **Logistic Regression** | 88.50 | 87.64 | 88.50 | 87.36 |
| **Linear SVM** | 88.91 | 87.64 | 88.91 | 88.12 |
| **XGBoost** | 88.31 | 87.38 | 88.31 | 87.24 |
| **CNN-LSTM + Attention** | 91.25 | 90.63 | 91.25 | 90.56 |
| **CNN-LSTM** | 89.29 | 89.09 | 89.29 | 88.93 |
| **PhoBert(Base) + FeedForward** | 92.99 | 92.41 | 92.99 | 92.43 |
| **PhoBert(Base) + CNN-LSTM** | **93.24** | **92.92** | **93.24** | **92.81** |

## 3.2 Comparison with other methods

Table 5 demonstrates that the proposed methods achieve performance that is either superior to or at least on par with previous state-of-the-art (SOTA) approaches. Deep learning models such as Bi-LSTM (Nguyen et al, 2018) and Bi-GRU + Attention (Trang and Hung, 2024) attained F1-scores ranging from 89% to 92%, indicating that RNN-based and Attention-enhanced architectures provide certain benefits. Meanwhile, models utilizing pre-trained language models, such as XLM-R + VnEmoLex (Doan and Luu, 2022), have achieved higher performance, with an F1-score of approximately 93.97%, reflecting the growing trend of leveraging pre-trained Transformer models to enhance sentiment classification effectiveness.

**Table 5. Performance comparison with other Methods on UIT-VSFC (%).**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Study** | **Accuracy** | **F1-Score** | **Recall** | **Precision** |
| **BERT + CNN + BiLSTM + LSTM (Huynh et al, 2020)** | **-** | 92.79 | **-** | **-** |
| **Bi-GRU + Attention (Trang and Hung, 2024)** | 89.26 | 88.50 | 89.26 | 88.38 |
| **DNN-P (Vu Xuan et al, 2021)** | 88.56 | 89.90 | 94.18 | 86.00 |
| **XLM-R + VnEmoLex (Doan and Luu, 2022)** | **94.25** | **93.97** | **-** | **-** |
| **Bi-LSTM (Nguyen et al, 2018)** | **-** | 92.00 | 93.40 | 90.80 |
| **CNN-LSTM + Attention (Ours)** | 91.25 | 90.63 | 91.25 | 90.56 |
| **PhoBert(Base) + CNN-LSTM (Ours)** | 93.24 | 92.92 | 93.24 | 92.81 |

In this study, CNN-LSTM (Ours) and PhoBERT + CNN-LSTM (Ours), have shown significant improvements. The CNN-LSTM + Attention (Ours) model achieved an Accuracy of 91.25% and an F1-Score of 90.63%, which is comparable to or outperforms some previous studies. Notably, PhoBERT + CNN-LSTM (Ours) achieved the highest performance, with Accuracy, F1-Score, Recall, and Precision all around 93%. These results indicate that the combination of pre-trained language models (PhoBERT) with CNN/LSTM architectures enables the model to leverage deep contextual features and local feature extraction, thereby enhancing classification performance.

Overall, the proposed methods not only keep up with but also have the potential to surpass previous state-of-the-art (SOTA) models. The combination of pre-trained language models with appropriate CNN/RNN architectures has demonstrated significant effectiveness in Vietnamese sentiment analysis. Future research directions may focus on experimenting with various datasets to assess the model's generalization ability, as well as optimizing deployment performance to enhance real-world applicability.

**Table 6. Sentiment Classification Results of CNN-LSTM + Attention and PhoBERT + CNN-LSTM**

| **Sentence** | **Type** | **Label** | **CNN-LSTM + Attention** | **PhoBERT + CNN-LSTM** |
| --- | --- | --- | --- | --- |
| 1 | Giáo viên không giảng dạy kiến thức , hướng dẫn thực hành trong quá trình học .(Teachers do not provide instruction or practical guidance during the learning process.) | Raw | Negative | Negative | Negative |
| Giảng viên không giảng dạy kiến thức hướng dẫn thực hành trong quá trình học(The lecturer do not provide instruction or practical guidance during the learning process.) | Standardized | **Negative** | **Negative** | **Negative** |
| 2 | Cụ thể doubledot về việc hướng dẫn bài tập về nội dung đó.(Specifically, doubledot regarding guiding exercises on that content.) | Raw | Neutral | Negative | Positive |
| Cụ thể về việc hướng dẫn bài tập về nội dung.(Specifically, regarding guiding exercises on the content.) | Standardized | **Neutral** | **Positive** | **Neutral** |
| 3 | Cô vui tính colonsmilesmile.(She is cheerful colonsmilesmile.) | Raw | Positive | Positive | Positive |
| Giảng viên vui tính smile(The lecturer is cheerful smile.) | Standardized | **Positive** | **Positive** | **Positive** |

Table 6 presents the sentiment classification results of our models: CNN-LSTM with Attention and PhoBERT with CNN-LSTM, applied to Vietnamese student feedback. The input data includes both raw and standardized sentences to evaluate the impact of preprocessing on model performance. The results show that the models generally align with the original sentiment labels in straightforward cases. For example, the sentence "Giáo viên không giảng dạy kiến thức, hướng dẫn thực hành trong quá trình học." (Teachers do not provide instruction or practical guidance during the learning process.) was correctly classified as negative by both models. However, discrepancies appear in cases where sentences exhibit neutral sentiment or require deeper contextual understanding. For instance, the sentence "Cụ thể về việc hướng dẫn bài tập về nội dung đó." (Specifically, regarding guiding exercises on that content.) was originally labeled as neutral. The CNN-LSTM + Attention model misclassified it as negative, while the PhoBERT + CNN-LSTM model predicted a positive sentiment. On the other hand, in the case of positive sentiment, both models classified correctly. For example, the sentence "Cô vui tính colonsmilesmile (She is cheerful colonsmilesmile.)", and its standardized version "Giảng viên vui tính smile." (The lecturer is cheerful smile.) were both labeled as positive, and both models predicted correctly. These results highlight variations in model performance when processing student feedback, especially for neutral statements. Additionally, input standardization can influence model predictions, sometimes leading to shifts in sentiment classification.

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