A SYSTEM FOR ANALYZING TOPICS AND EVALUATING SATISFACTION LEVELS FROM VIETNAMESE STUDENT FEEDBACK USING NAIVE BAYES CLASSIFIER

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ABSTRACT

As universities strive to improve teaching quality and enhance the overall learning experience, student feedback provides indispensable insights. The ability to automatically analyze open-ended comments has therefore become a crucial step toward developing efficient and evidence-based evaluation systems. This paper proposes a method based on the Naive Bayes Classifier (NBC) to address two tasks simultaneously: (i) classifying the topics of student feedback and (ii) evaluating the satisfaction levels expressed in the feedback. The dataset consists of comments collected during the Summer semester of the 2024–2025 academic year at Duy Tan University, which were preprocessed using techniques such as Term Frequency–Inverse Document Frequency (TF-IDF) and n-gram modeling. Experimental results demonstrate that the NBC model achieves an accuracy of 91.20% in topic classification and 90.62% in satisfaction classification. In addition, the paper provides visual illustrations through analytical charts for each class, highlighting the effectiveness of the model. The findings confirm that a simple yet powerful model such as NBC can be effectively applied in student feedback analysis, paving the way for the development of automatic evaluation systems in educational environments.

KEYWORDS

Naive Bayes Classifier; TF-IDF; n-gram; Student Feedback; Topic Classification; Satisfaction Level.

1. INTRODUCTION

Gathering and analyzing student feedback has become a vital practice for institutions seeking to improve teaching standards and enhance learners' academic experiences. However, extracting useful information from free-text comments, particularly in Vietnamese, remains a challenge due to the characteristics of the language, including unstandardized vocabulary and diverse sentence structures. This has motivated the need for automated machine learning approaches to classify and analyze student feedback more effectively.

The Naive Bayes Classifier (NBC) is a probabilistic model that relies on Bayes' theorem. It is favored in text classification due to its straightforward formulation, efficiency in training, and competitive accuracy in many natural language processing applications [1-3]. Several studies in Vietnam have applied NBC for sentiment analysis of Vietnamese texts and obtained promising results. However, these studies typically concentrate only on classifying polarity (positive or negative) rather than tackling multiple aspects simultaneously, such as distinguishing feedback topics or measuring detailed satisfaction levels.

In this study, we propose the application of NBC to classify student feedback along two parallel

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dimensions: (i) content topics (e.g., teaching, facilities and tuition) and (ii) satisfaction levels (positive, negative, neutral). The input feedback text undergoes a preprocessing pipeline that includes cleaning and normalization, Part-of-Speech (POS) tagging [4-6], n-gram modeling [7], and Term Frequency–Inverse Document Frequency (TF-IDF) representation [8].

The extracted features are then used as input to the NBC model for training and prediction. The study aims to develop a simple, effective, and practical system for analyzing Vietnamese student feedback. The main contributions of this paper are threefold: (i) we propose a solution that combines sentiment analysis with topic classification to leverage multidimensional feedback, (ii) we integrate a specialized preprocessing pipeline for Vietnamese to improve accuracy, and (iii) we conduct comparative experiments with other machine learning models to evaluate the applicability of NBC in real-world educational settings.

2. BACKGROUND AND RELATED WORK

In recent years, several studies in Vietnam have attempted to apply machine learning techniques to extract information from student feedback. However, most approaches focus on a single dimension, such as sentiment classification or topic identification, without handling both simultaneously or leveraging advanced preprocessing techniques tailored to Vietnamese. Below are three representative studies:

Nguyen Van Kiet et al: Student Feedback Analysis using Naive Bayes and TF-IDF [9]:

- Idea: Apply machine learning models to analyze student feedback;
- Techniques and Models: In their work, TF-IDF was applied to convert textual data into numerical vectors, which were subsequently classified using the Naive Bayes model;
- Dataset: Student feedback on teaching quality and learning services;
- Experimental Results: Feedback classified into two sentiment groups, positive and negative, with relatively high accuracy;
- Strengths and Limitations: Simple and easy to implement, but only focuses on binary sentiment classification without analyzing topics or applying advanced preprocessing such as POS tagging or n-gram.

Pham Thi Kim Ngoan et al: Student Feedback Analysis using Traditional Machine Learning Models [10]:

- Idea: Implement a student feedback analysis system based on traditional machine learning methods;
- Techniques and Models: Use ViTokenizer for preprocessing, represent features with Bag-of-Words combined with TF-IDF, and apply Naive Bayes and Support Vector Machine for classification;
- Dataset: 2,953 student feedback entries from Nha Trang University, divided into four main topics: teaching methods, lecturer attitudes, facilities, and others;
- Experimental Results: Naive Bayes achieved 90.10% accuracy, while SVM achieved 92.13% accuracy;
- Strengths and Limitations: High effectiveness with simple models, however the approach does not address sentiment polarity or multi-level satisfaction, and does not integrate advanced semantic preprocessing techniques.

Ton Nu Thi Sau et al: Aspect and Sentiment Analysis of Student Feedback using Bi-LSTM with Attention [11]:

- Idea: Develop an aspect-based feedback analysis system using deep learning
- Techniques and Models: Apply a Bi-directional Long Short-Term Memory (Bi-LSTM) model combined with an Attention mechanism to simultaneously analyze aspects and sentiment;
- Dataset: More than 2,000 student feedback entries annotated by aspects (teaching, facilities, content, etc.) and sentiment levels (positive, neutral, negative)
- Experimental Results: The model achieved strong performance in simultaneously recognizing aspects and sentiments;
- Strengths and Limitations: Deep learning techniques are capable of capturing semantic features and usually deliver higher accuracy in classification tasks. Nevertheless, they demand considerable computational resources, which makes their deployment challenging for educational institutions with limited technical capacity.

A review of domestic research shows that machine learning has already been introduced into student feedback analysis and has yielded some promising results. However, most studies still focus on a single perspective, such as sentiment analysis or topic identification, typically employing traditional approaches like Naive Bayes or Support Vector Machines, or using deep learning architectures such as Bi-LSTM. These works share common limitations: many restrict sentiment classification to binary polarity and fail to simultaneously address multiple dimensions of feedback, particularly the combination of content topics and satisfaction levels. In addition, several models have not incorporated advanced preprocessing techniques for Vietnamese, such as Part-of-Speech tagging or n-gram–based contextual representations.

3. DATA AND METHODOLOGY

Based on these gaps, this study is proposed to develop a more comprehensive method that enables the simultaneous analysis of topics and satisfaction levels from Vietnamese student feedback, while incorporating advanced language preprocessing techniques to improve accuracy and practical applicability in real educational environments. These aspects will be presented in detail in the following sections.

3.1. Dataset Collection

The dataset used in this study was collected from an online survey distributed by the authors at Duy Tan University during the Summer semester of the 2024–2025 academic year. The survey focused on student feedback related to courses, lecturers, and facilities, with the objective of evaluating overall satisfaction with the learning experience.

The feedback entries were recorded in free-text format in Vietnamese, reflecting diverse and unstandardized individual opinions. In total, approximately 3,000 feedback entries were employed in this study.

Each feedback entry was manually annotated along two main dimensions to support systematic analysis. The first dimension is the feedback topic, categorized into three groups: teaching, facilities, and tuition, corresponding to key aspects of the student learning experience. The second dimension is the satisfaction level, divided into five categories: very dissatisfied, dissatisfied, neutral, satisfied, and very satisfied. The annotation was performed manually under controlled conditions to ensure consistency and objectivity across the dataset, providing a reliable foundation for subsequent analysis and model training.

The dataset was annotated by three annotators with backgrounds in computer science and natural language processing. To assess annotation reliability, Cohen's kappa was calculated, yielding 0.82, which indicates strong agreement. In cases of disagreement, the annotators discussed to reach consensus; unresolved cases were decided by a senior researcher. This procedure ensured the credibility, consistency, and validity of the annotated dataset.

3.2. Data Preprocessing

Since the collected feedback dataset is in free-text, unstandardized form, a series of language preprocessing steps are required to prepare suitable input for the machine learning model. The preprocessing steps were implemented as follows:

• **Text cleaning and normalization:** This process includes removing invalid characters, common spelling errors, special symbols, emojis, and meaningless filler words such as "uhm", "à", "@@", etc. In addition, all text was converted to lowercase to ensure consistency across the dataset

• **Vietnamese word segmentation:** As Vietnamese does not use whitespace to clearly separate words like English, accurate segmentation of lexical units is essential. This study employed the ViTokenizer tool to segment Vietnamese sentences into individual word units

• **Stop word removal:** Stop words are common words with little discriminative value, such as "là", "và", "của", "này", "đó". Removing these words helps reduce noise and improve the generalization ability of the machine learning model during feature learning

• **Part-of-Speech (POS) tagging:** Each word in a sentence was assigned a grammatical label such as noun, verb, or adjective to support semantic feature extraction. POS tagging allows the model to better capture the context and syntactic roles of words within sentences
Through this preprocessing pipeline, the text data was prepared at an optimal level for subsequent feature extraction and model training steps.

3.3. Text Feature Extraction

After preprocessing, the feedback text needs to be converted into a numerical representation to serve as input for the machine learning model. This study employed two common techniques, n-gram and TF-IDF, to extract meaningful features from the text.

• **The n-gram technique**: allows the representation of the local context of the text by extracting sequences of n consecutive words. For a sentence with a length of m words, the number of n-grams that can be generated is determined by the formula:

$$S_{n\text{-gram}} = L - n + 1 \tag{1}$$

Where: $S_{n\text{-gram}}$ denotes the total number of n-gram sequences that can be extracted from a sentence, L represents the length of the sentence in terms of word count, and n indicates the chosen size of the n-gram.

For example, the sentence “giảng viên nhiệt tình” when applying unigram (n = 1) is segmented into {“giảng”, “viên”, “nhiệt”, “tình”}, while with bigram (n = 2) it becomes {“giảng_viên”, “viên_nhiệt”, “nhiệt_tình”}. Using both unigram and bigram enables the model not only to capture the semantic meaning of individual words but also to detect common word combinations that frequently appear together in student feedback.

• **The TF-IDF technique** is a method of assigning weights to each word (or n-gram) in the text, reflecting the importance of that word in a given document relative to the entire corpus. The TF-IDF weight is calculated according to the formula:

$$\text{TF-IDF}(t,d,D) = \text{TF}(t,d) \times \log\left(\frac{N}{\text{DF}(t)}\right) \quad (2)$$

Where: t denotes the term under analysis (a word or phrase), d indicates a particular document and D is the collection of all documents. $\text{TF}(t,d)$ is the frequency of occurrence of t in document d, $\text{DF}(t)$ epresents the number of documents within D that include, t while N is is the total number of documents in the collection D

This method increases the weight of words that are distinctive for a particular document but appear less frequently in other documents, while reducing the influence of common words that carry little discriminative value. This is particularly useful in detecting distinctive terms or patterns in student feedback.

The combination of n-gram and TF-IDF techniques enhances the model’s ability to better understand the context and semantic content of feedback, thereby improving classification performance along both dimensions: topic identification and satisfaction level.

where $N_{x_i,C}$ is the number of times feature x_i appears in class C, α is the smoothing parameter, and $|V|$ is the size of the vocabulary.

Based on the input features represented by TF-IDF, this study implements two independent classification models using the Multinomial Naive Bayes Classifier (NBC).

3.4. Naive Bayes Classification Model

To classify text feedback by topic and satisfaction level, this study employs the Naive Bayes Classifier (NBC), a simple yet highly effective probabilistic classification model. The model operates based on Bayes’ theorem combined with the conditional independence assumption among input features.

For a document d, the probability that it belongs to a class C (for example, the class "teaching" or "very satisfied") is calculated using Bayes’ formula as follows:

$$P(C|\,d) = \frac{P(C)\cdot P(d|\,C)}{P(d)} \quad (3)$$

Where: $P(C|\,d)$ indicates the posterior probability that a document d belongs to class C, $P(C)$ denotes the prior probability of class C, $P(d|\,C)$ represents the likelihood of observing document d given class C, and $P(d)$ corresponds to the marginal probability of document d aggregated over all classes.

Since $P(d)$ does not change across classes, it can be omitted when selecting the class with the highest probability. Formula (4) can therefore be simplified as:

$$P(C|\, d) \propto P(C) \cdot \prod_{i=1}^{n} P(x_i |\, C) \tag{4}$$

Where: x_i is the feature (word or n-gram) at position i in the document, n is the number of features in the document, and $P(x_i |\, C)$ is the probability that feature x_i appears in class C.

However, in practice, some features may not appear in the corresponding training class, leading to a probability value of zero. To overcome this issue, this study applies the Laplace smoothing technique, defined as follows:

$$P(x_i |\, C) = \frac{N_{x_i,C} + \alpha}{\sum_{k=1}^{|V|} N_{x_k,C} + \alpha \cdot |V|} \tag{5}$$

Specifically:

- Model 1: Classify feedback topics into three main classes: teaching, facilities and tuition
- Model 2: The satisfaction scale is divided into five groups: from “very dissatisfied” through “neutral,” up to “very satisfied

The Naive Bayes Classifier (NBC) was chosen due to its effectiveness in handling discrete features and its suitability for text representation in the form of frequency vectors or TF-IDF. The use of Laplace smoothing helps to overcome the zero-probability problem when encountering new words that did not appear in the training set.

To assess the effectiveness of the classification, common evaluation metrics in machine learning were applied, such as:

- Accuracy: The proportion of correctly predicted samples over the total number of samples;
- Precision: The correctness of predictions for each class;
- Recall: Ratio of correctly identified samples of a class;
- F1-score: The harmonic mean of Precision and Recall, reflecting the balance of the model.

Training and evaluating these two independent NBC models enables the simultaneous analysis of feedback content and student satisfaction levels, thereby providing valuable information to support improvements in teaching activities and learning services at the university.

3.5. Experimental Setup

This study designed experiments to assess the effectiveness of the Naive Bayes model in classifying student feedback across two dimensions: (i) feedback topics and (ii) satisfaction levels. The dataset consisted of 3,000 free-text feedback entries collected from student surveys during the Summer semester of the 2024–2025 academic year at Duy Tan University. Each feedback entry was manually annotated along two dimensions: three topic categories (teaching, facilities, and tuition) and five satisfaction levels (very dissatisfied, dissatisfied, neutral, satisfied, and very satisfied).

After collection, the data underwent several natural language preprocessing steps, including text cleaning, normalization, word segmentation, stop word removal, and Part-of-Speech (POS) tagging. The input features were extracted using the TF-IDF model combined with n-gram (utilizing unigram and bigram). The classification model applied was the Naive Bayes Classifier (NBC), which is suitable for discrete text data.

All experiments were conducted on a personal computer running Windows 11 with an Intel Core i5-1135G7 @ 2.40GHz processor and 8GB of RAM. The implementation was developed in Python 3.9, with support from libraries including Scikit-learn 1.3.0, pandas, and underthesea for Vietnamese language processing.

The model performance was evaluated using standard machine learning metrics, including Accuracy, Precision, Recall, and F1-score, applied separately for each classification task. The separation of feedback into two dimensions allowed for accurate evaluation of model performance on each specific aspect, while also providing a foundation for the development of automated feedback analysis systems in the future.

4. RESULTS

This section presents the evaluation results of the Naive Bayes model for classifying student feedback on the dataset that was preprocessed and represented using TF-IDF combined with n-gram. Two tasks were performed in parallel: classification by feedback content (teaching, facilities, and tuition) and classification by satisfaction level (from very dissatisfied to very satisfied). To evaluate model performance, standard metrics such as Accuracy, Precision, Recall, and F1-score were applied. The obtained results provide an assessment of the suitability of the proposed method for feedback analysis in the context of higher education.

4.1. Experimental Results

For the task of feedback topic classification, the Naive Bayes Classifier (NBC) was trained to assign each student feedback entry to one of three main topic categories: teaching, facilities and tuition. Prior to model training, the dataset was processed through text normalization, word segmentation, stop word removal, and feature representation using TF-IDF combined with n-gram.

To evaluate model performance, this study employed metrics including Precision, Recall, and F1-score for each class, along with overall Accuracy for the entire model. The detailed results are presented in Table 1.

Table 1. Results of feedback topic classification using the NBC model.

Topic category	Precision (%)	Recall (%)	F1-score (%)
Teaching	92.65	93.52	93.08
Tuition	89.81	91.29	90.54
Facilities	88.24	91.02	89.60

From Table 1, it can be observed that the NBC model achieved good performance across all feedback topic classes. Among them, the Teaching class achieved the highest F1-score (93.08%), followed by Tuition (90.54%) and Facilities (89.60%). Precision and Recall values also remained at high levels, demonstrating the model's accuracy and overall capability in recognizing feedback topics.

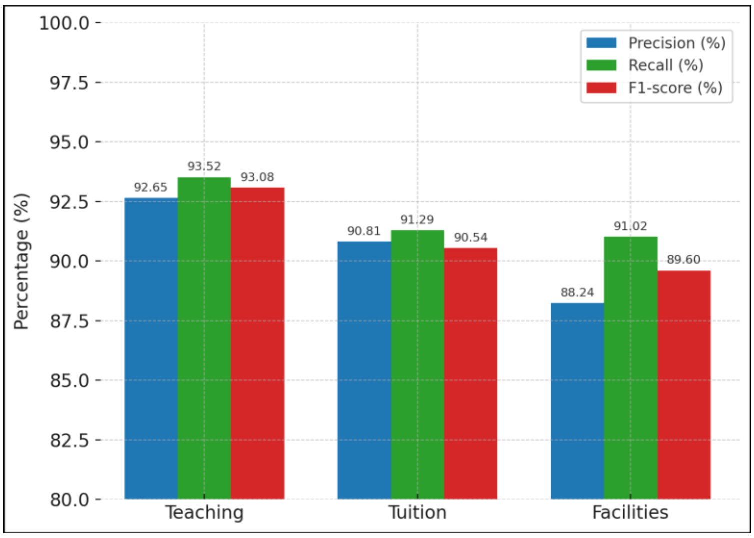

Figure 1. Performance of the NBC Model by Topic Classes

Although only three evaluation metrics (Precision, Recall, and F1-score) are reported for each class, the model achieved an overall Accuracy of 91.20% on the test set, confirming the effectiveness and reliability of the NBC model.

To provide a clearer comparison across topic categories, Figure 1 displays bar charts of these three metrics, showing the strong performance of the Teaching category and the greater difficulty in classifying feedback in the Facilities category.

Similar to the task of topic classification, the Naive Bayes Classifier (NBC) was also applied to the problem of determining student satisfaction levels. Specifically, each feedback entry was labeled into one of five categories: very dissatisfied, dissatisfied, neutral, satisfied, and very satisfied.

Before training, the data was preprocessed through steps such as text normalization, stop word removal, and feature representation using TF-IDF combined with n-gram. This method enables the model to better capture contextual relationships between consecutive terms, thereby improving its ability to distinguish different satisfaction levels.

Table 2 presents the model's evaluation results, reported with three performance metrics: Precision, Recall, and F1-score for each class. The overall accuracy reached 90.62%, indicating that the model has strong generalization ability in extracting sentiment from Vietnamese text.

Table 2. Results of satisfaction level classification.

Satisfaction Level	Precision (%)	Recall (%)	F1-score (%)
Very dissatisfied	84.02	86.65	85.31
Dissatisfied	86.73	88.18	87.44
Neutral	90.52	92.05	91.28
Satisfied	91.84	92.89	92.36
Very satisfied	88.06	91.44	89.72
Average	88.63	90.26	89.22

The results in the table show that the model performed best on the "Satisfied" class with an F1-score of 92.36%, followed by "Neutral" (91.28%) and "Very satisfied" (89.72%). Meanwhile, the two negative classes, "Dissatisfied" and "Very dissatisfied," obtained F1-scores of 87.44% and 85.31%, respectively, reflecting the challenges in distinguishing negative states due to diverse expressions and imbalanced data distribution.

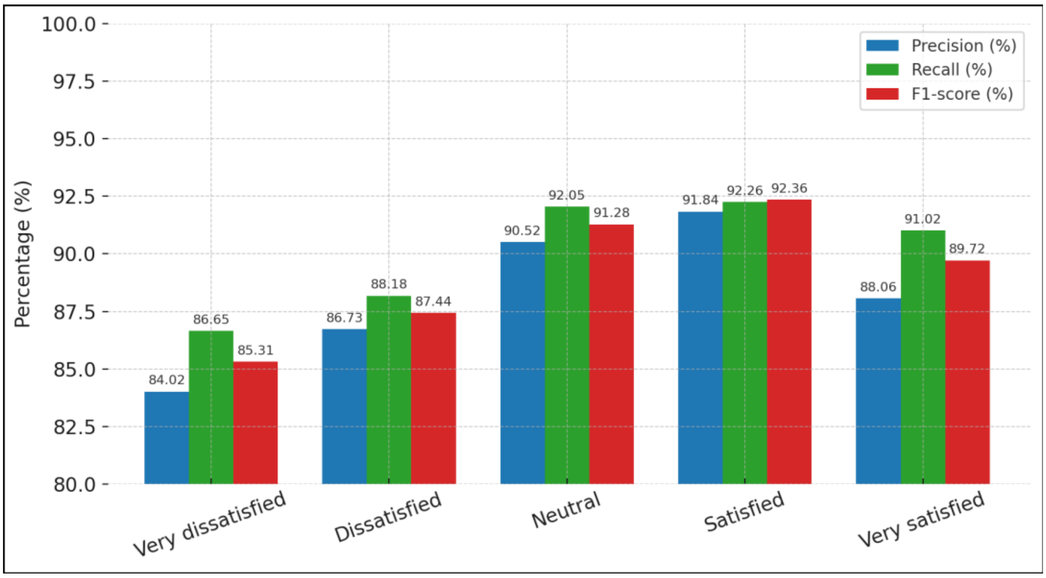

Figure 2. Performance of the NBC Model by Satisfaction Levels

Based on the outcomes shown in Table 2, Figure 2 illustrates how the model differentiates between satisfaction levels. The chart specifically presents the three metrics: Precision, Recall, and F1-score, for each feedback class, allowing clearer identification of performance differences. Notably, neutral and positive classes such as "Neutral" and "Satisfied" were handled more consistently by the model, whereas distinguishing between dissatisfaction levels proved more challenging due to overlapping negative semantics and less explicit textual expressions.

An analysis of the dataset revealed class imbalance across both topic categories and satisfaction levels, with certain classes such as "Teaching" and "Satisfied" containing more samples than others. Although no explicit re-sampling was applied, the Naive Bayes Classifier inherently considers class probabilities during training. To further examine the effects of imbalance, confusion matrices were generated, which show that the model performs strongly on majority classes while exhibiting lower performance on minority classes such as "Facilities" and "Very dissatisfied." This highlights both the robustness of the model and its limitations, suggesting future work could explore balancing strategies such as re-sampling or class weighting to further improve classification performance.

In addition to the quantitative results, some misclassified examples were analyzed to better understand model limitations. For instance, a feedback entry stating “The classroom is too crowded, and it makes learning uncomfortable” was incorrectly classified as related to “Teaching” instead of “Facilities.” Similarly, a comment such as “The lecturer explained well, but the tuition is too high” was misclassified under “Teaching” rather than “Tuition.” These errors highlight the difficulty of handling overlapping contexts in Vietnamese feedback, where multiple aspects are expressed in a single sentence or where negative semantics are implicit rather than explicit.

4.2. Demonstration Interface of the Student Feedback Classification Application

To validate the practical deployability of the Naive Bayes Classifier (NBC) model, a web-based demonstration application was developed on the Webform platform within the .NET Framework environment.

Designed to be straightforward and user-oriented, the interface consists of the following key elements:

- Feedback input field: Provides a text box that allows users to enter free-text feedback related to teaching, facilities and tuition;
- Prediction button: Activates the analysis process and performs classification of the input feedback using the pre-trained NBC model;
- Prediction results: Displays two classification outputs, including (i) feedback topics (teaching, facilities and tuition) and (ii) satisfaction levels (Very dissatisfied, Dissatisfied, Neutral, Satisfied, Very satisfied);
- Model accuracy panel: Reports the NBC model’s performance on the test dataset, covering Topics and Satisfaction, thereby helping users evaluate the reliability of the system;
- Instruction message: Suggests that users enter a feedback text of minimum length to ensure prediction quality.

The application was implemented in C# and integrated with ML.NET to deploy the NBC model trained on real Vietnamese student feedback data. For extended versions, the system could incorporate advanced deep learning models such as BERT, utilizing ONNX Runtime for inference from pre-trained models stored in the .onnx format.

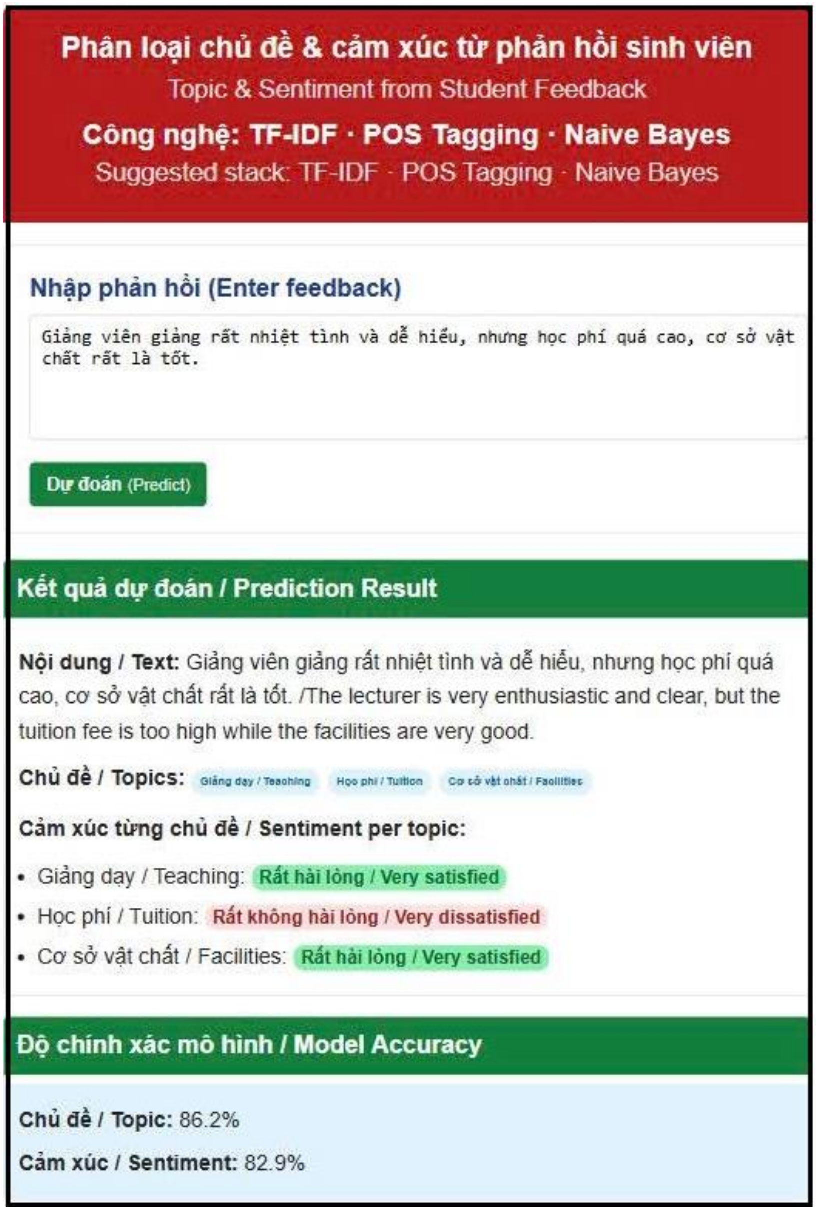

Figure 3. User interface of the NBC-based application for student feedback classification

Figure 3 illustrates the application interface. In the example, the system correctly predicted three topics (Teaching, Facilities, and Tuition) together with their corresponding satisfaction levels, demonstrating the model's capability for multi-dimensional feedback analysis.

5. Conclusion

This paper proposed and successfully implemented a student feedback analysis system based on the Naive Bayes Classifier (NBC), which is capable of simultaneously classifying feedback topics and satisfaction levels from Vietnamese text data. The experimental results showed strong performance, with 91.20% accuracy for topic classification and 90.62% accuracy for satisfaction classification, confirming the effectiveness and suitability of NBC in the educational context.

In addition to its technical contribution, the study also developed a practical web-based interface on the Web Forms platform, enabling visualization of classification results and assisting educational administrators in monitoring and evaluating training quality in a more objective and convenient manner.

Compared with previous studies, this research is notable for its ability to process two feedback dimensions in parallel (topic and satisfaction level) and for the successful application of Vietnamese text feature representation using TF-IDF and n-gram. This approach achieved high accuracy while avoiding the need for complex computational infrastructure.

Looking forward, potential research directions include enhancing feature representation with semantic models such as Word2Vec [12], FastText [13], or Vietnamese BERT [14]; adopting advanced deep learning frameworks (e.g., Bi-LSTM, Transformer) for more precise sentiment classification; and developing real-time automated feedback systems integrated into student management platforms to expand practical applicability in higher education.

Finally, it is important to acknowledge ethical considerations when applying automated sentiment and topic analysis in educational contexts. Issues such as protecting student privacy, ensuring data security, and maintaining transparency in automated decision-making must be carefully addressed. These factors are essential to building trust in such systems and ensuring their responsible deployment in real educational environments.

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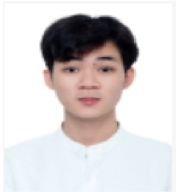

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