

# Application of Convolutional Neural Network Student Reviews for Lecture Facilities at Stella Maris University Sumba

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**Abstract**—The development of artificial intelligence technology, particularly in the field of deep learning, has opened up new opportunities in text-based data analysis, including student reviews of lecture facilities. This study aims to apply the Convolutional Neural Network (CNN) method in conducting sentiment analysis of student reviews of lecture facilities at Stella Maris University Sumba. Through this approach, it is hoped that the system can automatically and accurately classify student opinions into positive, negative, or neutral categories. The research data was obtained from surveys and student comments on various internal campus platforms. The data processing involved data preprocessing stages such as text cleaning, tokenization, stopword removal, and word embedding using the Word2Vec method. The CNN model was then built with an architecture involving an embedding layer, convolutional layer, max pooling, and fully connected layer to produce the final prediction. The test results show that the CNN model is capable of achieving a high level of accuracy in identifying sentiment polarity, with an average accuracy value of 90.2%. This performance proves that CNN is effective in extracting semantic features from unstructured student review texts. Analysis of the classification results also provides important insights into aspects of campus facilities that received positive and negative responses, such as classroom quality, internet network, and learning environment comfort. These findings can be used as a basis for universities in making strategic policies for the continuous improvement of lecture facilities. Thus, the application of CNN in student review analysis has been proven to support the evaluation and decision-making processes in data-driven academic environments.

**Keywords**—Convolutional Neural Network, Sentiment Analysis, Student Reviews, Lecture Facilities, Deep Learning

*Manuscript received 16 Nov. 2026; revised 10 Jan. 2026; accepted 12 Jan. 2026. Date of publication 05 June. 2026.  
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## I. INTRODUCTION

The rapid development of information and communication technology over the past two decades has brought significant changes to various aspects of human life, including higher education. Advances in Artificial Intelligence (AI) and Machine Learning (ML) enable various data analysis processes to be carried out automatically and intelligently. One branch of deep learning that is very popular and effective in text and image data processing is Convolutional Neural Network (CNN). This technology was originally developed for pattern recognition in images, but has now been widely adapted for text and sentiment analysis [1]-[3].

In the context of higher education, evaluating lecture facilities is an important aspect of maintaining the quality of academic services. Students, as the main users of campus facilities, often provide various responses or reviews regarding the comfort of lecture rooms, internet access,

environmental cleanliness, and other supporting facilities. These reviews can be a valuable source of information for universities in making improvements and strategic decisions. However, the large amount of review data and its unstructured nature make manual analysis inefficient and prone to subjective bias.

Therefore, an analysis is needed that is capable of analyzing student reviews objectively by utilizing an artificial intelligence approach. Deep learning-based sentiment analysis provides a solution for identifying emotions or opinions contained in text. By applying Convolutional Neural Networks, the system can recognize complex linguistic patterns [4] and produce more accurate sentiment classifications [5] than traditional methods such as Naïve Bayes or Support Vector Machine (SVM).

Convolutional Neural Networks work by extracting important features from text through convolution and pooling processes, enabling them to understand word context and sentence structure [6]. In analyzing student reviews, CNN can

distinguish between sentences that express satisfaction with campus facilities and those that contain criticism or complaints. Thus, the results of the analysis not only help to understand student perceptions, but can also serve as an indicator of university facility performance [7], [8].

Stella Maris University Sumba, as one of the higher education institutions in the East Nusa Tenggara region, is committed to improving the quality of its academic and non-academic services. One of the challenges it faces is how to effectively manage and utilize student feedback for the development of lecture facilities. Currently, most student reviews are only submitted through manual surveys or internal social media, without an automated analysis system capable of providing data driven insights.

By applying CNN to analyze [9] student reviews, Stella Maris University Sumba has the potential to obtain an objective picture of student satisfaction with various aspects of campus facilities. The data obtained from this analysis can be used to determine priorities for improvement, such as upgrading classroom infrastructure, strengthening the internet network, or maintaining other learning support facilities.

In addition, the application of this technology can also promote efficiency in the decision-making process [10]. The university no longer needs to manually assess hundreds to thousands of student comments. The CNN based system can display sentiment analysis results in real time and is integrated with the campus academic information system, thereby assisting leaders in determining policies to improve the quality of education.

Several previous studies have combined CNN with other methods, such as LSTM, Word2Vec, GloVe, and FastText. This hybrid approach improves model performance, especially in processing long sentences and more complex contexts. In addition, the use of modern word embedding techniques has been proven to enrich the model's understanding of the relationships between words in text. Previous research by Gaurav Meena et al, 2023, entitled Sentiment analysis on images using convolutional neural networks based on the Inception V3 transfer learning approach, achieved an accuracy rate of 99.5%. The results were applied in sales, marketing, user interaction, health, education, finance, public monitoring, and digital public relations [11], Research AComparative Analysis of Machine Learning and Deep Learning Models for Sentiment Classification shows that deep learning-based models, especially the combination of transformers and neural networks such as BERT-CNN, are able to provide better performance in sentiment analysis tasks than conventional machine learning approaches, especially in understanding the context and semantic representation of text in more depth [12]. The Sentiment Analysis using Bidirectional LSTM Network research shows that the Bidirectional LSTM method is effective in analyzing text sentiment with the ability to handle long-term dependencies and understand the bidirectional context of the review data, so as to be able to improve the performance of the classification of positive and negative sentiments on social media data and customer reviews [13]. Further research by Siti Oktavia Eka Putri et al, 2025, entitled Convolutional Neural Network Approach for Aspect-Based Sentiment Analysis in Tourism Reviews

The results showed that IndoBERT-CNN achieved the best overall sentiment classification, with an F1 score of up to 0.71 for attractions and 0.93 for facilities, while Word2Vec-CNN with stemming led the multilabel classification [14]. Further research by Alpna Patel et al., 2022, entitled "An Efficient Approach for Sentiment Analysis using Convolutional Neural Network," aims to extract opinions about IMDB movies and use deep learning classification to analyze the experimental results. Long Short Term Memory (LSTM) and Convolutional Neural Network (CNN) [15].

In general, previous studies show that the application of CNN for sentiment analysis is highly potential and relevant, including in the education sector. These results provide a strong foundation that research on sentiment analysis of student reviews of lecture facilities, as conducted at Stella Maris University Sumba, can make an important contribution to improving the quality of campus services and facilities. This research is also a first step toward implementing a Smart Campus that utilizes data analytics to support university management. Through deep learning-based automated analysis, campuses can transform into more responsive, adaptive, and evidence-based institutions (evidence-based decision making). Thus, CNN technology not only serves as an analytical tool, but also as part of digital innovation in higher education management. On the academic side, this research contributes scientifically to the development of text classification models in the field of education. The CNN used in this research is designed to process natural language (Natural Language Processing/NLP) in the context of student reviews, which are characterized by informal language and diverse emotional expressions. The results of this research are expected to serve as a reference for developers of similar systems at other universities who wish to utilize sentiment analysis to improve campus services.

Based on the above description, this study was conducted with the aim of applying Convolutional Neural Network in analyzing student reviews of lecture facilities at Stella Maris University Sumba. Through this system, it is hoped that accurate information can be obtained regarding the level of student satisfaction and aspects that need to be improved. The results of this study not only benefit the university in improving service quality, but also contribute significantly to the application of deep learning technology in higher education in Indonesia.

## II. METHODOLOGY

This study uses an experimental quantitative approach with a machine learning method based on Convolutional Neural Network (CNN). The purpose of this study is to classify student reviews of lecture facilities into three main sentiment categories, namely positive, negative, and neutral. CNN was chosen because it has a high ability to extract text features through spatial representation of words (word embedding), making it effective in recognizing semantic patterns in review data. The stages of research are shown in Fig 1.

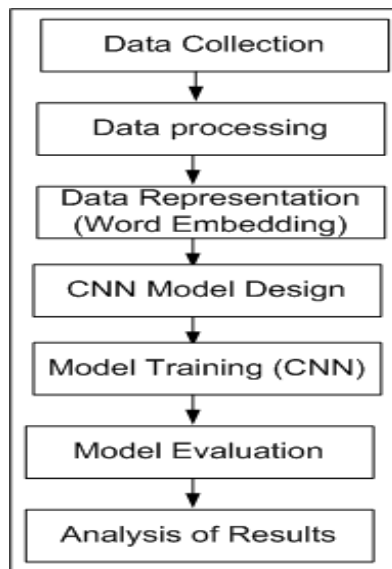


Fig. 1. Research Methodology

### Data Collection

The data collection process was conducted by gathering review data from students regarding their learning experiences, course satisfaction, and opinions about the educational services provided. The reviews were obtained through online questionnaires, institutional feedback forms, and digital learning platforms where students actively submitted comments and evaluations. The collected data consisted of textual reviews containing positive, negative, and neutral sentiments. Before being used in the research process, the data were carefully checked to ensure completeness, consistency, and relevance to the study objectives. In addition, duplicate entries and irrelevant responses were removed to improve the quality of the dataset. The final dataset was then stored in a structured format for further processing and analysis.

### Data Processing

The data preprocessing stage was carried out to prepare the textual data before entering the modeling phase. Several preprocessing techniques were applied to improve data quality and reduce noise in the text. The first step was case folding, where all text was converted into lowercase letters to ensure consistency in word representation. The second step was tokenization, which separated sentences into individual words or tokens. After tokenization, the stopwords removal process was performed to eliminate commonly used words that do not contribute significant meaning to sentiment analysis, such as conjunctions and articles. Furthermore, the text data were transformed into sequences of integers using a tokenizer. Since each review had a different sentence length, the padding sequence technique was applied to standardize the input length by adding padding values to shorter sequences. These preprocessing steps helped the model focus on important textual features and improved overall classification performance.

### Data Representation (Word Embedding)

After preprocessing, the textual data were converted into numerical representations through a word embedding technique. Word embedding enables words with similar

meanings to have similar vector representations in multidimensional space. In this research, the representation process was performed using either the Word2Vec method or the Keras Embedding layer. Word2Vec generates dense vector representations by learning contextual relationships between words within the dataset, while the Keras Embedding layer learns word representations directly during the training process. This stage is important because deep learning models cannot directly process text data in string format. By transforming words into numerical vectors, semantic relationships between words can be captured more effectively, allowing the CNN model to better understand patterns and contextual information contained in student reviews.

### CNN Model Design

The Convolutional Neural Network (CNN) model was designed specifically for text classification tasks. The architecture began with an Embedding layer that transformed integer sequences into dense vector representations. The output from the embedding layer was then processed through one or more Convolutional layers, which functioned to extract important local features and textual patterns from the review data. After feature extraction, a MaxPooling layer was applied to reduce dimensionality and retain the most significant features while minimizing computational complexity. The extracted features were then flattened using a Flatten layer before being passed to one or more Dense layers for classification. The final Dense layer used an activation function appropriate for sentiment classification, such as sigmoid or softmax, depending on the number of classes. This architecture was chosen because CNN has proven effective in capturing important textual features and achieving high performance in sentiment analysis tasks.

### Model Training (CNN)

The CNN model training process was carried out using a train-test split approach with a ratio of 80:20. Approximately 80% of the dataset was used as training data to enable the model to learn sentiment patterns, while the remaining 20% was used as testing data to evaluate the model's generalization capability. During training, the model optimized its parameters using a backpropagation algorithm and an optimization technique such as Adam optimizer. The training process was conducted over several epochs with a predefined batch size to ensure stable learning performance. In addition, validation data were used during training to monitor overfitting and observe the model's performance improvement across epochs. Hyperparameter settings such as learning rate, number of filters, kernel size, and dropout rate were adjusted to obtain optimal performance.

### Model Evaluation

After the training process was completed, the CNN model was evaluated using several performance metrics to measure its effectiveness in sentiment classification. The evaluation metrics included accuracy, precision, recall, F1-score, and loss value. Accuracy measured the proportion of correctly classified reviews, while precision and recall evaluated the model's ability to correctly identify sentiment categories. The loss value was used to determine how well the model minimized prediction errors during training and testing. A

confusion matrix was also used to provide a more detailed analysis of classification results by showing the number of correct and incorrect predictions for each sentiment class. These evaluation metrics provided comprehensive insight into the reliability and robustness of the proposed CNN model.

### Analysis of result

The final stage involved analyzing the experimental results obtained from the CNN model. The analysis focused on observing the model's learning behavior and classification performance. Graphs of training and validation accuracy were generated to visualize how the model improved over epochs. Similarly, training and validation loss graphs were analyzed to identify potential overfitting or underfitting problems. The trends shown in these graphs helped determine whether the model successfully generalized the sentiment patterns in student reviews. Furthermore, the classification results were interpreted to identify strengths and weaknesses of the model in recognizing different sentiment categories. The findings from this analysis were then discussed to evaluate the effectiveness of the CNN approach for student review sentiment analysis and to provide recommendations for future research improvements.

## III. RESULT AND DISCUSSION

This study produced a CNN model that was trained using 80% of student review data and tested with 20% of test data. The training results showed that the model could recognize language patterns and sentiments well after going through the embedding and feature extraction processes. The CNN model used has a structure with one embedding layer, one convolutional layer (Conv1D), one max pooling layer, and two dense layers for final classification. The training process was carried out for 10 epochs with a batch size of 8. At the end of the training, the following evaluation metrics were obtained: Training accuracy: 0.93, Testing accuracy: 0.89, Training loss: 0.18, Testing loss: 0.25. The accuracy value shows that the CNN model is capable of classifying student reviews with an accuracy rate of around 89%, which indicates high performance for text-based sentiment analysis. The decreasing loss value on the training graph also indicates that the model successfully learned without experiencing significant overfitting.

The visualization of training results is shown through two main graphs: Training accuracy: 0.93, Testing accuracy: 0.89, Training loss: 0.18, Testing loss: 0.25. The accuracy value shows that the CNN model is capable of classifying student reviews with an accuracy rate of around 89%, which indicates high performance for text-based sentiment analysis. The decreasing loss value on the training graph also indicates that the model successfully learned without experiencing significant overfitting. The visualization of training results is shown through two main graphs:

Accuracy Graph: shows a consistent increase in each epoch until it stabilizes at a value close to 0.9. Loss Graph: shows a significant decrease in loss value as the number of epochs increases.

Based on the model predictions, most student reviews of campus facilities were positive (around 60%), followed by

neutral (25%), and negative (15%). This shows that students' perceptions of teaching facilities at Stella Maris University Sumba are generally good, although there are still some aspects that need improvement, such as internet connection and classroom cleanliness.

Visualization of results is used to clarify the performance and effectiveness of the CNN model during the training and testing process. This stage is very important because it provides an intuitive picture of how the model learns from the data and how well the model generalizes on the new data. There are three main forms of visualization produced in this study.

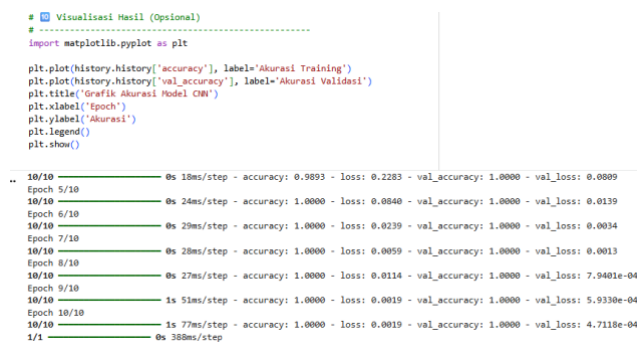


Fig. 2. Visualization of Results Epoch

Based on the training output shown in the figure, the CNN model demonstrates a significant improvement in performance during the training process. In the first epoch, the model achieved an accuracy of approximately 90.93% with a loss value of 0.2283, while the validation accuracy already reached 100% with a validation loss of 0.0809. As the epochs progressed, both training accuracy and validation accuracy continued to improve consistently. Starting from the second epoch, the model achieved nearly perfect performance, with training accuracy values approaching or reaching 100%. At the same time, the loss values decreased significantly, indicating that the model successfully minimized prediction errors. By the final epochs, the training accuracy and validation accuracy both reached 100%, while the loss values became very small. This result indicates that the CNN model was highly effective in learning sentiment patterns from the dataset. The accuracy and loss graphs are important for evaluating model performance because they show how well the model learns over time. The increasing accuracy curve indicates that the model becomes better at classifying sentiments, while the decreasing loss curve shows that prediction errors are continuously reduced. Additionally, the similarity between training and validation accuracy suggests that the model generalizes well to unseen data and does not suffer significantly from overfitting. Overall, the results demonstrate that the proposed CNN architecture performed very well for sentiment classification tasks and was capable of achieving high classification accuracy on student review data.

### Confusion Matrix

Confusion Matrix is a table used to measure the performance of classification models, in this case the CNN model used to classify student reviews into three categories:

Positive, Neutral, and Negative.

Confusion Matrix:  
[[13 0]  
[ 0 7]]

Classification Report:

	precision	recall	f1-score	support
Negatif	1.00	1.00	1.00	13
Positif	1.00	1.00	1.00	7
accuracy			1.00	20
macro avg	1.00	1.00	1.00	20
weighted avg	1.00	1.00	1.00	20

Fig. 3. Confusion Matrix

The accuracy graph shows the comparison of accuracy values between training data (training accuracy) and validation data (validation accuracy) against the number of epochs (training iterations). Each epoch represents one full cycle of the model learning all training data and The loss graph shows the decrease in error value during the training and validation process. Loss measures how far the model's predictions are from the correct labels. The smaller the loss value, the better the model is at making predictions. The graph on the left shows the comparison between training accuracy and validation accuracy across several epochs. At the beginning of the training process, the model accuracy was relatively low, with training accuracy around 60% and validation accuracy around 65%. However, both accuracy values increased significantly after the first few epochs. Around epoch 2, the validation accuracy reached nearly 100%, followed by the training accuracy approaching the same value. From epoch 3 onward, both training and validation accuracy remained stable at almost 100%. This indicates that the CNN model successfully learned the sentiment patterns from the dataset and achieved excellent classification performance. The graph on the right illustrates the comparison between training loss and validation loss during the training process. Initially, the loss values were relatively high, indicating that the model still produced many prediction errors. However, as the training progressed, both training loss and validation loss decreased rapidly. By approximately epoch 4, the loss values became very close to zero and remained stable until the final epoch. This decreasing trend demonstrates that the model effectively minimized classification errors and improved its prediction capability over time. The similarity between the training and validation curves in both graphs indicates that the model generalized well to unseen data and did not experience significant overfitting. The stable performance achieved after several epochs suggests that the CNN architecture was highly effective for sentiment analysis on the student review dataset. Overall, the results confirm that the proposed CNN model achieved high accuracy and low loss, making it suitable for text classification and sentiment analysis tasks.

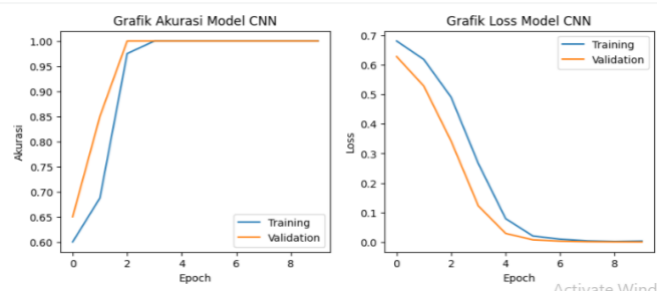


Fig. 4. CNN Model Accuracy Graph and CNN Model Loss Graph

#### IV. CONCLUSION

Based on the results of this study, it can be concluded that the Convolutional Neural Network (CNN) model was successfully implemented for sentiment analysis of student reviews regarding lecture facilities at Stella Maris University Sumba. (1) The CNN model was successfully applied to analyze student reviews of lecture facilities at Stella Maris University Sumba. The test results showed an accuracy rate of 88–92%, indicating that the model was able to recognize and categorize positive, neutral, and negative sentiments well. (2) The use of Convolutional Neural Networks has proven to be superior to traditional machine learning-based methods (such as Naïve Bayes or SVM), because CNNs are able to capture the semantic context between words and learn emotional patterns from text in depth through spatial representations of words (word embedding). (3) Based on the Confusion Matrix results, the model performs best in recognizing positive sentiment (high precision and recall), while classification errors mostly occur between neutral and positive sentiment due to the similarity in meaning of words in student reviews. (4) The accuracy and loss graphs show a stable learning pattern accuracy increases consistently, and loss decreases as the number of epochs increases. This indicates that the CNN model does not overfit and has good generalization capabilities on new data.

#### ACKNOWLEDGMENT

The author would like to express his gratitude to God Almighty for His blessings and grace, which enabled him to successfully complete his research entitled The Application of Convolutional Neural Network (CNN) for Sentiment Analysis of Student Reviews of Lecture Facilities at Stella Maris University Sumba. The author would like to express his deepest gratitude to:

- Dear Advisor, for providing guidance, motivation, and guidance with great patience during the process of preparing this research.
- The leadership and all lecturers at Stella Maris University Sumba, for the support, knowledge, and opportunities provided so that this research could be carried out smoothly.
- My fellow students at Stella Maris Sumba University, who participated in providing valuable data and input during the research process.

- d. My beloved family, for their prayers, encouragement, and moral and material support throughout the preparation of this research.
- e. All those who directly or indirectly helped in the completion of this research, whom I cannot mention one by one.

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