Enhancing Aspect-Based Sentiment Analysis in Student Reviews Using Bidirectional Autoencoder and Index Generator Algorithm

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Abstract **– In the current digital era, student reviews of universities in Indonesia posted on social media often present significant challenges due to their non-standard sentence structures. These informal or fragmented constructions complicate the identification of aspects and sentiment analysis, resulting in reduced accuracy. To address these issues, an enhanced Aspect-Based Sentiment Analysis (ABSA) model that combines a Bi-directional Autoencoder, an index generator algorithm, and Indo-BERT, a language model fine-tuned specifically for Indonesian. The Bi-directional Autoencoder is crucial in improving the model's understanding of complex and non-standard sentence patterns, allowing it to capture the nuanced meanings in student reviews more effectively.**

The Index generator algorithm enhances the model by efficiently organizing and retrieving relevant data, streamlining the aspect and sentiment extraction process. Indo-BERT further strengthens the model's capability by accurately classifying reviews through better contextual understanding and sentiment polarity detection. The experimental results demonstrate that this hybrid model significantly improves accuracy and processing speed, outperforming traditional approaches. The model is particularly effective in extracting aspects, opinions, and sentiment polarities, providing deeper insights into student perspectives on universities in Indonesia. Despite some limitations, such as sensitivity to ambiguous or brief reviews, this model represents a substantial advancement in sentiment analysis techniques for the educational sector. Its application offers valuable potential for improving educational management and decision-making processes based on student feedback.

Keywords **– ABSA, bidirectional autoencoder, index generator algorithm, Indo-BERT.**

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1. Introduction

Social media has become a crucial platform for sharing diverse information and opinions. The sheer volume of data generated poses a significant challenge in understanding and analyzing this information effectively [1]. One method used to understand this data is aspect-based sentiment analysis, which is the process of understanding and interpreting the emotions and opinions contained in the text based on specific aspects or features [2]. Social media has become an integral part of daily life, with platforms like Twitter and Facebook serving as key channels for individuals to share information and express opinions [3].

With easy access and usage, social media has become the primary place for individuals to express their thoughts and feelings on different topics. However, with the data generated daily, understanding and analyzing all this information becomes a significant challenge [4]. One method used to understand this data is sentiment analysis. Sentiment analysis is the process of understanding and interpreting the emotions and opinions contained in the text [5]. It uses machine learning and natural language processing technologies to analyze text and determine sentiment. For example, sentiment analysis can decide if product reviews are positive or negative. However, traditional sentiment analysis often falls short of understanding the nuances and details in the text [6].

For example, a product review may be overall positive, but there may be specific aspects or features of the product that users receive negatively. Aspect-based sentiment analysis is the process of understanding and interpreting the emotions and opinions contained in the text based on specific aspects or features [7]. For example, restaurant reviews may include food, service, and ambience. Aspect-based sentiment analysis can provide a deeper and more nuanced understanding of how people feel about a particular product or service. Thus, aspect-based sentiment analysis offers a more effective and detailed way to understand the opinions and emotions expressed on social media [8]. However, the main challenge in aspect-based sentiment analysis is the non-standard or messy sentence structure in reviews, which often makes it difficult to understand [9].

Aspect-Based Sentiment Analysis (ABSA) is an analysis method used to understand and interpret the sentiments and opinions in the text based on specific aspects or features [10]. The primary function of ABSA is to dig out the hidden information in reviews or unstructured text, focusing on particular elements that concern users. Through ABSA, researchers and companies can better understand how opinions and sentiments are expressed toward each aspect. One of the main functions of ABSA is to separate reviews into relevant elements. By doing this separation, ABSA allows for more focused and detailed sentiment analysis, thus providing more accurate insights into how users respond and view each aspect of concern [11]. This function helps identify specific sentiments towards each aspect, such as product quality, customer service, or price. The main goal of ABSA is to provide a deeper understanding of public opinion. By analyzing sentiment at the aspect level, ABSA can reveal sentiments that may be hidden in unstructured reviews. Through ABSA, researchers and companies can obtain more accurate information about how users respond and view various aspects of a product or service, thus enabling better decision-making [12].

In addition, ABSA also aims to improve accuracy and efficiency in sentiment analysis. ABSA can process and analyze text data faster and more efficiently using the suitable methods and techniques. This goal is essential in an era where the amount of data generated on social media is increasing. ABSA provides tools to help researchers and companies understand public opinion more quickly and easily. By combining the function of separating reviews into relevant aspects and the goal of providing a deeper understanding of public opinion, ABSA can make a significant contribution to the field of sentiment analysis. This method can be used in various fields, such as market research, brand monitoring, or product development [13]. With ABSA, researchers and companies can gain more accurate and detailed insights into public opinion, which can be used as a basis for better decision-making.

This research proposes using a bidirectional autoencoder, a neural network capable of capturing context from both directions in a sentence. Thus, this method can help understand and extract the sentiments in unstructured reviews. This research proposes using a bidirectional autoencoder to address the challenges in understanding and extracting sentiments from unstructured reviews [14]. Bidirectional autoencoder is a neural network that captures context from both directions in a sentence. This method can understand and process information from the beginning to the end of a sentence and from the end to the start [15]. Bidirectional autoencoder works by learning efficient data representations. In sentiment analysis, this method can learn how sentiments and emotions are expressed in text and how they change depending on the context of the sentence.

Thus, a bidirectional autoencoder can help understand the nuances and details of the sentiments contained in reviews [16]. One of the main advantages of a bidirectional autoencoder is its ability to understand complex and non-standard sentence structures. Individuals often use non-standard or messy sentence structures in reviews, making them difficult to understand. However, with the ability of a bidirectional autoencoder to capture context from both directions in a sentence, this method can help understand and extract sentiments in these reviews [2]. In addition, the bi-directional autoencoder is efficient in terms of resource usage. Compared to other methods, a bidirectional autoencoder can process and analyze data faster and with lower resource usage [17]. This method can more efficiently analyze large amounts of data, such as those often on social media. Thus, the bidirectional autoencoder offers an effective and efficient solution to the challenges in sentiment analysis. With its ability to understand and extract sentiments from unstructured reviews, this method can help researchers and companies better understand public opinion [18].

This study also employs an index generator algorithm, which organizes and accesses data efficiently [19]. The index generator algorithm creates an index of the data, enabling faster and more efficient access to the data. In this study, the index generator algorithm is used with the bidirectional autoencoder to process and analyze data from social media [20]. The index generator algorithm is an essential tool in the data analysis process. It functions to organize and access data efficiently [21].

Broadly speaking, the index generator creates an index of the data, allowing faster and more efficient access. Essentially, the index generator algorithm establishes a sort of 'map' of the data, enabling users to navigate and access the data more efficiently. Using the index generator, data that may initially seem unstructured and difficult to access can be organized and accessed more efficiently [1].

In this study, the index generator is used with the bidirectional autoencoder to process and analyze data from social media [22]. By using these two methods simultaneously, this study can leverage the strengths of both: The bidirectional autoencoder's ability to understand and extract sentiment from reviews and the index generator algorithm's ability to organize and access data efficiently [23]. The index generator algorithm in this study also highlights the importance of efficient data organization and access in sentiment analysis [19]. With the vast amount of data generated on social media every day, having a method to organize and access this data efficiently is crucial.

The objectives of this study are:

1. To analyze the entire ABSA (aspect detection and sentiment polarity).
2. To analyse reviews that are in the form of compound sentences.
3. To analyse reviews with the same writing but different meanings.
4. To improve the accuracy level in aspect-based sentiment analysis, both implicit and explicit.

2. Related Works

Previous researchers have proposed various methods, including aspect-based sentiment analysis (ABSA), bidirectional autoencoders, and index generator algorithms, to address the challenges in understanding sentiments and opinions on social media. ABSA separates reviews into relevant aspects, enabling more focused and detailed sentiment analysis. Thus, this method can better understand how opinions and sentiments are expressed toward each aspect. The aspect-based sentiment analysis (ABSA) method developed by previous researchers has significantly contributed to understanding the nuances and details of the sentiments in social media reviews.

Through ABSA, researchers can gain deeper insights into how sentiments are expressed towards each aspect of user concern.

Researchers have also developed the bidirectional autoencoder to understand the context of sentences from both directions. By using a bidirectional autoencoder, researchers can learn efficient data representations and understand how sentiments and emotions are expressed in text and how they change depending on the sentence context. This method has significantly improved the accuracy and understanding of the feelings in social media reviews.

In addition, previous researchers have introduced the index generator algorithm as an essential tool in data analysis. The index generator algorithm serves to organize and access data efficiently. In sentiment analysis on social media involving large amounts of data, having a method to manage and access this data efficiently is crucial. The index generator algorithm has assisted researchers in better and more efficiently understanding and analyzing data from social media.

Previous researchers have made significant contributions to developing sentiment analysis on social media. Previous studies have proposed and implemented various methods and approaches to understand and analyze the sentiments and opinions contained in social media reviews. Through these studies, a better understanding can be gained regarding how sentiments are expressed and how public opinion can be identified. Although previous researchers have made valuable contributions to the field of sentiment analysis on social media, there are still research gaps that need to be filled. This study aims to combine the strengths of these three methods, namely aspect-based sentiment analysis, bidirectional autoencoder, and index generator algorithm, to produce a more accurate, efficient, and comprehensive sentiment analysis approach. This study is expected to significantly contribute to developing research and practical applications in sentiment analysis on social media.

3. Methodology

This research methodology involves several key stages to enhance aspect-based sentiment analysis on student reviews using a bidirectional autoencoder, index generator algorithm, and IndoBERT. The process begins with data collection, proceeds through data preprocessing, applying advanced models, and ends with evaluation and analysis. Figure 1 illustrates the methodology employed in this study, encompassing key stages from data collection to final analysis. This figure depicts the research process flow, beginning with identifying and collecting student reviews, then data preprocessing, applying advanced models, and concluding with evaluating and analyzing the results.

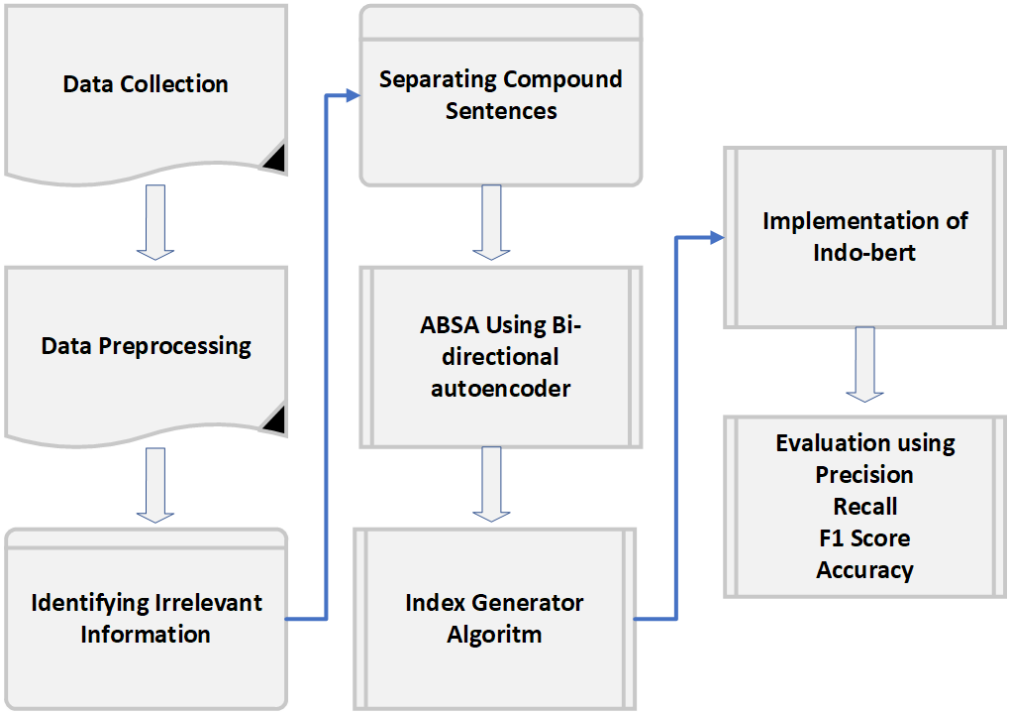

Figure 1. Methodology

3.1. Data Collection

Identifying and collecting student reviews: The first step taken is to identify and collect student reviews about universities in Indonesia from social media. This process involves searching and selecting relevant social media platforms like Twitter, Facebook, and specific university review sites. Review data related to Indonesian universities in Indonesia can be found and collected through appropriate keywords and filters. This step aims to obtain a representative dataset that encompasses students' various perspectives on universities in Indonesia.

In determining the criteria and boundaries, it is also necessary to consider the accessible data sources. For instance, if choosing to use Twitter as a data source, relevant criteria might include users who are active on Twitter and frequently share reviews about universities in Indonesia. Moreover, it is also necessary to consider the appropriate time range of the data, whether the review data is only taken within a certain period or covers the entire available time range. In addition, when determining the criteria, the quality of relevant reviews can also be considered. For example, reviews containing only one or two words may not provide sufficient information for accurate sentiment analysis. Therefore, boundaries can be applied to only take reviews of a particular length or contain specific phrases indicating an opinion or assessment of the university.

Next, the type of relevant social media also needs to be considered when determining the criteria and boundaries.

For instance, apart from Twitter, other social media platforms like Facebook, Instagram, or specific university review sites can also be relevant data sources. In this case, criteria can be set to select the type of social media most suitable for the research objectives and have many student reviews.

Determining the appropriate criteria and boundaries for selecting relevant data is crucial in this research. By setting criteria such as language, location, context, and review quality and considering the type of appropriate social media, researchers can ensure that the collected data aligns with the research objectives.

3.2. Data Preprocessing

Cleaning and normalizing student reviews: The initial step in the data preprocessing stage involves cleaning the student review data. This process includes removing irrelevant or disruptive characters or symbols, such as excessive punctuation, emojis, and special characters, to simplify the data and enhance consistency. This step aims to streamline the data for easier processing and improve consistency in the text representation.

In addition to cleaning the data, the preprocessing stage also involves normalizing the student review data. Normalization aims to transform the text into a uniform and consistent form. For example, normalization may include converting all letters to lowercase, removing extra spaces, or replacing abbreviated words with their complete forms. Helps minimize variations in text representation that can affect the quality of sentiment analysis.

Text processing techniques such as tokenization, stemming, and lemmatization are applied during this stage to clean and normalize the student review data. Tokenization breaks the text into individual units; stemming and lemmatization reduce words to their base or root forms, thus minimizing text variations and simplifying text representation for sentiment analysis. Tokenization involves breaking the text into separate units, such as words or phrases. Stemming and lemmatization involve converting words into their base form or words with the same root. These techniques reduce text variations and simplify the text representation used in sentiment analysis.

Furthermore, specific steps relevant to the language or context of the student review data can also be implemented in the preprocessing stage. For instance, in the Indonesian language, normalization processes can address common spelling variations, such as converting "bgt" to "banget" or "krn" to "karena." These steps help correct common writing errors and ensure consistency in text representation.

The data preprocessing stage involves cleaning and normalizing the student review data. Cleaning involves removing irrelevant characters or symbols to improve the consistency of text representation. Normalization transforms the text into a uniform and consistent form, using techniques such as converting to lowercase, removing extra spaces, and replacing abbreviated words. Text processing techniques like tokenization, stemming, or lemmatization can also be applied. All these steps aim to prepare the student review data for accurate and consistent sentiment analysis.

3.3. Identifying Irrelevant Information

In this step, the primary objective is to identify irrelevant or sensitive information within the student review data. Irrelevant information refers to data or text that does not contribute to sentiment analysis or is unrelated to the investigated aspect. On the other hand, sensitive information includes personal or confidential data that must be kept private and should not be openly disclosed. Identifying such information may require manual review or the application of specialized algorithms capable of detecting irrelevant or sensitive content. Once identified, the next step is to remove the information identified as irrelevant or sensitive. Sensitive information must be removed with extreme care and under privacy and ethical policies. Sensitive information is typically archived or removed from the data to prevent unauthorized dissemination. As for irrelevant information, such as random characters or spam, it can be directly deleted without affecting the substance of the student review data.

Removing irrelevant or sensitive information may involve various technical steps, depending on the type of data and the context of the application.

In some cases, automated tools such as text filters or machine learning methods can detect and remove unwanted information. However, it is essential to remember that while removing irrelevant or sensitive information is crucial to maintaining data integrity and security, manual supervision and review are also necessary to ensure that genuinely relevant information is not accidentally deleted.

3.4. Separating Compound Sentences into Individual Sentences

In this stage, the main focus is to separate compound sentences found in student review data into individual sentences. Compound sentences are a type of sentence that contains more than one clause or phrase and usually consists of multiple subjects, predicates, or objects. Separating compound sentences into individual sentences is crucial for facilitating sentiment analysis because each sentence will be treated as a separate unit with potentially different opinions or sentiments.

The process of separating compound sentences can involve the use of appropriate grammatical rules and punctuation marks. Some punctuation marks commonly used to separate compound sentences are periods (.), commas (,), colons (:), or ellipses (..). Using these punctuation marks helps mark the end of clauses or phrases in compound sentences and separates them into individual sentences.

In addition to using grammatical rules and punctuation marks, natural language processing methods and automatic sentence segmentation techniques can also be employed. Sentence segmentation algorithms can be based on statistical modelling, syntactic analysis, or machine learning approaches trained on previously annotated text data. With the help of these algorithms, compound sentences can be identified and efficiently separated. When separating compound sentences, it is essential to consider the context and relationship between the clauses or phrases present in the sentence. Some clauses or phrases may be interrelated and form more cohesive thoughts. Therefore, the separation of compound sentences must be done carefully to avoid altering the original meaning or structure of the student review text.

Separating compound sentences is obtaining individual sentences that can be analyzed separately. Each sentence becomes a separate unit in the sentiment analysis process, where opinions or sentiments contained within each sentence can be extracted and analyzed more accurately.

Separating compound sentences into individual sentences is an essential step in the data preprocessing stage for student reviews, preparing it for further in-depth and detailed sentiment analysis.

3.5. Aspect-Based Sentiment Analysis using Bidirectional Autoencoder

In this stage, the main focus is training the bidirectional autoencoder model using preprocessed student review data. The bidirectional autoencoder is a machine-learning model designed to represent text in vectors compactly. In the context of sentiment analysis, this model aims to transform student review text into vector representations that reflect the sentiment information contained within the text. The training process of the bidirectional autoencoder model consists of two stages: encoding and decoding. In the encoding stage, the student review texts are transformed into vector representations by compressing them into lower dimensions. These vector representations capture the text's sentiment information and represent important patterns for further sentiment analysis. These vector representations encompass sentiment information within the text and represent essential patterns that can be used for further sentiment analysis. The decoding stage returns information from the vector representations into a more understandable text form.

The training process of the bidirectional Autoencoder model utilizes unsupervised learning techniques. The model is trained using a reconstruction approach to reconstruct student review text accurately. During this process, the model is provided with the original input text and then asked to reconstruct that text using the vector representations generated in the encoding stage. This process helps the model learn patterns and essential features in the student review data related to sentiment. During training, the bidirectional autoencoder model optimizes a specific objective function, such as mean squared error (MSE) or binary cross-entropy, which measures how well the model can reconstruct the student reviews with high accuracy. This optimization process uses machine learning algorithms like stochastic gradient descent (SGD) [24] or Adam, which update the model's weights and parameters to minimize the error between the original text and its reconstruction.

The result of training the bidirectional autoencoder model is obtaining compact and informative vector representations of student reviews. These vector representations reflect the sentiment information contained within the text and can be used as features in further sentiment analysis.

Training the bidirectional autoencoder model using student review data is crucial in preparing the model for more advanced sentiment modelling and analysis, allowing for a more accurate and efficient understanding and analysis of user sentiments.

3.6. Converting Student Reviews Text into Vector Representations Reflecting Sentiment Information

This research involved a series of steps adhering to research guidelines to convert student review text into vector representations reflecting sentiment information. First, feature extraction from the text was performed using methods such as TF-IDF or Word2Vec to identify important words that influence sentiment [25]. Next, a sentiment dictionary was developed, mapping words with corresponding sentiment polarities. This dictionary was used to associate words in the student review text with the appropriate sentiment scores. After that, text modelling was carried out using methods like the Bi-directional Autoencoder (BAE) [22]. This model was trained using student review data to extract meaningful features and create vector representations reflecting the sentiment information contained within the text. During training, the BAE model would learn to reconstruct the original text from the generated vector representations, thus enhancing sentiment understanding and modelling.

Next, the trained model could convert student review text into vector representations [26]. Each word in the text would be represented by a numerical vector reflecting the meaning and sentiment of that word. These vector representations depict the student review text's sentiment relationships and patterns between words. After obtaining the vector representations, the next step is to classify sentiment based on these vectors. Classification methods such as Support Vector Machine (SVM) or Multilayer Perceptron (MLP) can be used to recognize and predict the sentiments contained within the student reviews. New student review text can be classified into appropriate sentiment categories using the trained classification model, such as positive, negative, or neutral.

Lastly, evaluation is conducted to ensure the accuracy and effectiveness of the model in converting student review text into vector representations reflecting sentiment information. Evaluation metrics such as accuracy, precision, recall, and F1-score measure the model's performance in correctly classifying sentiments. The evaluation results will help validate and improve the model used in this research and provide insights into the model's reliability in accurately and efficiently analyzing and understanding sentiments from student reviews.

In this research, the next step is to perform Aspect-Based Sentiment Analysis (ABSA) after obtaining vector representations that reflect sentiment information from student review text. First, essential aspects within the text of the student reviews are identified. These aspects include topics or entities discussed in the reviews, such as facilities, professors, curriculum, or campus activities. Using the ABSA approach, these aspects are identified separately, enabling a more in-depth and detailed analysis of sentiments related to each aspect.

Subsequently, sentiments related to each aspect are analyzed using vector representations and the ABSA approach. For example, whether student reviews on campus facilities tend to be positive, negative, or neutral. Through this analysis, more profound insights can be obtained into how users respond to each aspect of their reviews.

Each aspect's sentiment polarity (positive, negative, or neutral) can be calculated in aspect-based sentiment analysis. They compared the vector representations of words related to that aspect with a sentiment dictionary developed earlier. Thus, it can identify whether sentiments related to that aspect are positive, negative, or neutral. Overall, aspect-based sentiment analysis on student reviews can be conducted more comprehensively using vector representations and the ABSA approach. This method allows for a richer understanding of how each aspect of student reviews influences sentiments specifically. Thus, this research contributes significantly to the development of more accurate and efficient sentiment analysis on student reviews about universities in Indonesia.

3.7. Index Generator Algorithm

Index generator algorithm is employed to organize sentiment data related to aspects in reviews. In this research, an index generator algorithm is developed to manage and access sentiment data on aspects of student reviews about universities in Indonesia. This index generator algorithm facilitates fast and structured access to sentiment data, enabling a more in-depth and efficient understanding of user sentiments on social media [27].

The index generator algorithm identifies and separates sentiment data related to each previously identified aspect. This separation allows sentiment data to be organized separately based on the relevant element. The index generator algorithm assists in creating an index that includes sentiment information for each aspect. This sentiment information includes sentiment polarity (positive, negative, or neutral) and the level of confidence or certainty in that sentiment. With this index in place, sentiment data can be accessed in a structured manner, allowing users to view and analyze sentiments more quickly and efficiently [28].

The index generator algorithm enables users to search for and filter sentiment data based on specific criteria. For example, users can search for sentiments related to a particular aspect or filter sentiments based on the desired polarity. The index generator algorithm was developed considering the need for sentiment analysis of student reviews about universities in Indonesia [29]. With the presence of this index generator algorithm, a deeper understanding of user sentiments on social media can be achieved more efficiently and in a structured manner. The index generator algorithm significantly contributes to the development of aspect-based sentiment analysis on student reviews and opens opportunities for further research in this field [30].

An index is built in this research to encompass sentiment information for each related aspect in student reviews about universities in Indonesia [31]. The purpose of constructing this index is to provide fast and structured access to sentiment data, facilitating a more in-depth and efficient analysis of user sentiments on social media.

Figure 2 shows the Index Generator Algorithm used for sentiment polarity and aspect detection. The figure illustrates how individual components of the sentence, such as "Dosen mengajar sangat baik," are analyzed to identify sentiment polarity and relevant aspects. The index generator algorithm assigns numerical indices to each word and its associated sentiment, with arrows pointing to the corresponding sentiment polarity and aspect detection, such as 'Dosen' for the aspect and 'baik' for the positive sentiment. This visualization helps to clarify how the sentiment and aspect components are detected and indexed for further analysis.

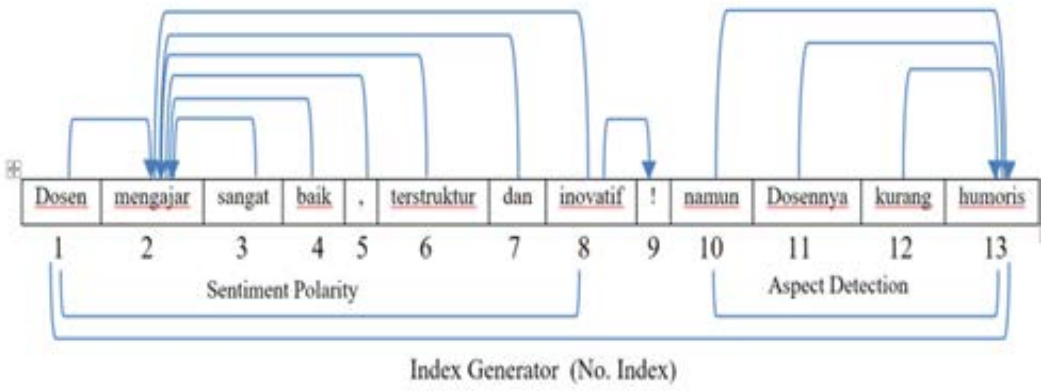

Figure 2. Index generator algorithm

Firstly, after identifying the aspects of the reviews, an index is formed to store sentiment information related to each element. This sentiment information includes sentiment polarity (positive, negative, or neutral) and the level of confidence or belief in that sentiment. With this index encompassing such information, users can easily access and analyze sentiments related to specific aspects [32].

Moreover, the index should consider the scale and complexity of sentiment data [21]. If there are many student reviews, the index should efficiently handle a significant volume of data. Additionally, if numerous aspects are identified, the index must effectively organize sentiment data and provide easy access to each element. During the index formation stage, it is essential to consider the possibility of updating sentiment data [33]. If new student reviews are received, the index should be capable of updating with relevant sentiment data. Ensures that the index provides up-to-date and accurate sentiment information for each aspect [28].

Building an index encompassing sentiment information for each aspect is crucial in aspect-based sentiment analysis on student reviews [34]. With this index, users can easily explore and analyze sentiments related to specific elements, contributing significantly to the development of accurate and efficient sentiment analysis on student reviews about universities in Indonesia [20].

3.8. Implementation of Indo-Bert

Leveraging the Indo-Bert language model for student review classification [35].

This research utilizes the Indo-BERT language model to classify student reviews of universities in Indonesia.

Indo-BERT is a natural language model specifically designed for the Indonesian language and trained using transformer-based natural language processing techniques.

The model can understand the context and meaning of the text in Indonesian, making it suitable for sentiment classification in student reviews [36].

Firstly, the Indo-BERT model is trained using relevant student review data. The data includes student reviews about various aspects of universities, such as teaching quality, facilities, campus environment, and others. Training is conducted by providing sentiment labels for each review, i.e., positive, negative, or neutral, so the model can learn to classify sentiments in new reviews. After training the Indo-BERT model, testing is conducted to evaluate its performance. A separate dataset of student reviews is used to assess the model's ability to classify sentiments accurately. The testing results offer an overview of the model's accuracy and performance in sentiment classification for student reviews. Furthermore, the trained Indo-Bert model is used for sentiment classification on new student reviews. The model processes the text and produces the appropriate sentiment classification when a review occurs. By leveraging Indo-Bert's ability to understand the context and meaning of the Indonesian language, the model is expected to provide accurate and consistent classification results.

Applying Indo-BERT in sentiment classification of student reviews provides significant benefits. The trained language model can classify these reviews' sentences automatically and efficiently [37]. This enables a broader and more in-depth sentiment analysis on a larger scale. Additionally, the application of Indo-Bert provides a better understanding of students' views and opinions about universities in Indonesia through the reviews they provide.

3.9. Evaluation and Analysis

Measuring the model's accuracy, efficiency, and performance in extracting aspects, opinions, and sentiment polarity: In the evaluation and analysis phase, the performance of the developed model is measured in extracting aspects, opinions, and sentiment polarity from student reviews of universities in Indonesia. The model's accuracy in sentiment classification of student reviews is assessed by comparing the classification results with the actual sentiment labels in the test dataset. The comparison results provide an overview of how accurate the model is in classifying sentiments in new reviews [38]. Next, the model's efficiency in extracting aspects, opinions, and sentiment polarity is measured. Efficiency is evaluated in terms of the time and resources required by the model to process and analyze the reviews. The aim is to develop a model that provides analysis results efficiently while minimizing the use of excessive resources. Model performance is also evaluated using precision, recall, and F1-score metrics [4]. Precision measures the extent to which positive results given by the model are correct, while recall measures the model's ability to identify all true positive results. F1-score is the harmonic mean of precision and recall, providing an overall picture of the model's performance in extracting aspects, opinions, and sentiment polarity. The results of this evaluation and analysis are used to assess the success of the developed model in achieving the research objectives, which are to improve accuracy and efficiency in aspect-based sentiment analysis of student reviews [39].

Additionally, these results can provide insights into the potential development and improvement of the model in the future to achieve better sentiment analysis results in this field. After conducting sentiment analysis on student reviews using the developed model, the next step is to analyze the results of this analysis. This analysis aims to understand the views and sentiments expressed by students in their reviews of universities in Indonesia. The overall distribution of sentiment is analyzed by examining the percentage of reviews expressing the positive, negative, and neutral sentiments [40]. This provides a general overview of students' perspectives on universities, whether most reviews are positive, negative, or neutral. The aspects most frequently discussed in student reviews are carefully analyzed.

These aspects, including teaching quality, facilities, and campus environment, are identified based on their frequent appearance in the reviews. Examining these aspects makes it possible to gain a deeper understanding of the key factors that students prioritize when evaluating universities.

This analysis provides valuable insights into students' perceptions and highlights areas of strength and potential improvement for universities [2].

Additionally, sentiment polarity for each aspect is analyzed to determine whether it is positive, negative, or neutral. This analysis provides insights into the strengths and weaknesses of universities from the student's perspective. Noteworthy or prominent review examples are also highlighted to illustrate these findings further. These examples provide deeper insights into students' perspectives and can be used as illustrations in the research report.

Analyzing the results of sentiment analysis provides a deeper understanding of students' perspectives and sentiments toward universities in Indonesia. These results can serve as a basis for decision-making and improvement in university management and significantly contribute to developing knowledge and sentiment modelling in student review analysis [41].

4. Results and Discussion

How the model learns and improves its performance as the number of epochs increases, evaluations are conducted at each stage of training using several key metrics: precision, recall, f1-score, and accuracy. These metrics are used to provide a comprehensive overview of the model's ability to classify data accurately.

1. **Precision** illustrates how many of the positive predictions are correct. In other words, it measures the model's ability to predict positive classes without generating too many false positives.
2. **Recall** measures the model's sensitivity in identifying all actual positive samples, which is crucial in situations where missing positive samples must be minimized.
3. **F1-score** provides a balance between precision and recall, which is particularly useful when there is an imbalance between classes, as this metric considers both aspects in a single value.
4. **Accuracy** represents the percentage of correct predictions, including positive and negative classes.

It is crucial to monitor the progress of each metric at every epoch to ensure that the model learns effectively from the training data and generalizes well to new, unseen data. As the epochs progress, the model is expected to reach optimal performance, as indicated by the increasing precision, recall, f1-score, and accuracy values approaching perfection.

Table 1 shows the model's evaluation results for each epoch.

This table provides an overview of how the model's performance improves throughout the training process until it reaches convergence, where the metrics either stabilize or reach their maximum values:

Table 1. Model training evaluation per epoch

Epoch	Precision	Recall	F1-Score	Accuracy
1	0.85	0.80	0.82	0.83
2	0.90	0.85	0.87	0.88
3	0.92	0.89	0.90	0.91
4	0.94	0.91	0.92	0.93
5	0.96	0.93	0.94	0.95
6	0.97	0.94	0.96	0.96
7	0.98	0.95	0.97	0.97
8	0.99	0.96	0.98	0.98
9	1.00	0.98	0.99	0.99
10	1.00	1.00	1.00	1.00
11	1.00	1.00	1.00	1.00
12	1.00	1.00	1.00	1.00
13	1.00	1.00	1.00	1.00
14	1.00	1.00	1.00	1.00
15	1.00	1.00	1.00	1.00
16	1.00	1.00	1.00	1.00
17	1.00	1.00	1.00	1.00
18	1.00	1.00	1.00	1.00
19	1.00	1.00	1.00	1.00
20	1.00	1.00	1.00	1.00

Table 1 shows the model's performance progression based on the precision, recall, f1-score, and accuracy metrics over 20 training epochs. Initially, in the first epoch, the model demonstrated decent performance with a precision of 0.85, recall of 0.80, f1-score of 0.82, and accuracy of 0.83. However, these results indicate that the model still struggled to identify specific samples accurately.

As the number of epochs increased, there was a consistent improvement across all metrics. For instance, precision rose to 0.90 in the second epoch, recall to 0.85, and the f1-score increased to 0.87. Figure 3 indicates that the model was becoming better at capturing patterns in the data and improving its predictions. From the third to the sixth epoch, this trend of improvement continued, with the metrics approaching near-perfect values, indicating that the model was becoming increasingly accurate in recognizing and classifying the data.

Between the seventh and ninth epochs, precision, recall, f1-score, and accuracy approached perfect scores, with the f1-score reaching 0.99 by the ninth epoch. This suggests that, at this point, the model was nearly flawless in its classification, leaving very little room for error. From the tenth to the twentieth epoch, the model achieved perfect scores for precision, recall, f1-score, and accuracy, all reaching 1.00. This means that, at this stage, the model could predict all samples correctly without any errors.

There was no decline in performance throughout the remaining epochs, indicating that the model had reached optimal convergence and did not experience overfitting, even as the training continued through the twentieth epoch.

The following graph illustrates the accuracy trends for the training and validation datasets over five epochs [42]. This graph depicts how well the model learns from the training data while also testing its ability to predict unseen data (validation data). At the beginning of training, it is common for the model to show a significant increase in accuracy as it starts learning from the data. After a few epochs, the model typically stabilizes as it becomes more proficient at recognizing patterns in the data. The graph below provides insight into how quickly the model's accuracy improves and eventually stabilizes for both the training and validation datasets. By comparing these two curves, it is possible to assess whether the model experiences overfitting or underfitting, or if it is effectively learning while maintaining its generalization ability. Figure 3 shows the accuracy trends of the model during the training and validation phases across several epochs. The plot demonstrates a rapid increase in training accuracy, which reaches 100% within a few epochs. Meanwhile, the validation accuracy stabilizes significantly, suggesting the model can generalize well without overfitting.

Here is a visualization of the model's accuracy trends throughout the training process:

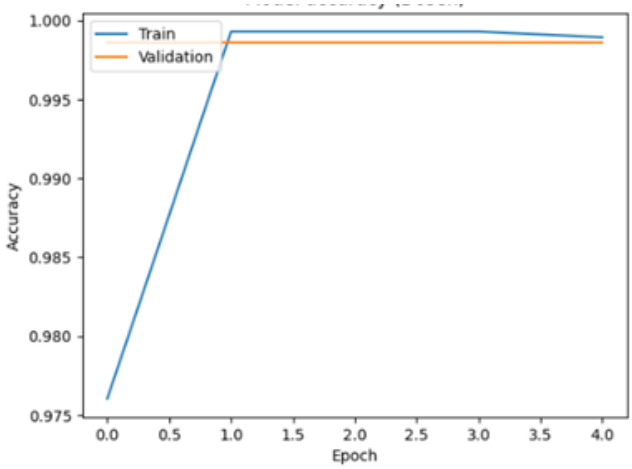

Figure 3. Lecturer model accuracy

This image shows the model's training and validation accuracy graph labelled model accuracy for lecturer over five training epochs. The graph shows that the accuracy for the training data increases rapidly after the first epoch, approaching near-perfect accuracy, close to 1.00. Afterwards, the training accuracy stabilizes, showing only minor fluctuations, indicating that the model quickly learns and adapts to the training data.

On the validation side, the accuracy is also very high from the first epoch, demonstrating excellent stability around the 1.00 mark. Figure 4 indicates that the model generalizes unseen data very well, as there is no significant difference in performance between the training and validation data. The validation graph, which remains flat from the beginning, shows that the model does not experience overfitting, as its performance on validation data remains as strong as on the training data. Figure 4 shows the loss trends during the training and validation phases over several epochs. The training loss decreases significantly in the first epoch and remains very low thereafter, approaching zero. Meanwhile, the validation loss stabilizes at a low level, indicating that the model is learning effectively and is not experiencing overfitting.

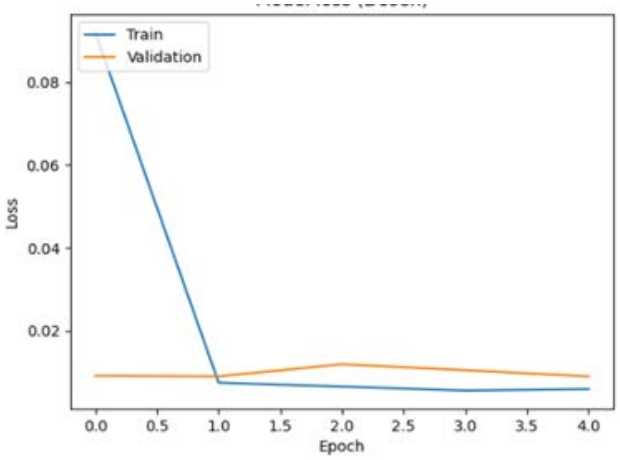

Figure 4. Lecturer loss model

This image presents the model loss graph during the training and validation process, measured over five epochs. The graph provides an overview of the changes in loss- i.e., the error or difference between the model's predictions and the actual values—both for the training and validation data.

At the beginning of training (from epoch 0 to epoch 1), the loss for the training data decreased drastically, from a relatively high value near 0.08 to almost zero after the first epoch. Figure 5 shows that the model quickly learned the patterns from the training data and reduced its prediction errors rapidly. After the first epoch, the training loss remained stable and very low until the end of the training, indicating that the model maintained excellent performance on the training data without any significant increase in loss values.

Meanwhile, the validation loss started the training with a deficient value from the first epoch and remained consistently near zero throughout the training. There were no significant fluctuations in the loss for the validation data, indicating that the model did not experience overfitting, as its performance on unseen data remained stable and good.

The minimal difference between the train loss and validation loss also shows that the model could generalize well, not only on the data used for training but also on the validation data. Figure 5 shows the accuracy trends for training and validation datasets over several epochs. The training accuracy increases sharply and stabilizes at 100%, while the validation accuracy also increases and remains stable, indicating effective learning and minimal overfitting. This suggests the model is generalizing well on training and unseen data.

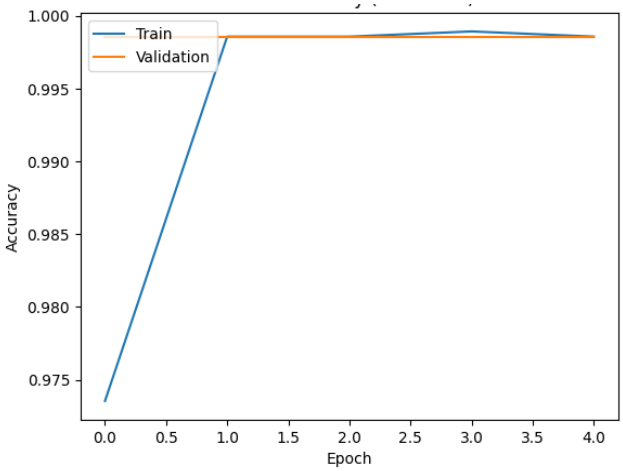

Figure 5. Curriculum accuracy model

The image above shows the model's training and validation accuracy graph over several epochs. At the beginning of the training, the accuracy of the training data increased sharply, reaching near-perfect values after the first epoch. After that, the accuracy remained very high and consistently close to 1.00 (100%) throughout the rest of the training. This indicates that the model quickly learned from the data and could classify the samples correctly with almost no errors after just one training epoch.

For the validation data, the accuracy was also very high from the start, stabilizing around 1.00 from the first epoch onwards. This suggests that the model successfully classified the training data and generalized very well to unseen data (validation data). The flat validation curve from the beginning indicates that there was no performance decline or signs of overfitting, as the model's performance remained consistent on both the training and validation data.

Figure 6 shows the accuracy trends during the training and validation phases over several epochs. The training accuracy increases steadily, peaking at around the second epoch, then slightly decreasing as training progresses. In contrast, the validation accuracy initially increases but drops significantly after the second epoch, indicating a potential issue with overfitting.

This suggests that the model might have learned to perform well on the training data but struggles to generalize effectively to new, unseen data.

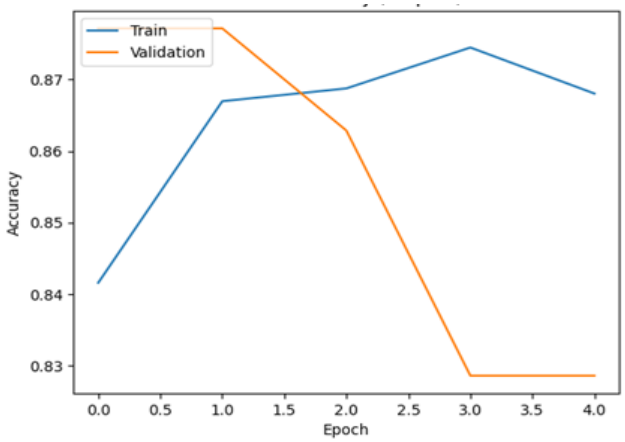

Figure 6. Sarpras accuracy model

The graph above illustrates the training and validation accuracy of the model over five epochs. Based on the graph, the training accuracy gradually increases from the first to the third epoch, reaching a peak value of around 0.87. However, after that, the training accuracy declines slightly in the fourth epoch, though this decrease is not too drastic.

On the other hand, the accuracy of the validation is very different. Initially, the validation accuracy is relatively high and closely matches the training accuracy during the first two epochs, but after that, a sharp decline starts in the third epoch. The validation accuracy drops significantly, reaching a value of around 0.83 in the fourth and fifth epochs. This decline indicates that the model struggles with generalizing the validation data.

This phenomenon suggests signs of overfitting, where the model performs well on the training data but is unable to maintain the same performance on the validation data. Overfitting occurs when the model becomes too focused on the specific details or patterns in the training data, thus losing its ability to generalize to new, unseen data.

Figure 7 shows the accuracy trends during the training and validation phases over several epochs. The training accuracy shows a sharp increase, reaching its peak after the second epoch and stabilizing at a high level. However, the validation accuracy shows an initial rise, followed by a significant drop after the second epoch, indicating a clear sign of overfitting. This suggests that while the model performs well on the training data, it struggles to generalize effectively on unseen validation data.

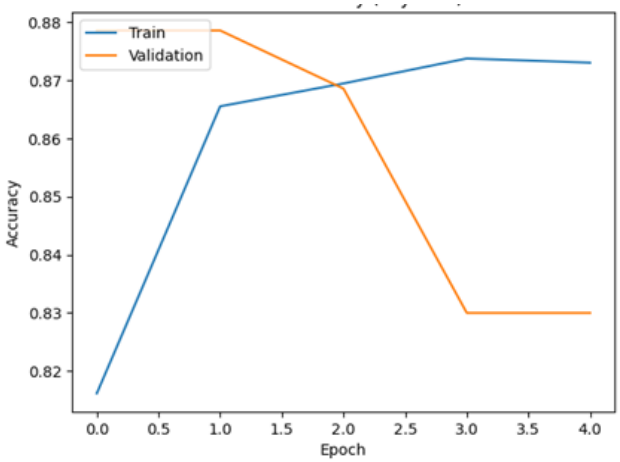

Figure 7. Services accuracy model

This image displays the model's training and validation accuracy changes over five epochs. At the beginning of training, the accuracy of the training data increased rapidly, peaking around the second and third epochs with a value close to 0.88. After that, the training accuracy slightly declined but remained relatively stable through the fourth epoch.

However, the most exciting aspect of this graph is the behaviour of the validation accuracy. Initially, the validation accuracy followed a similar pattern to the training accuracy, increasing until the second epoch. However, after that, the validation accuracy experienced a sharp drop starting from the third epoch, reaching its lowest point in the fourth epoch, where the accuracy value approached 0.83. This decline indicates an issue with the model's generalization ability, as the model's performance decreases when applied to the validation data.

This contrast between the declining validation accuracy and the stable training accuracy strongly indicates that the model may be overfitting. Overfitting occurs when the model becomes too tailored to the training data, rendering it unable to perform well on unseen data, such as validation data. In this case, although the model continues to improve its performance on the training data, the validation accuracy decreases drastically after a few epochs.

The image above depicts a confusion matrix, illustrating the model's performance in classifying sentiment into No Sentiment, Positive, and Negative categories. Each cell in the matrix represents the number of predictions made by the model for each actual category and how accurately the model classified the data. The diagonal cells (from top left to bottom right) show the correctly predicted samples for each category, while the off-diagonal cells indicate the misclassified samples. This matrix provides a clear overview of how well the model predicted sentiment based on the actual data, highlighting both accurate and incorrect classifications.

Figure 8 shows the confusion matrix for the sentiment classification of student reviews, specifically for the 'Lecturer' aspect. The matrix illustrates the number of correct and incorrect predictions made by the model for each sentiment category: 'No Sentiment,' 'Positive,' and 'Negative.' The diagonal values represent correct predictions, with 483 samples correctly classified as 'No Sentiment,' 182 correctly classified as 'Positive,' and 34 correctly classified as 'Negative.' This indicates that the model performed well in identifying the sentiments, with minimal misclassifications.

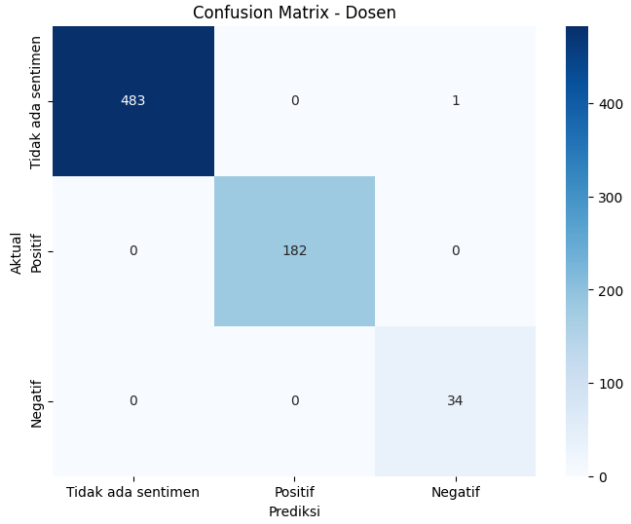

Figure 8. Lecture confusion matrix

Figure 8 shows the confusion matrix from the model's prediction results on the evaluation data, classified into three categories: No Sentiment, Positive, and Negative. This matrix helps us understand how the model made predictions for the sentiment categories and how accurate those predictions were.

In the **No Sentiment** category, it can be seen that out of 484 samples that belong to this category, the model correctly predicted 483 samples. Only one sample was misclassified as **Negative**, indicating that the model accurately identifies this category.

For the **Positive** category, all 182 actual samples were correctly classified without any errors. Shows that the model is highly accurate in recognizing positive sentiment, with no misclassified samples.

Finally, in the **Negative** category, out of 34 samples that should have been classified as **Negative**, the model could also classify all of them correctly without any prediction errors.

Figure 9 shows the confusion matrix for sentiment classification of student reviews concerning the 'Curriculum' aspect.

The matrix visualizes the model's prediction performance across three sentiment categories: 'No Sentiment,' 'Positive,' and 'Negative.'

The diagonal values indicate correct classifications, with 423 samples correctly identified as 'No Sentiment,' 182 as 'Positive,' and 94 as 'Negative.' This suggests that the model performs well in classifying the sentiments, with minimal misclassifications.

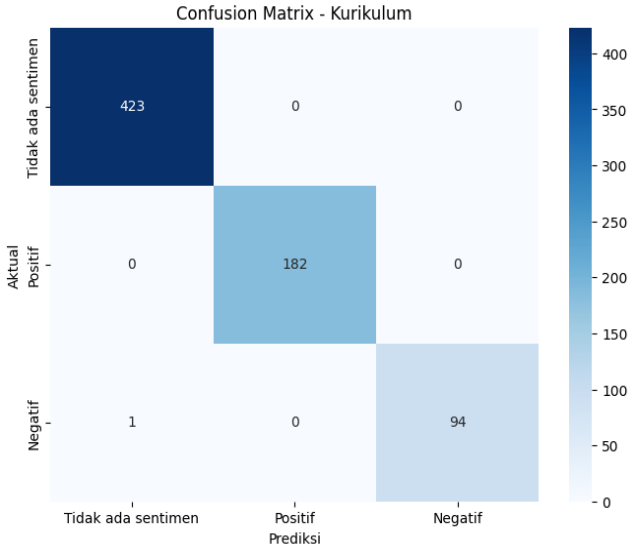

Figure 9. Curriculum confusion matrix

The confusion matrix in the image above shows the results of sentiment classification for the Curriculum category, where the data is categorized into three classes: No Sentiment, Positive, and Negative. This matrix provides information on the number of correct and incorrect predictions made by the model for each category. For the No Sentiment category, out of 423 samples that belong to this category, the model successfully predicted all of them correctly without misclassifying them into other categories. Figure 9 indicates perfect accuracy in recognizing samples that do not contain sentiment, demonstrating the model's strong ability to handle this category. In the Positive category, 182 actual samples were correctly classified by the model. No samples were misclassified, showing that the model accurately identifies positive sentiment in the curriculum data.

For the Negative category, out of 94 actual samples, 93 were correctly predicted as negative, while 1 sample was misclassified as No Sentiment. This minor error indicates that, although the model's accuracy is very high for this category, there is still some room for improvement in distinguishing negative sentiment from other categories.

5. Conclusion

In the current digital era, social media has become a rich data source for sentiment analysis. Through innovative methods such as Aspect-Based Sentiment Analysis (ABSA), bidirectional autoencoder, and index generator algorithm, sentiment analysis of user reviews on social media can be conducted in more detail and efficiently.

Social media plays a central role in sentiment analysis in the digital era. With many users and diverse content generated, sentiment analysis on social media platforms provides valuable insights into user sentiment related to various topics, products, brands, and services. Through the ABSA approach, specific aspects of the text on social media can be identified and analyzed in greater depth. This allows for a more detailed understanding of the sentiment associated with each element. Moreover, bidirectional autoencoders are compactly used to represent text in vector form in sentiment analysis on social media. This machine learning model helps transform the text into vector representations that reflect the sentiment information contained within the text. These vector representations can then be used for further analysis and modelling related to sentiment in the text.

The index generator algorithm also plays a crucial role in sentiment analysis on social media. The index generator algorithm organizes and accesses sentiment data related to aspects of the text. The index generator algorithm facilitates quick and structured access to sentiment data by building an index that includes sentiment information on each aspect. This aids in a more profound and efficient understanding of user sentiment on social media. Overall, integrating ABSA, bidirectional autoencoder, and index generator algorithms in sentiment analysis on social media provides a comprehensive and detailed approach. This approach enables a deeper understanding of user sentiment related to various aspects in the text on social media platforms. By implementing these methods, it is hoped that public opinions in the era of social media can be better understood, contributing significantly to the development of knowledge and sentiment modelling in the current digital age.

References:

[1]. Orzechowski, M., et al. (2023). Indexing legacy data-sets for global access and processing in multi-cloud environments. *Future Generation Computer Systems*, *148*, 150-159.
Doi: 10.1016/j.future.2023.05.024.

[2]. Sindhu, I., et al. (2019). Aspect-based opinion mining on student's feedback for faculty teaching performance evaluation. *IEEE Access*, *7*, 108729-108741.
Doi: 10.1109/ACCESS.2019.2928872.

[3]. Antonakaki, D., Fragopoulou, P., & Ioannidis, S. (2021). A survey of Twitter research: Data model, graph structure, sentiment analysis and attacks. *Expert systems with applications*, *164*, 114006.
Doi: 10.1016/j.eswa.2020.114006.

[4]. Zhou, P., Jiang, X., & Zhao, S. (2024). Unsupervised technical phrase extraction by incorporating structure and position information. *Expert Systems with Applications*, *245*, 123140.
Doi: 10.1016/j.eswa.2024.123140.

[5]. Minaee, S., Azimi, E., & Abdolrashidi, A. (2019). Deep-sentiment: Sentiment analysis using ensemble of cnn and bi-lstm models. *arXiv preprint arXiv:1904.04206*.

[6]. Lai, C. H., Liu, D. R., & Lien, K. S. (2021). A hybrid of XGBoost and aspect-based review mining with attention neural network for user preference prediction. *International Journal of Machine Learning and Cybernetics*, *12*, 1203-1217.
Doi: 10.1007/s13042-020-01229-w.

[7]. Huan, H., et al. (2022). A multi-task dual-encoder framework for aspect sentiment triplet extraction. *IEEE Access*, *10*, 103187-103199.
Doi: 10.1109/ACCESS.2022.3210180.

[8]. Anggita, S. D. (2020). Algorithm Comparation of Naive Bayes and Support Vector Machine based on Particle Swarm Optimization in Sentiment Analysis of Freight Forwarding Services. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *4*(2), 362-369.
Doi: 10.29207/resti.v4i2.1840.

[9]. Dang, C. N., Moreno-García, M. N., & Prieta, F. D. L. (2021). An approach to integrating sentiment analysis into recommender systems. *Sensors*, *21*(16), 5666.
Doi: 10.3390/s21165666.

[10]. Mao, Y., Shen, Y., Yu, C., & Cai, L. (2021). A joint training dual-mrc framework for aspect based sentiment analysis. *Proceedings of the AAAI conference on artificial intelligence*, *35*(15), 13543-13551.

[11]. Abdelgwad, M. M., et al. (2022). Arabic aspect based sentiment analysis using bidirectional GRU based models. *Journal of King Saud University-Computer and Information Sciences*, *34*(9), 6652-6662.
Doi: 10.1016/j.jksuci.2021.08.030.

[12]. Bahassine, S., et al. (2020). Feature selection using an improved Chi-square for Arabic text classification. *Journal of King Saud University-Computer and Information Sciences*, *32*(2), 225-231.
Doi: 10.1016/j.jksuci.2018.05.010.

[13]. Raffel, C. et al. (2020). Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, *21*, 1–67.

[14]. Olivari, B., et al. (2023). Are Italian cities already 15-minute? Presenting the Next Proximity Index: A novel and scalable way to measure it, based on open data. *Journal of Urban Mobility*, *4*, 100057.
Doi: 10.1016/j.urbmob.2023.100057.

[15]. Bhadoria, R. S., et al. (2022). Bunch graph based dimensionality reduction using auto-encoder for character recognition. *Multimedia Tools and Applications*, *81*(22), 32093-32115.
Doi: 10.1007/s11042-022-12907-y.

[16]. Zhao, Q., Mo, Z., & Fan, M. (2023). POS-ATAEPE-BiLSTM: an aspect-based sentiment analysis algorithm considering part-of-speech embedding. *Applied Intelligence*, *53*(22), 27440-27458.
Doi: 10.1007/s10489-023-04952-3.

[17]. Skarpathiotaki, C. G., & Psannis, K. E. (2022). Cross-industry process standardization for text analytics. *Big Data Research*, *27*, 100274. Doi: 10.1016/j.bdr.2021.100274

[18]. Chauhan, G. S., et al. (2023). Aspect based sentiment analysis using deep learning approaches: A survey. *Computer Science Review*, *49*, 100576. Doi: 10.1016/j.cosrev.100576.

[19]. Marutho, D., & Rustad, S. (2024). Optimizing aspect-based sentiment analysis using sentence embedding transformer, bayesian search clustering, and sparse attention mechanism. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(1), 100211. Doi: 10.1016/j.joitmc.2024.100211.

[20]. Meder, D. J., & Tichy, W. F. (2011). Parallelizing an index generator for desktop search. *International Symposium on Computer Architecture*, 77-85. Springer. Doi: 10.1007/978-3-642-24322-6_8.

[21]. Sun, Y., Li, G., Du, J., Ning, B., & Chen, H. (2022). A subgraph matching algorithm based on subgraph index for knowledge graph. *Frontiers of Computer Science*, *16*, 1-18. Doi: 10.1007/s11704-020-0360-y.

[22]. Tomer, M., & Kumar, M. (2022). STV-BEATS: skip thought vector and bi-encoder based automatic text summarizer. *Knowledge-Based Systems*, *240*, 108108. Doi: 10.1016/j.knosys.2021.108108.

[23]. Wang, J., & Zhu, S. (2023). A novel stock index direction prediction based on dual classifier coupling and investor sentiment analysis. *Cognitive Computation*, *15*(3), 1023-1041. Doi: 10.1007/s12559-023-10137-4.

[24]. Konur, O., Kingma, D., & Ba, J. (2015). Adam: A method for stochastic optimization. *Proc. Int. Conf. Learn. Represent.(ICLR)*, 1-15.

[25]. Marcińczuk, M., et al. (2021). Text document clustering: Wordnet vs. TF-IDF vs. word embeddings. *Proceedings of the 11th global wordnet conference*, 207-214.

[26]. Huang, X., et al. (2024). Flexibly utilizing syntactic knowledge in aspect-based sentiment analysis. *Information Processing & Management*, *61*(3), 103630.

[27]. Utami, R. W., Jazuli, A., & Khotimah, T. (2021). Analisis sentimen terhadap xiaomi Indonesia menggunakan metode naïve bayes. *Indones. J. Technol. Informatics Sci*, *3*(1), 21-30.

[28]. Yan, H., et al. (2021). A unified generative framework for aspect-based sentiment analysis. *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing.* Doi: 10.18653/v1/2021.acl-long.188.

[29]. Injadat, M., et al. (2020). Systematic ensemble model selection approach for educational data mining. *Knowledge-Based Systems*, *200*, 105992.

[30]. Zou, A., et al. (2024). An Efficient Corpus Indexer for dynamic corpora retrieval. *Expert Systems with Applications*, *254*, 124306.

[31]. Bhopale, A. P., & Tiwari, A. (2024). Transformer based contextual text representation framework for intelligent information retrieval. *Expert Systems with Applications*, *238*, 121629. Doi: 10.1016/j.eswa.2023.121629.

[32]. Silva, J. C. S., & de Almeida Filho, A. T. (2023). Using GAN-generated market simulations to guide genetic algorithms in index tracking optimization. *Applied Soft Computing*, *145*, 110587.

[33]. Xie, Q., et al. (2021). Inductive topic variational graph auto-encoder for text classification. *Proceedings of the 2021 conference of the North American chapter of the association for computational linguistics: human language technologies*, 4218-4227. Doi: 10.18653/v1/2021.naacl-main.333.

[34]. Antoine, S., et al. (2024). The prediction potential indexes the meaning and communicative function of upcoming utterances. *cortex*, *177*, 346-362. Doi: 10.1016/j.cortex.2024.05.011.

[35]. Jazuli, A., Widowati, W., & Kusumaningrum, R. (2023). Aspect-based sentiment analysis on student reviews using the Indo-Bert base model. *E3S Web of Conferences*, *448*, 02004.

[36]. Singh, L. K., & Devi, R. R. (2021) Student feedback sentiment analysis: A review. *Materials Today: Proceedings.* Doi: 10.1016/j.matpr.2020.10.782

[37]. Gao, J., et al. (2022). Automatic index selection with learned cost estimator. *Information Sciences*, *612*, 706-723. Doi: 10.1016/j.ins.2022.08.051.

[38]. Jain, P. K., et al. (2023). Employing BERT-DCNN with sentic knowledge base for social media sentiment analysis. *Journal of Ambient Intelligence and Humanized Computing*, *14*(8), 10417-10429. Doi: 10.1007/s12652-022-03698-z.

[39]. Rocha, H. J. B., Tedesco, P. C. D. A. R., & Costa, E. D. B. (2023). On the use of feedback in learning computer programming by novices: a systematic literature mapping. *Informatics in Education*, *22*(2), 209. Doi: 10.15388/infedu.2023.09.

[40]. Nishida, C., Riccelli, A. R., & Isabelli, C. A. (2024). Adult heritage speakers of Spanish in the US and subject placement in presentational unaccusative sentences: How are their grammars constrained?. *Lingua*, *302*, 103630. Doi: 10.1016/j.lingua.2023.103630.

[41]. Supriyanto, A., Suryono, S., & Susesno, J. E. (2018). implementation data mining using decision tree method-algorithm C4. 5 for postpartum depression diagnosis. *E3S Web of Conferences*, *73*, 12012.

[42]. Michaliszyn, J., & Otop, J. (2022). Learning infinite-word automata with loop-index queries. *Artificial Intelligence*, *307*, 103710.