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ASPECT-BASED SENTIMENT ANALYSIS ON TWITTER TWEETS ABOUT THE MERDEKA CURRICULUM USING INDOBERT

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Abstract— *The curriculum has changed once again with the introduction of the Merdeka Curriculum to address learning loss in the education sector. Its implementation has elicited various responses, such as support for granting teachers the freedom to innovate, focusing on essential materials, offering diverse learning methods, and fostering student creativity. However, criticism has also arisen, including issues related to teachers' lack of understanding, parents' concerns, and the increased workload on students due to numerous projects. To improve educational policies, an in-depth analysis of these responses is essential. This study aims to analyze public sentiment toward the Merdeka Curriculum by applying Aspect-Based Sentiment Analysis (ABSA) using data from Twitter. The research focuses on four main aspects: Teaching Modules (MA), Education Reports (RP), the Merdeka Teaching Platform (PMM), and the Strengthening of the Pancasila Student Profile Projects (P5). Data were collected using specific and relevant keywords for each aspect, followed by preprocessing, labeling, and filtering based on sentiment and aspect. The final dataset comprised 2,359 valid tweets. The ABSA model was developed using IndoBERT with fine-tuning, then tested and evaluated. The results showed that the aspect classification model achieved an accuracy of 97%, F1 score of 97%, recall of 97%, and precision of 97%. Meanwhile, the sentiment classification model achieved an accuracy of 85%, F1 score of 85%, recall of 85%, and precision of 85%. This ABSA model is expected to assist in monitoring public responses and provide valuable insights for policy development, particularly within the context of the Merdeka Curriculum.*

Keywords: *aspect-based sentiment analysis, deep learning, indobert, merdeka curriculum, twitter.*

Intisari— *Perubahan kurikulum kembali terjadi dengan hadirnya Kurikulum Merdeka untuk mengatasi learning loss di dunia pendidikan. Implementasinya telah memunculkan berbagai respons, seperti dukungan terhadap kebebasan guru dalam berinovasi, fokus pada materi esensial, metode pembelajaran yang beragam, dan pengembangan kreativitas siswa. Namun, kritik juga muncul terkait kurangnya pemahaman pendidik, kekhawatiran orang tua, dan meningkatnya beban siswa karena banyaknya proyek. Untuk meningkatkan kebijakan pendidikan, diperlukan analisis lebih mendalam terhadap respons ini. Penelitian ini bertujuan untuk menganalisis sentimen masyarakat terhadap Kurikulum Merdeka dengan menerapkan Aspect-Based Sentiment Analysis (ABSA) dengan data dari Twitter. Penelitian ini memfokuskan pada empat aspek utama: modul ajar (MA), rapor pendidikan (RP), platform Merdeka Mengajar (PMM), dan proyek penguatan Profil Pelajar Pancasila (P5). Data dikumpulkan menggunakan kata kunci spesifik dan relevan untuk setiap aspek, diikuti pra-pemrosesan, pelabelan, dan penyaringan data berdasarkan sentimen dan aspek. Total data yang valid adalah 2359 tweet. Selanjutnya, model ABSA dibangun menggunakan IndoBERT dengan di fine-tuning, kemudian diuji dan dievaluasi. Hasil penelitian menunjukkan bahwa model klasifikasi aspek mencapai nilai akurasi sebesar 97%, skor F1 sebesar 97%, Recall sebesar 97%, dan Presisi sebesar 97%. Sedangkan model klasifikasi sentimen mencapai nilai akurasi sebesar 85%, skor F1 sebesar 85%, Recall sebesar 85%, dan Presisi sebesar 85%. Model ABSA yang dikembangkan ini diharapkan dapat digunakan untuk melakukan monitoring dan memberikan gambaran umpan balik untuk pengembangan kebijakan ke depan, khususnya pada konteks Kurikulum Merdeka.*

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Kata Kunci: *aspect-based sentiment analysis, deep learning, indobert, kurikulum merdeka, twitter.*

INTRODUCTION

The Merdeka Curriculum, implemented in the 2022/2023 academic year, aims to address learning loss by emphasizing deep learning that strengthens competencies and conceptual understanding. Its implementation focuses on four main aspects: the Education Report (RP), Teaching Modules (MA), the Merdeka Teaching Platform (PMM), and the Strengthening of the Pancasila Student Profile Projects (P5). These four components work synergistically to ensure the effective implementation of the Merdeka Curriculum within the education system.

The Education Report is a web application that presents evaluation data to assist schools and local governments in identifying issues, reflecting, and improving the overall quality of education [1]. Teaching Modules serve as learning tools that are more comprehensive than Lesson Plans (RPP), designed for learning activities with essential, engaging, relevant, contextual, and sustainable criteria, integrated with the Pancasila Student Profile [2]. PMM supports teachers in enhancing competencies and collaboration within the Merdeka Curriculum, providing teaching resource references, assessments, self-paced training, inspirational videos, and a space for teachers to share best practices through the "My Portfolio" feature [3]. Additionally, the Pancasila Student Profile (P5) is a project-based learning approach that involves interdisciplinary collaboration to address real-world problems in the surrounding environment, aiming to develop students who are competent, have strong character, and embody Pancasila values [4].

However, the implementation of the Merdeka Curriculum has sparked both pros and cons among the public [5]. These reactions come not only from educators but also from parents. Some view it as a positive breakthrough, offering teachers the freedom to innovate, focusing on essential materials, diversifying learning methods, increasing flexibility in teaching, and fostering student creativity. On the other hand, criticism arises concerning the perceived short preparation time, weak academic studies, and parental concerns about their children's education [6]. Furthermore, many educators still lack a clear understanding of the Merdeka Curriculum concept and face challenges in mastering the modules and evaluation models applied within it [7]. These issues can lead to ineffective curriculum implementation and negatively impact the quality of teaching in practice.

These diverse reactions highlight the importance of evaluating the implementation of the Merdeka Curriculum. This curriculum has been applied in 2,500 pilot and non-pilot schools [8]. According to data from the Ministry of Education, Culture, Research, and Technology (KemdikbudRistek), as of now, 143,265 schools have adopted the Merdeka Curriculum [9], and this number will continue to grow at all levels, from Kindergarten (TK), Elementary School (SD), and Junior High School (SMP) to Senior High School (SMA) [10]. Policy evaluation is necessary to measure the effectiveness of the curriculum, examine its impact on the teaching and learning process, and understand the various aspects and sentiments developing in the community. Therefore, sentiment analysis is essential to understand the public's response and perception of the Merdeka Curriculum's implementation. The results of this analysis not only aim to provide insights but also serve as a foundation for further policy development that is more responsive to the needs and aspirations of the public.

The data used for sentiment analysis comes from Twitter. The choice of Twitter as a data source related to the Merdeka Curriculum is based on its wide coverage of public issues, where people often share their opinions in real time. Indonesia has 24.85 million active Twitter users, ranking 4th in the world [11]. Twitter allows direct monitoring of sentiment changes over time, provides more immediate and informal insights, and uses everyday language. The potential virality of tweets is also an important factor in identifying emerging trends and thoughts. Therefore, analyzing data from Twitter enables a deeper understanding of the public's feelings and perspectives.

According to Ingkafi, sentiment analysis has evolved through text classification approaches using Classical Machine Learning methods such as Naive Bayes, Logistic Regression, and Support Vector Machine (SVM) [12]. Traditional sentiment analysis often struggles to capture the complex nuances in public opinion. Therefore, in the context of the Indonesian language, the application of Transformer models such as BERT (Bidirectional Encoder Representations from Transformers) and its local variant, IndoBERT, is an effective method due to its ability to understand natural language context. IndoBERT is a pre-trained Indonesian language model based on the BERT architecture

[13]. designed to understand complex linguistic structures and context. BERT itself is a language model architecture that uses a pre-training approach to generate better word representations and retain bidirectional context from text [14], enabling a deeper understanding of word relationships.

Aspect-Based Sentiment Analysis (ABSA) is an effective solution for obtaining a more in-depth picture of sentiment analysis based on specific aspects of the curriculum currently implemented [15]. Aspect-based sentiment measurement is conducted by classifying specific aspects, allowing the identification of positive, negative, and neutral sentiments associated with each aspect. Integrating the BERT method in the ABSA approach is expected to result in sentiment analysis that is more accurate, contextual, and relevant to the specific aspects of the education policy, enabling a better understanding of public responses.

Previous research has used machine learning methods such as Naïve Bayes, K-Nearest Neighbors, Support Vector Machine (SVM) [16], and Decision Tree in sentiment analysis [17]. Exploration and development continue with the application of deep learning methods such as LSTM [18]. Previously, ABSA research on Indonesian data has been conducted on the subject of PayPal using the Decision Tree method [19]. Other research has explored ABSA on the subject of restaurants using the SVM model [20]. Another study on ABSA compared the effectiveness of machine learning algorithms with IndoBERT in processing online student reviews related to the learning process, and the results showed that the IndoBERT method outperformed in performance [21]. The advantages of IndoBERT provide a new dimension in aspect-based sentiment analysis, especially for gaining deeper insights into the natural language context within the Indonesian language environment. This makes IndoBERT highly relevant for analyzing public sentiment toward the implementation of the Merdeka Curriculum.

The Merdeka Curriculum is a crucial element in the foundation of education. To ensure this curriculum is effectively developed and sustained, it is essential to monitor and analyze public feedback. This feedback can be analyzed using ABSA to identify positive, negative, and neutral sentiments on various aspects of the curriculum through social media platforms such as Twitter. Therefore, this study aims to develop an ABSA model to analyze sentiments on the four main aspects of the Merdeka Curriculum: the Education Report (RP), Teaching Modules (MA), the Merdeka Teaching Platform (PMM), and the Pancasila Student Profile (P5), using data sourced from Twitter and a transformed model specifically trained for the Indonesian language, namely IndoBERT. For classification evaluation, a confusion matrix comprising Precision, Recall, F-score, and Accuracy will be used to assess the model's performance.

This study will provide data-driven insights to support policy decisions that are more responsive to public needs, especially in improving the effectiveness of the four main aspects of the Merdeka Curriculum. Using the Aspect-Based Sentiment Analysis (ABSA) approach, public sentiment analysis on the education curriculum can be conducted in-depth, focusing on specific aspects of the text. Once the ABSA model trained with IndoBERT is obtained, this information can be used to evaluate public responses, including those of teachers, students, and parents, enabling the government and stakeholders to identify areas that require special attention. The evaluation results are expected to serve as a strategic foundation for improving curriculum implementation and creating a more responsive and effective educational environment that meets public needs.

MATERIALS AND METHODS

This study uses the Aspect-Based Sentiment Analysis (ABSA) method based on IndoBERT, designed to analyze public opinions on the main aspects of the Merdeka Curriculum, which include Teaching Modules (MA), Education Reports (RP), the Merdeka Teaching Platform (PMM), and the Strengthening of the Pancasila Student Profile Projects (P5). The data used is sourced from social media, specifically Twitter, with modeling conducted using IndoBERT. The research involves several stages. First, data collection from Twitter using predetermined keywords to ensure relevance to each aspect of the Merdeka Curriculum. Second, data labeling and filtering, performed manually with the assistance of AI tools to ensure data relevance and to categorize sentiments and aspects. Next, data preprocessing to clean and prepare the data for analysis. The dataset is then divided into three parts: training data, validation data, and testing data, with a distribution ratio of 80:10:10. The following step involves modeling using IndoBERT, optimized through hyperparameter tuning to achieve accurate classification. Finally, the model is evaluated using test data based on various metrics such as accuracy, precision, recall, and F1-score. A comprehensive overview of the research methodology stages is provided in Figure 1.

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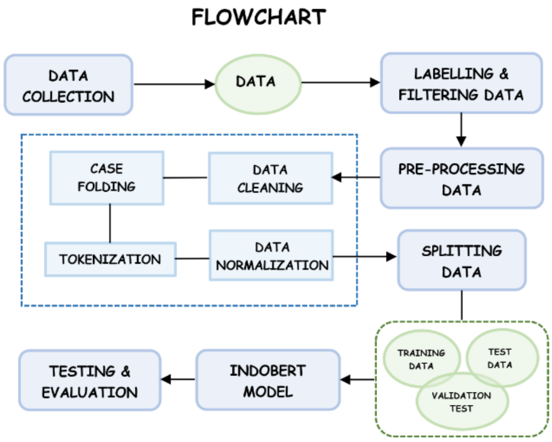

Source: (Research Results, 2024)

Figure 1. Research Flowchart

Data Collection

Data collection involved gathering Indonesian tweets from Twitter using predetermined keywords based on the aspects of the Merdeka Curriculum. The keywords for the *Modul Ajar (MA)* aspect are *"modul ajar"* and *"perangkat pembelajaran"* or *"perangkat ajar."* The keywords for the *Rapor Pendidikan (RP)* aspect are *"rapor pendidikan," "ANBK,"* and *"asesmen nasional."* For the *Platform Merdeka Mengajar (PMM)* aspect, the keywords are *"platform rapor pendidikan"* and *"PMM."* Meanwhile, for the *Proyek Penguatan Profil Pelajar Pancasila (P5)* aspect, the keywords are *"profil pelajar pancasila"* and *"P5."*

The keywords for the Teaching Modules (MA) aspect are *"modul ajar"* and *"perangkat pembelajaran"* or *"perangkat ajar."* The keywords for the Education Report (RP) aspect are *"rapor pendidikan," "ANBK,"* and *"asesmen nasional."* For the Merdeka Teaching Platform (PMM) aspect, the keywords used are *"platform rapor pendidikan"* and *"PMM."* Meanwhile, for the Pancasila Student Profile Projects (P5) aspect, the keywords used are *"profil pelajar pancasila"* and *"P5."* These keywords were utilized during the Twitter data search process to ensure that the collected tweets are directly related to the topics and aspects being studied. The data collection process started on September 2, 2023, and continued until May 22, 2024, for each aspect. The results of this data collection process are a set of Indonesian tweets reflecting public responses, discussions, and opinions regarding the implementation and experiences with aspects of the Merdeka Curriculum. This dataset serves as the foundation for aspect-based sentiment analysis using IndoBERT.

Labelling and Filtering Data

The collected data initially lacked labels. Therefore, sentiment labeling was conducted by categorizing the data into three categories: positive, negative, and neutral. This process also involved filtering data, including identifying, selecting, or removing irrelevant data based on specific criteria. Additionally, tweets were grouped based on the aspects of the Merdeka Curriculum: Pancasila Student Profile Projects (P5), Education Reports (RP), Teaching Modules (MA), and the Merdeka Teaching Platform (PMM). Aspect identification was carried out using predetermined relevant keywords; for instance, data collected with the keyword *"profil pelajar pancasila"* was directly categorized under the P5 aspect. A similar approach was applied to other aspects.

Each tweet was labeled by a labeler trained in labeling procedures and understanding sentiment categories for each aspect to be identified in the data. To ensure accuracy and consistency, AI-based tools such as ChatGPT were used when encountering ambiguities in the data. Once the labeling process was completed, the data was revalidated by researchers with a background and expertise in education to ensure the relevance and accuracy of the labeling results.

After the labeling and filtering processes were completed, the total dataset comprised 2,359 tweets, distributed as follows: 649 tweets under the Pancasila Student Profile Projects aspect, 643 tweets under the Education Reports aspect, 579 tweets under the Teaching Modules aspect, and 515 tweets under the Merdeka Teaching Platform aspect.

Table 1. Dataset Sentiment And Aspect

	Aspect				
Sentiment	*P5*	*RP*	*MA*	*PMM*	Total
Positive	282	204	53	146	733
Neutral	209	324	256	277	991
Negative	158	115	270	92	635
Total	649	643	579	515	2359

Source: (Research Results, 2024)

Detailed information about the dataset used in this study can be seen in Table 1. Based on total sentiment, there were 733 positive categories, 635 negative categories, and 991 neutral categories. For the P5 aspect, positive sentiment dominated with 43.4%, followed by neutral sentiment at 32.2%, and negative sentiment at 24.4%. In contrast, the sentiment distribution for the RP aspect was similar to that of the PMM aspect, where neutral sentiment exceeded 50%, followed by positive sentiment. For the MA aspect, the percentage of positive sentiment was very low, less than 10%, while neutral and negative sentiments were relatively similar, each exceeding 40%. This distribution ensures that the collected data reflects various public perspectives on the aspects of the Merdeka Curriculum.

The displayed data can be visualized to determine whether there is significant class imbalance. If imbalances are found, data balancing techniques such as oversampling for minority classes or undersampling for majority classes will be applied to ensure fair representation for all classes. However, based on Table 1, the data distribution is fairly balanced, so balancing techniques are not necessary for this study.

Pre-Processing Data

The data preprocessing stage aims to improve the dataset quality for optimal use in the model training process. This process involves several steps: data cleaning, case folding, tokenization, and normalization. Data cleaning is a crucial step in preprocessing, involving the removal of irrelevant elements such as emoticons, Twitter usernames, links, punctuation, and HTML characters. This ensures that only essential information is retained for analysis. Case folding converts all text to lowercase to standardize formatting and facilitate analysis. Tokenization is the process of breaking text into smaller units called "tokens," allowing analysis at the word or phrase level. Normalization stage involves converting informal or non-standard words into their standard forms based on a predefined dictionary. This step is particularly important in the Indonesian context, as informal variations often lead to misinterpretation. For instance, *"gimana"* is normalized to *"bagaimana,"* and *"bgt"* is normalized to *"banget."* Normalization helps standardize word variations, making text analysis and understanding easier.

Overall, the result of this process is a cleaner, structured dataset ready for further sentiment analysis, enhancing data quality and preparing it for the model training process.

Splitting Data

After the preprocessing stage is complete, the dataset will be divided into three main parts to ensure the model has sufficient training data, as well as representative validation and testing data. The dataset is divided into training data, validation data, and testing data, with a distribution ratio of 80% for training, 10% for validation, and 10% for testing. Training data is used to train the model so it can recognize patterns and relationships between features and labels in the data. This stage is the core of the model's learning process. Validation data is used to evaluate the model's performance during the training process. Validation data helps adjust model parameters, such as the learning rate and the number of epochs, to improve the model's performance and avoid overfitting. Testing data is used to measure the model's final performance. This data is never seen by the model during training, providing an indication of how well the model can predict new data.

This distribution ensures the model has sufficient data for learning while reserving adequate data for validation and testing. With this proportion, the model is expected to achieve optimal performance in analyzing sentiment and aspects from the available dataset.

IndoBERT Model

The preprocessed dataset is transformed into a format suitable for IndoBERT, a Transformer model specifically designed to understand and process Indonesian text. Built using the PyTorch framework, IndoBERT Tokenizer converts text into word vector representations. This enables the model to comprehend the context of each word more deeply, essential for aspect-based sentiment analysis. Subsequently, fine-tuning is performed on the IndoBERT model for aspect-based sentiment classification tasks. This process allows the model to learn specific sentiment patterns related to the main aspects of the Merdeka Curriculum: Education Reports, Teaching Modules, Merdeka Teaching Platform, and Pancasila Student Profile Projects. Fine-tuning ensures the model delivers accurate, relevant, and context-sensitive analysis results.

In this study, due to the relatively small dataset size of 2,359 data points, the range of hyperparameters was selected on a smaller scale to avoid the risk of overfitting. Based on references from several studies using IndoBERT with similar datasets, a hyperparameter range of 3-10 for epochs and a learning rate of 1e-5 to 5e-5 was selected [22]. It should be noted that these hyperparameters can vary depending on the case, as values that are too large or too small may lead to suboptimal solutions. In this experiment, when larger hyperparameter values showed a decline in the validation curve, indicating potential overfitting. Therefore, the hyperparameters were limited to a range of 3-5 for epochs, 16-64 for batch size, and 1e-5 to 3e-5 for the learning rate.

Hyperparameter selection was conducted using the grid search technique, which systematically tests various combinations of potential values. Each combination was evaluated through cross-validation to assess the model's performance, and the best combination based on accuracy metrics on the validation data was selected. This strategy ensures the model achieves

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optimal results while avoiding the risks of overfitting or underfitting.

Testing and Evaluation

The testing and evaluation process aims to measure the model's performance in classifying sentiments and aspects of the Merdeka Curriculum. The previously separated test dataset is used to evaluate the trained model. Evaluation is conducted using a confusion matrix, which includes metrics to assess the model's performance in sentiment and aspect classification. Metrics such as True Positives (TP), False Positives (FP), True Negatives (TN), False Negatives (FN), True Neutrals (NTR), and False Neutrals (FNR) are considered. The confusion matrix is essential for calculating various performance metrics, including accuracy, precision, recall, and F1-score [23]. These metrics are highly relevant for evaluating the model's performance in addressing the research objectives. The confusion matrix table can be seen in Table 2.

Table 2. Three Confusion Matrix Classes

Actual Class	Predicted Class		
	C1	C2	C3
C1	TP	FP	FP
C2	FN	TN	FN
C3	FNR	FNR	TNR

Source: (Muhammadi et al., 2022)

Here are the translation of the evaluation metrics formulas:

1. Accuracy: Measures how well the model can predict all sentiment and aspect classes correctly.

$$\text{Accuracy} = \frac{TP+TN+TNR}{TP+FP+FP+FN+TN+FN+FNR+FNR+TNR} \quad (1)$$

2. Precision: Measures the model's ability to accurately predict the positive class or specific aspects

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP+FP}} \quad (2)$$

3. Recall or Sensitivity: Evaluates how well the model can identify all actual positive cases.

$$\text{Recall} = \frac{TP}{TP+FN+FNR} \quad (3)$$

4. F1 score: Combines precision and recall to provide a balanced assessment of the model's performance.

$$\text{F1-score} = 2\ x\ \frac{Precision\ x\ Recall}{Precision+Recall} \quad (4)$$

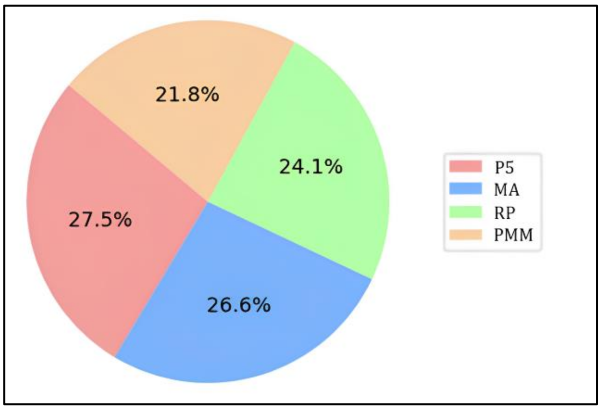
The results of the confusion matrix analysis provide further insights into how well the model can classify sentiment accurately. For aspect classification, evaluation is conducted similarly by calculating metrics such as accuracy, precision, recall, and F1-score. Each metric is computed using the formulas mentioned above, adjusted to the context of the specific aspects being analyzed.

Through this method, the study produced a sentiment classification model and an aspect classification model. The evaluation results provide a clear overview of the model's ability to classify sentiments and aspects accurately. Additionally, the evaluation helps identify areas for further improvement, such as refining the dataset or adjusting hyperparameters, to enhance model performance in the future. Thus, using the ABSA method with the IndoBERT model, this study processes Twitter data to produce sentiment analysis on the main aspects of the Merdeka Curriculum.

RESULTS AND DISCUSSION

Aspect Classification Result

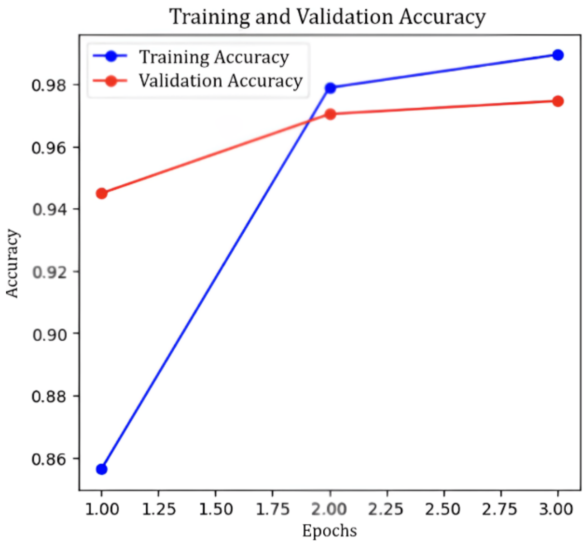
This study uses a dataset consisting of 2359 tweets, which are divided into several aspects of the Merdeka Curriculum. Figure 2 illustrates the results of data collection across these aspects, with 649 instances of P5 aspect, 627 instances of MA aspect, 568 instances of RP aspect, and 515 instances of PMM aspect. The distribution proportions of each aspect can be seen in Figure 2.



Source: (Research Results, 2024)

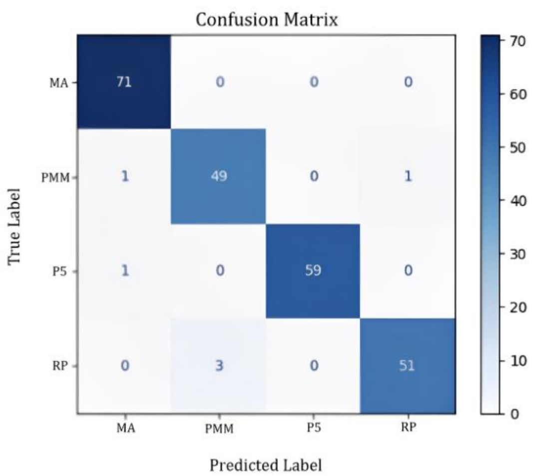
Figure 2. Aspect Distribution

After testing the Merdeka Curriculum dataset across four aspects (P5, MA, RP, and PMM), the results obtained are shown in Figure 3. This testing used hyperparameters of 3 epochs, a batch size of 32, and a learning rate of 2e-5 during the training process. Figure 3 illustrates the training performance curve for aspect classification based on the selected parameters.



Source: (Research Results, 2024)
Figure 3. Training History in Aspect Classification

Based on Figure 3, the curve shows a clear upward trend to the right, indicating a well-trained model. Aspect classification with the IndoBERT model achieved impressive average accuracy, precision, recall, and F1-score scores of 97%. The choice of 3 epochs for training was based on the convergence observed in the training performance curve, as shown in Figure 3, where the model reached optimal training with minimal risk of overfitting. This classification result aligns with previous research by Fitrianto et al., who also utilized the IndoBERT model for text classification and achieved high accuracy rates. Their study found that IndoBERT excelled in understanding Indonesian language contexts [24].



Source: (Research Results, 2024)
Figure 4. Confusion Matrix for Aspect Classification

Following that, the model trained with the new dataset was evaluated to determine its performance. To assess the model's effectiveness, this study used a confusion matrix. The model evaluation on the testing dataset for aspects can be seen in Figure 4.

Based on Figure 6, the test data results show that 71 data points were correctly classified as MA aspects, 49 data points as PMM aspects, 59 data points as P5, and 51 data points as RP.

After developing and evaluating the aspect classification model, the next step is to conduct a review to identify which data points were correctly or incorrectly predicted by the model. Table 3 contains several review data points that do not match their predicted aspects.

Table 3. Review Testing Table

Review	Actual	Prediction
pendekatan yang digunakan tidak mendorong penghargaan terhadap keragaman budaya	P5	MA
sudah banyak praktik dari dalam implementasi kurikulum merdeka contohnya yaitu praktik baik yang dibagikan ibu dewi nurdamayanti beliau mengajak anak didiknya bersama sama mengolah limbah cangkang telur menjadi kerupuk	P5	PMM
pmm bukan saja alat bantu kami dalam proses pembelajaran tetapi juga sebagai alat bantu dalam mencari inspirasi modul ajar yang menyenangkan dan berpusat pada murid	PMM	MA

Source: (Research Results, 2024)

Based on Table 3, examples of mispredictions in aspect classification by the model are shown. In the first sentence, it should have been classified as the P5 aspect, but the model predicted it as MA because the phrase "*keragaman budaya*" is ambiguous. This phrase can be used in the context of Pancasila values (P5) as well as in MA emphasizing the theme of cultural diversity, which confuses the model. In the second sentence, the model misclassified the P5 aspect as PMM because the word "*praktik*" can be interpreted in various contexts. Although the sentence explicitly refers to P5 project activities, the model failed to recognize that "*mengolah limbah*" is part of the P5, which supports character and skills-based education. In the third sentence, it should have been classified as PMM but was predicted as MA. This error was caused by the presence of two aspect keywords, namely "*modul ajar*" and "PMM," in a single sentence. The model focused more on the keyword "*modul ajar*", ignoring the context that mentioned PMM as the main keyword. In fact, the phrase "*mencari inspirasi modul ajar*" actually supports the

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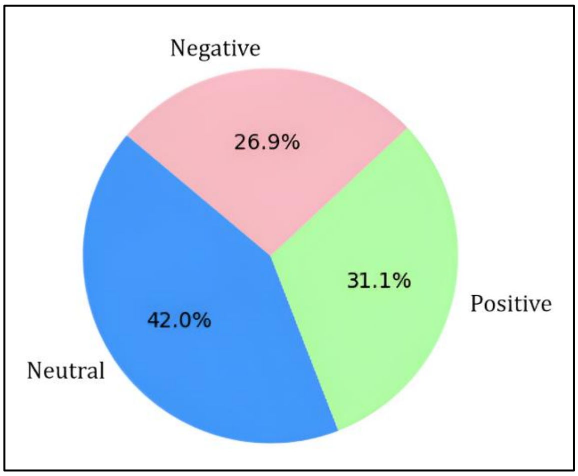
PMM aspect, but the IndoBERT-based classification model failed to capture the full context of the sentence.

Overall, the mispredictions in the aspect classification model are caused by ambiguity in phrases or keywords that can refer to multiple aspects, as well as the sentence context not being effectively identified by the model. These errors indicate that the model tends to rely on keywords without considering the full context of the sentence, making it difficult to distinguish between similar aspects. This is similar to the findings of Imron et al., which showed that some misclassified reviews occurred due to the presence of similar or identical words across different aspects [25]. To address this issue, it is necessary to improve the quality and diversity of the training data, such as adding more examples that cover ambiguous phrases and broader contexts. These examples should reflect the usage of words like "*keragaman budaya*", "*praktik*" and "*modul ajar*" in various contexts. Additionally, data augmentation using paraphrases, synonyms, and variations in sentence structure can enhance the model's ability to handle linguistic variations and context effectively.

Sentiment Classification Result

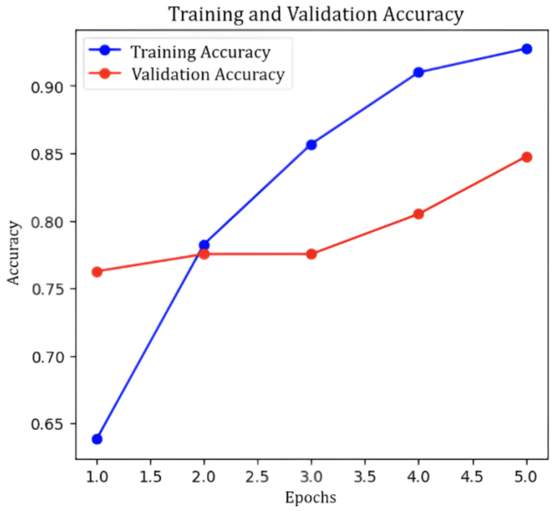
Total dataset consisting of 2359 tweets for sentiment analysis is divided into 3 categories. Figure 3 illustrates the labeling results, with 733 positive labels, 635 negative labels, and 991 neutral labels. It can be seen that the positive category covers 31.1% of the data, while the negative category covers 26.9%, and the neutral category covers 42.%.



Source: (Research Results, 2024)

Figure 5. Sentiment Distribution

After testing the Merdeka Curriculum dataset with three sentiment categories (positive, negative, neutral), the results obtained are shown in Figure 6. This testing used hyperparameters of 5 epochs, a batch size of 16, and a learning rate of *2e-5* during the training process. Figure 6 illustrates the training performance curve for sentiment classification based on the selected parameters.



Source: (Research Results, 2024)

Figure 6. Training History in Sentiment Classification

According to Figure 6, the curve shows that the training accuracy continues to increase, while the validation accuracy remains relatively stable after reaching a certain point. This indicates that the model learns well from the training data without experiencing significant overfitting, as the validation accuracy does not drastically decrease. The stable validation accuracy suggests that the model generalizes well to unseen data. These results are consistent with findings by Batra et al., who observed that BERT models demonstrate strong generalization capabilities in sentiment classification tasks [26].

Sentiment classification using the IndoBERT model showed promising results with an average accuracy score of 85%, precision of 85%, recall of 85%, and F1-score of 85%. These classification results are comparable to the findings of Geni et al., who also used the IndoBERT model for sentiment classification and achieved similar accuracy levels [27]. This demonstrates that the BERT-based approach is consistent across different languages and contexts.

Additionally, the model trained on the new dataset was evaluated to assess its performance. To gauge the effectiveness of the model, this study used a confusion matrix. The evaluation of the model on sentiment testing data is illustrated in Figure 7.

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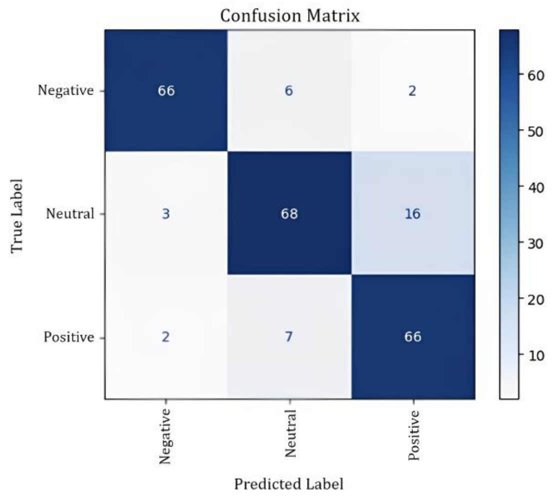

Source: (Research Results, 2024)
Figure 7. Confusion Matrix for Sentiment Classification

Based on Figure 7, the test results show that 66 data points were correctly classified as positive sentiment, 66 data points as negative sentiment, and 68 data points as neutral sentiment. After developing and evaluating the sentiment classification model, the next step is to conduct a review to identify which data points were predicted correctly or incorrectly by the model. In Table 4, there are several review data points whose sentiment predictions do not match their actual sentiments.

Table 4. Review Testing Table

Review	Sentiment	Sentiment Prediction
Apa inspirasi baru yang anda dapatkan dari upaya tindak lanjut di platform merdeka mengajar	Neutral	Negative
Eh nanti sma kamu tuh kurikulum merdeka bukan kalau sudah pakai kurikulum itu nanti ada proyek begitu namanya proyek profil pelajar pancasila	Neutral	Positive
Saya lagi membuat modul ajar kenapa malah ngingetin tugas	Neutral	Positive
Sudah memiliki akun nanti bisa masuk ke platform merdeka mengajar disitu tersesia banyak macam kebutuhan	Positive	Negative
Tolong saya sudah gumoh sama modul ajar rpp	Negative	Neutral

Source: (Research Results, 2024)

Based on Table 4, examples of sentiment prediction errors by the sentiment classification model are shown. The review table results indicate that the model tends to fail in fully recognizing emotional context, particularly in sentences with ambiguous expressions or informal language. Some neutral sentences were predicted as positive or negative because the model overly relied on keywords, such as "*praktik*" or "*modul ajar*", which are often associated with specific sentiments in the training data. Conversely, sentences with negative sentiment, such as those containing distinctive emotional expressions like "*gumoh*," were predicted as neutral because the model was insufficiently trained on slang or informal terms. Additionally, the model exhibited bias in the training data, where an uneven distribution of sentiments or a lack of representation of neutral and informal phrases led to mispredictions in these categories. This highlights the model's limitations in capturing complex contexts and emotional nuances in sentences, making it more prone to errors when dealing with ambiguous or descriptive comments.

Overall, sentiment prediction errors are caused by several key factors. First, the model overly relies on specific keywords without fully understanding the context of the sentence, leading to frequent misclassification of sentences with ambiguous or descriptive expressions. Second, the uneven distribution of training data, where certain categories such as neutral or negative sentiments may be underrepresented, causes the model to be biased toward more dominant categories. Third, the model has limitations in recognizing informal language or slang often found on social media, such as the word "*gumoh*," resulting in its failure to identify clear emotional sentiments. The combination of these factors makes the model less effective in capturing complex linguistic and emotional nuances, particularly in text with high linguistic variability such as tweets.

To address sentiment prediction errors in the classification model, the training dataset needs to be improved with more diverse data, including various emotional expressions, as well as phrases or words commonly used to convey emotional nuances in both formal and informal contexts. Additionally, data augmentation with paraphrases, synonyms, and variations in sentence structure can help enhance dataset diversity. This aligns with the findings of Acheampong et al., which emphasize the need for more contextual and representative datasets to improve sentiment analysis accuracy [28]. These improvements should be accompanied by continuous evaluation using confusion matrices or in-depth error analysis to identify areas requiring refinement. With these steps, the model is expected to better capture emotional nuances, resulting in more accurate and relevant sentiment predictions.

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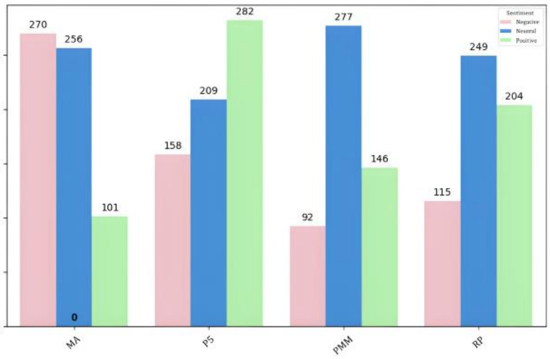
Aspect-Based Sentiment Analysis Results

After performing aspect and sentiment classification, the results of the ABSA analysis are presented in Figure 8 as a visualization. This visualization illustrates the public sentiment distribution across the four main aspects of the Merdeka Curriculum, which have been analyzed using the IndoBERT model.



Source: (Research Results, 2024)
Figure 8. Sentiment Distribution For Each Aspect

From the data visualization, it is evident that the MA aspect is dominated by negative sentiment, indicating significant criticism of its implementation in the Merdeka Curriculum. This criticism includes guidance on module development that is considered confusing and unrealistic, as well as teaching methodologies deemed less supportive of context-based and experiential learning, thereby adding to teachers' workloads. This aligns with the findings of Putri et al., which note that changes in the preparation of teaching materials often make it difficult for educators to develop effective modules [29]. In contrast, the P5 aspect is dominated by positive sentiment, indicating that the implementation of this project aligns with public expectations, particularly in strengthening student character. Meanwhile, the PMM and RP aspects, which are also dominated by positive sentiment, demonstrate good public acceptance, although there are criticisms that need to be addressed to improve their relevance and functionality.

These findings provide a strong basis for formulating concrete policies. For the MA aspect, an in-depth revision of module preparation guidelines is necessary to make them more relevant, practical, and easily applicable by educators. These guidelines should be developed based on the real needs of educators in the field, involving teachers directly in the revision process, to ensure that the teaching modules are not only aligned with academic standards but also support experiential and context-based learning. Additionally, special training for teachers on how to effectively utilize and develop teaching modules should be a key priority, particularly to reduce the frustration reflected in the high level of negative sentiment. This is also supported by the findings of Lingga et al., who highlight the need for teacher assistance to improve understanding of appropriate module preparation [30].

In the P5 aspect, which is dominated by positive sentiment, it is essential to maintain and strengthen the success of its implementation. Policies can focus on further integrating Pancasila values into P5 activities while allowing flexibility for schools to adapt the implementation according to local needs. For the PMM and RP aspects, although they are positively received, the criticisms present opportunities for further development. For example, the government can enhance PMM features to support more interactive learning, ensure easier access for teachers, and improve the platform's efficiency in addressing their learning needs. Meanwhile, for RP, it is crucial to improve the relevance and accuracy of evaluations conducted through ANBK (Computer-Based National Assessment), which is used to assess students' literacy, numeracy, and character as part of the comprehensive school evaluation. The main criticism of ANBK lies in its sampling method, which is considered unrepresentative, and its limited focus on assessment, making it less reflective of students' holistic abilities. This aligns with the findings of Nasikhah et al., which emphasize the need for more comprehensive and representative evaluations to ensure that the Education Report becomes an effective tool for improving the systemic quality of education [31].

The potential practical impact of these findings is significant for improving curriculum implementation quality. This analysis can be utilized by policymakers to identify areas requiring special attention and to design strategic, data-driven actions. For example, negative sentiment toward the teaching module indicates the need for direct intervention to improve the quality of materials and guidelines, while positive sentiment toward P5 and other aspects suggests that these programs can serve as models for other curriculum developments. By leveraging these analytical results, stakeholders can optimize the implementation of the Merdeka Curriculum, ensuring that the curriculum is not only academically relevant but also meets societal needs and expectations.

Furthermore, the Aspect-Based Sentiment Analysis (ABSA) approach applied in this study can serve as an example for other contexts. ABSA enables the extraction of deep insights into public perceptions of various aspects of programs, policies, or services, making it an effective tool for evaluating and improving implementation. For instance, this approach can be applied to analyze sentiment toward other educational programs, digital platform evaluations, student development projects, or even public service applications and policies. These findings support previous research showing that ABSA is an effective method for understanding societal needs and designing more relevant data-driven policies [32].

In other words, ABSA is not only relevant in the context of the Merdeka Curriculum but also has the flexibility to be applied in other scenarios. In this study, ABSA has provided a clear overview of how public perceptions of key aspects such as the teaching module, P5, PMM, and Education Report can be specifically identified. This analysis enables data-driven decision-making to strengthen existing advantages and address areas requiring attention. With this approach, ABSA becomes an applicable and relevant methodology to support policy innovation and program development across various sectors.

CONCLUSION

This study successfully developed and evaluated aspect and sentiment classification models using IndoBERT for datasets related to the Merdeka Curriculum. Based on the test results, the aspect classification model achieved impressive metrics with an accuracy of 97%, Recall of 97%, Precision of 97%, and an F1 score of 97%. Similarly, the sentiment classification model also performed well, achieving an accuracy of 85%, Recall of 85%, Precision of 85%, and an F1 score of 85%. These findings demonstrate the effectiveness of transfer learning using IndoBERT as a robust approach for aspect-based sentiment analysis on Indonesian tweet data.

Overall, the results of this study demonstrate the effectiveness of the IndoBERT model in analyzing aspects and sentiments related to the Merdeka Curriculum from tweet data. However, this study has several limitations that should be noted. First, there is a limitation in the variation and size of the dataset, which is relatively small. Second, although the IndoBERT model used has shown good performance, it remains vulnerable to ambiguous sentence contexts or overlapping categories, which lead to classification errors. Third, there are limitations in time and computational resources required to test all combinations of hyperparameters, which may result in potentially more optimal hyperparameter combinations not being detected through grid search. These limitations need to be further addressed and evaluated to improve the model used. Further improvements could address these limitations by expanding the dataset with more diverse tweet data, adding more aspect and sentiment categories, and fine-tuning the model with more varied hyperparameter settings, which could help identify more optimal configurations.

This study has important implications for more informative educational decision-making, identifying sensitive issues, and providing policymakers with deeper insights into public responses, especially in areas requiring improvement. Based on the sentiment distribution across the four main aspects of the Merdeka Curriculum, the Teaching Module (MA) aspect is dominated by negative sentiment, reflecting criticism of the module development guidelines, which are perceived as confusing and not supportive of learning. Conversely, the Pancasila Student Profile (P5) aspect is dominated by positive sentiment, indicating the success of its implementation in strengthening students' character. Meanwhile, the Merdeka Teaching Platform (PMM) and Education Report (RP) aspects are largely positively received, although there are some criticisms that can serve as input for further improvement.

These insights can serve as a foundation for formulating more relevant and effective data-driven policies. For instance, the analysis results can be used to adjust the teaching module guidelines to better meet the needs of teachers in the field or reevaluate the assessment methods used in the Computer-Based National Assessment (ANBK). Furthermore, the ABSA approach used in this study has the potential to be applied in various other contexts. ABSA enables in-depth insights into public perceptions of various aspects of programs, policies, or services, making it an effective tool for evaluating and improving implementation.

In general, this model also has the potential to be applied to other social media platforms, such as Instagram or Facebook, by adjusting data preprocessing to the specific characteristics of each platform. For instance, the type of text and unique features of platforms like Instagram or Facebook need to be considered to ensure that the model can perform well in various contexts. Continuous evaluation and improvement are essential for the model to be applied more broadly and remain reliable across different scenarios.

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