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Analysis of Public Opinion on Disability Services Using Sentiment Analysis and Latent Dirichlet Allocation Topic Modeling Methods

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Abstract

In 2023, the number of people with disabilities in Indonesia reached 8.5% of the total population. Despite this significant proportion, they continue to face barriers in accessing public services, education, healthcare, and employment. Therefore, there is an urgent need for public policy analysis supported by real-time insights into public perceptions. This study aims to analyze online data from Twitter to inform policy recommendations for enchancing disability services. IndoRoBERTa fine-tuning was applied to capture nuanced emotional polarity in Indonesian-language texts, while Latent Dirichlet Allocation (LDA) topic modeling was employed to identify the latent themes behind these opinions. The two methods were deliberately combined because sentiment analysis alone cannot uncover the substantive issues underlying public views, while topic modeling alone cannot show the polarity of those views together; they provide a more comprehensive analytical framework. The novelty of this research lies in integrating advanced sentiment analysis and topic modeling to support the formulation of disability policy in the Indonesian context, which remains underexplored. A total of 18,242 tweets were collected using four keywords: disability, disability services, disability facilities, and disability programs. The analysis revealed critical issues, including physical accessibility, bullying prevention, and educational programs to reduce early marriage. The proposed model achieved strong performance with 97.42% accuracy, and precision, recall, and F1-scores all exceeded 95%, surpassing previous studies with an accuracy of around 93%. These findings demonstrate that data mining of online public opinion can serve as a robust medium for formulating responsive public policies and enabling real-time monitoring of disability-related services.

Keywords: Disability; IndoRoBERTa; Public Policy; Topic Modelling; Twitter

1 Introduction

In this modern era, accessibility is a crucial issue that needs serious attention. The increasing complexity of technological development also requires solutions that are inclusive and accessible to the entire community, without distinguishing individual conditions, including those with disabilities. Lack of accessibility for people with disabilities can cause various obstacles in life, ranging from aspects of education, work, to social interaction.

Disability is the inability of an individual to perform activities normally expected of a human being, which is usually caused by an impairment and often results from a disorder (Pramashela & Rachim, 2022). According to data from the Kemenko PMK, the number of people with disabilities in 2023 reached 8.5% of Indonesia's population, or 22.97 million people (Islam et al., 2024). These people often face various problems due to their limitations, not to mention a few who are forced to make themselves physically and mentally healthy. One example of a gap that is often encountered is the lack of public service facilities and access to disability-friendly assistive devices. Other real-life examples also often occur in Transjakarta and KRL, which still have limited priority space and information system problems.

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Then, staff services are still not good, and the lack of disability-friendly infrastructure also often occurs. These various examples have illustrated the condition that making it difficult for people with disabilities to access various public services, such as transportation, education, health, and employment, is also a physical barrier for people with disabilities (Novialdi et al., 2021).

Several studies related to public sentiment have also been analyzed by various parties. Among the various aspects of sentiment analysis, we focus on classifying the sentiment of Twitter users towards existing disability services to identify which ones need improvement or enhancement. To understand the various responses or perceptions, clustering is done to group people's tweets. Then, sentiment analysis can be performed to determine whether the tweets appearing on Twitter reflect a positive, neutral, or negative view of disability support facilities. Following this, a Topic Modeling analysis is necessary to identify which sectors require improvement within each sentiment category.

Therefore, to help improve public policy regarding disability services, we conducted research using Fine-Tuning sentiment analysis, which can analyze comments and reviews from the public in the form of text, making it useful for addressing more specific problems (Putri & Ardiansyah, 2023). Then, followed by Topic Modeling analysis using the Latent Dirichlet Allocation (LDA) method, which can mine data in the form of text based on words or n-grams that have the same meaning, so that it can make classifications to find out valid alternatives to facilitate the evaluation process on which parts need to be improved (Pandur & Dobša, 2020).

Thus, this research aims to analyze public service policies for people with disabilities, with the goal of improving the through public responses (big data) by utilizing Twitter review data and processing it using IndoRoBERTa Fine-Tuning sentiment analysis and Topic Modeling classification. This research is expected to contribute to the development of new public policies that improve public services for people with disabilities. The methods employed can also provide consideration for related parties directly involved in managing public service accessibility.

2 Literature Review

As the foundation of the research, a review of the literature is necessary to add credibility and strengthen the theoretical basis through the use of scientific references. This affects further data mining opportunities and previous research that serves as reference material, ensuring that the research topic remains on track.

First, Abdurrazaq and Tjiong examined the Draft Law (KUHP), which drew criticism from Twitter. The method employed is BERT sentiment analysis, and the results of BERT analysis, with an accuracy of 81%, are 6% superior to those SVM, which achieved an accuracy of 75% (Abdurrazzaq et al., 2022). Second, Bogdanowicz and Guan examined Twitter data on the COVID-19 pandemic from April 3 to 13, 2020. The method used is LDA Sequence Topic Modeling, and the results obtained are 12 popular topics that discuss changes in the political, health, community, and economic sectors (Bogdanowicz & Guan, 2022). Third, Negara and Triadi examined Twitter data using the keyword “Indonesia” and obtained 9.094 tweets. The method used is LDA Topic Modeling, and the results obtained are 10 topics that can be utilized for text mining (Negara & Triadi, 2022).

Fourth, Uthirapathy and Sandanam examined Twitter data related to climate change that occurred. The methods employed are the BERT Model and LDA Topic Modeling, yielding the best results are with precision (91.35%), recall (89.65%), and accuracy (93.5%) (Uthirapathy & Sandanam, 2022). Fifth, Ahmad examined consumer reviews of the DLU Ferry application on the Google Play Store. The method used is the IndoBERT base pre-trained model, and obtained accuracy results (86%), learning rate (3e-6), and epoch (5) (Akhmad, 2023). Sixth, Nabiilah examined toxic comments on social media in Indonesia. The methods used are MBERT, IndoBERT, and Indo RoBERTa, which show that the most optimal model is obtained through the IndoBERT method with training (0.96), validation (0.88), and testing (0.89) (Nabiilah et al., 2022).

Seventh, Krak examined Ukrainian language reviews on e-commerce sites. The method used is RoBERTa, a neural network that forms a language semantic model from 7656 reviews, resulting in an accuracy rate of 92%, while the loss function is 29% (Zalutska et al., 2023). Eighth, Jahin examined sentiment analysis on the Twitter

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platform. The methods used are Attention-Based BiLSTM and Twitter-RoBERTa, which show results in the form of macro average precision (94%), recall (93%), and F1-score (94%) (Jahin et al., 2024).

3 Methodology

Topics related to services for people with disabilities on Twitter can be seen from each tweet that is used as an analysis in the form of data mining to determine what the community believes, and this research focuses on positive and negative sentiments to determine the topics obtained, which can be seen through the diagram provided (Vidya Chandradev et al., 2023).

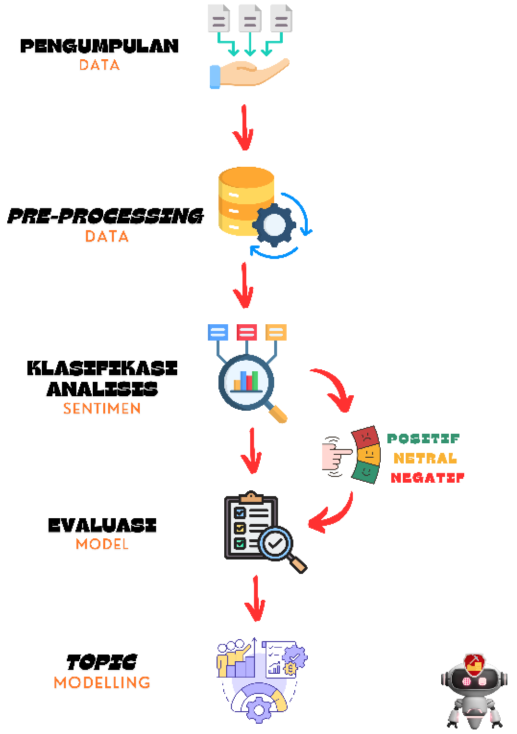

Figure 1. Methodology Flow Chart

Figure 1 illustrates the sentiment analysis workflow, comprising five primary stages. Data collection involves acquiring text from various sources (social media, reviews, news) and initial curation, such as deduplication and language filtering. Data pre-processing involves cleaning the text by removing noise (such as URLs, emojis, and punctuation), normalizing letters, tokenizing, and performing stemming / lemmatization for Indonesian text. Additionally, handling slang and class imbalance has also been addressed. Sentiment analysis classification is performed through feature extraction (using BERT) and algorithm training to categorize documents as positive, neutral, or negative.

Then, the model evaluation can measure performance using accuracy, precision, recall, and F1-score with cross-validation to ensure model reliability. The final stage, topic modeling, will identify latent themes using methods such as LDA to reveal the dominant issues that influence perception. This entire flow is systematic, replicable, and supports scientific interpretation.

3.1 Data Collection

The dataset used contains responses from the Indonesian public regarding accessibility services for people with disabilities from various tweets on Twitter. The researcher collected opinions using data scraping techniques, with Google Collaboratory serving as the platform, and utilized 18,242 data points from January 1, 2023, to June 3, 2024.

Table 1. Dataset

Keyword	Total Data
Disability	15000
Disability Services	538
Disability Facilities	854
Disability Program	1850

3.2 Data Pre-Processing

After collecting the data, the data pre-processing stage is carried out to ensure the quality of the data to be used in model training. The steps taken are eliminating URLs, mentions, hashtags, and special characters, such as irrelevant punctuation marks, to reduce noise in the data. Removal of duplicate data is also done to avoid bias in model training. Finally, all text was converted to lowercase to ensure consistency and facilitate further processing. Thus, the data will be prepared for sentiment analysis, ensuring that the sentiment results obtained are more accurate.

3.3 Sentiment Analysis Classification

To create a sentiment classification for all tweets, researchers employed a Fine-Tuning method that utilizes the pre-trained model of the Indonesia RoBERTa Base Sentiment Classifier, a further improvement of BERT that represents words and focuses on generating a language model. This pre-trained model is then Fine-Tuned to solve the problem by modifying the latest dataset, so that the parameters can be adjusted to the classification

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of data that has positive (0), neutral (1), and negative (2) sentiments (Husin, 2023).

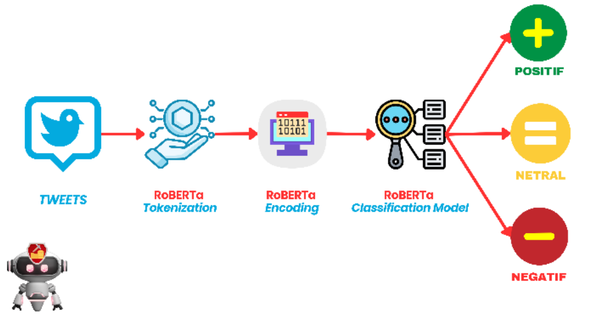

Figure 2. Sentiment Analysis Flow

Figure 2 illustrates the process that begins with collecting relevant datasets containing tweets for tokenization and encoding, which facilitates model classification. Then, model classification is performed using the IndoRoBERTa approach, which adjusts model weights based on various prediction errors and provides an in-depth analysis of data that may not have been seen before. After classification, three sentiment categories (positive, neutral, and negative) were obtained.

3.4 Model Evaluation

After classification, the stage proceeds with model evaluation, which is conducted to to generalize the entire text. The performance of the model will be evaluated using metric parameters such as accuracy which measures the extent to which the model can perform classification correctly, precision which measures the extent to which the model provides correct predictions, recall which measures the extent to which the model can correctly detect positive classes, and F1-score which combines precision and recall (Fadli & Saputra, 2023). If the evaluation results are satisfactory, the model can be used to model the topic in the next stage.

3.5 Topic Modelling

After performing sentiment analysis and model evaluation, Topic Modeling can be used to identify which sectors are satisfactory and which need improvement. The method used is LDA, which can ensure that the resulting topic model is accurate from the topic to the words within it. To complete this stage, the data will be converted into a library in the form of a gensim corpus, which is useful for determining the number of topics. This library is used as input for LDA Topic Modeling, which can later determine topics that can be visualized in the form of a coherence score diagram (Royani et al., 2024).

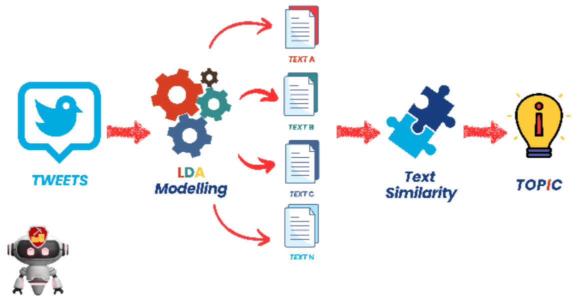

Figure 3. Topic Modelling Flow

4 Experiment Results

All datasets that have undergone cleaning will be labeled on a scale of 0 to 2, which will serve as a reference for sentiment analysis. After that, sentiment analysis can be tested using the IndoRoBERTa Fine-Tuning method on the dataset. Then, the evaluation of the Fine-Tuning model can be done by modeling using Topic-Modeling LDA, which is described in the form of PyLDAvis.

4.1 Fine-Tuning Result

The polarity results of the Twitter community's opinions on public services for people with disabilities are shown in Table 2.

Table 2. Fine-Tuning Result

Keyword	Sentiment Data		
	Positive	Neutral	Negative
Disability	2485	7820	3548
Disability Services	146	455	137
Disability Facilities	469	1042	69
Disability Program	58	444	20

The total number of datasets that have been cleaned is 16,693. The data is divided into four keywords, namely disability (13,853 data), disability facilities (738 data), disability programs (1,580 data), and disability services (522 data). Then, each keyword can be classified into positive sentiment (3,158 data), neutral (9,761 data), and negative (3,774 data).

4.2 Model Evaluation Result

Then, based on the sentiment generated, an evaluation can be carried out, and the results are obtained in terms of negative, neutral, and positive sentiment. Negative sentiment achieves precision values (0.9896), recall (0.9695), and F1-score (0.9794). Then, neutral sentiment achieves precision values (0.9804), recall (0.9824), and F1-score (0.9814). Then, positive sentiment achieves precision values (0.9369), recall (0.9550), and F1-score (0.9459).

The results of the fine-tuning model evaluation for the three sentiments shows the highest precision value, indicating that the ratio of positive correct predictions from the overall results is higher for the negative sentiment (0.9896). Then, the highest recall value, indicating the sensitivity of the comparison between data and model prediction results, is observed in neutral sentiment (0.9824). Then, the F1-score value indicating the harmonic meaning of the precision and recall is in neutral sentiment (0.9814). From these data, it can also be seen that the accuracy obtained is (0,9742) or 97.42% where the score obtained is quite high for each sentiment produced.

4.3 Topic Modelling LDA Result

Next, the results of the topic modeling regarding public services for people with disabilities, are presented in Table 3.

Table 3. Topic Modelling Result

Sentiment	Optimum Topic	Topic Details
Positive	15	Topic 1: Concern for inclusive facilities for people with disabilities. Topic 4: It has been proven that people with disabilities are more prosperous. Topic 11: Public facilities have been provided for people with disabilities Topic 12: The program for people with disabilities has been a tremendous help to them. Topic 14: Service facilities have been provided to people with special needs.
Neutral	5	Topic 1: Response to BPJS complaints that must be activated immediately must receive full attention. Topic 2: Regent's response to BPJS complaints. Topic 3: Production tools that are useful for business. Topic 4: Ganjar Mahfud has a public service facility program. Topic 5: Stories of high-achieving communities that must receive full attention.
Negative	5	Topic 1: The fate of the deaf who are still ignored. Topic 2: Bullying of children with disabilities during school. Topic 3: Bullying of women with disabilities in the workplace. Topic 4: Early marriage for the disabled. Topic 5: Lack of facilities for elderly people with disabilities.

The results of the topic modeling obtained indicate that there are 15 positive sentiments, primarily in the form of praise, suggesting good results from existing services. Then, there are neutral sentiments regarding 5 optimum topics that do not align with any particular sentiment, and negative sentiments related to 5 optimum topics, which are complaints experienced by people with disabilities, allowing for the formulation of solutions to improve public policies.

Next, there is one topic, namely topic 12, which accounts for 5.9% of the words and is relevant to the overall positive sentiment. This topic has several dominant response models, such as Mr. Ganjar, who is very caring, helpful, prosperous, and really salutes. Additionally, there is terminology related to programs and wheelchairs, so the topic that can be explored is a program for people with disabilities that has helped them, as shown in Figure 4.

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Then, when reviewed from the results of PyLDAvis, the neutral sentiment is attributed to topic 1, with 32.5% of the words relevant to the overall neutral sentiment. This topic is also related to the response to BPJS complaints, which must be immediately activated, receive full attention, and have several dominant response models. These models include ensuring BPJS is immediately activated, responding to complaints, having a business, utilizing production tools, and sharing community stories. Of course, the topics chosen are also relevant to the results of the word frequency, which is illustrated in, where the distribution of topic frequencies can be observed.

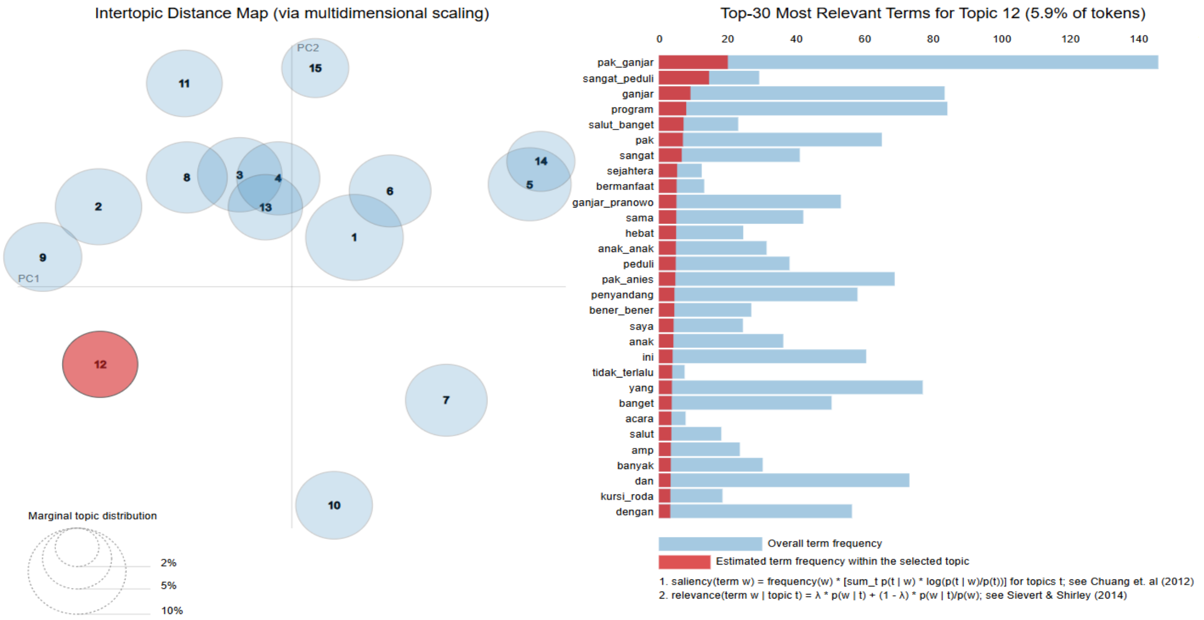

Figure 4. Positive Sentiment

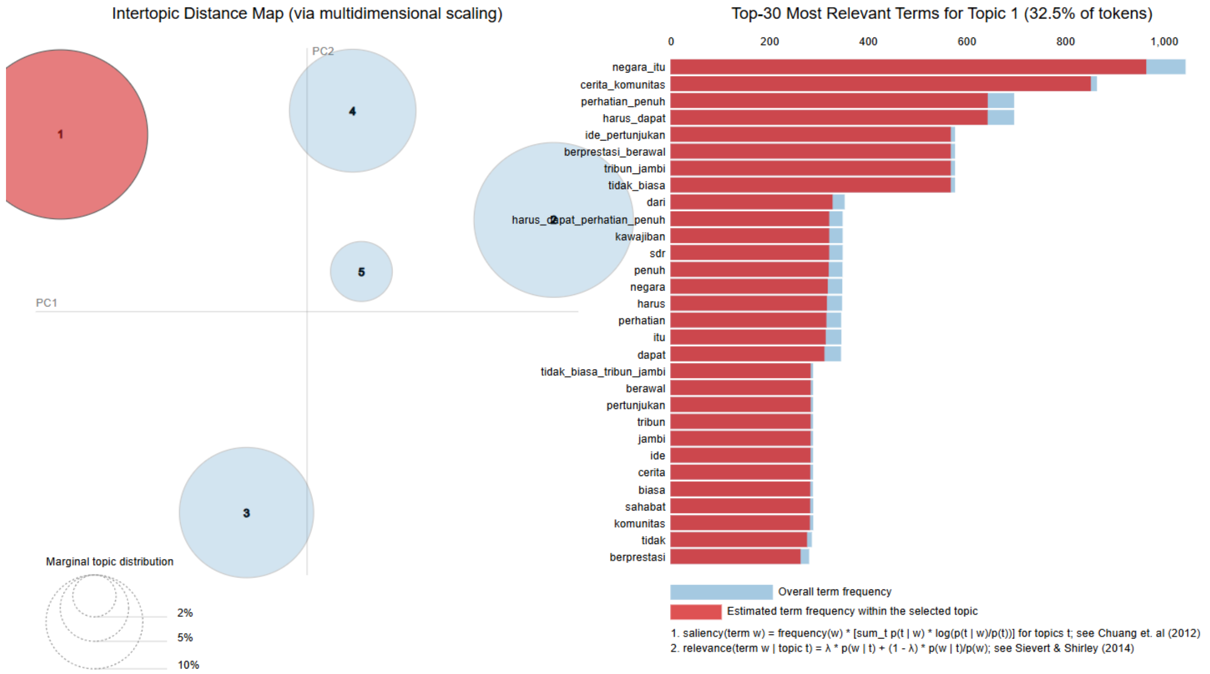

Figure 5. Neutral Sentiment

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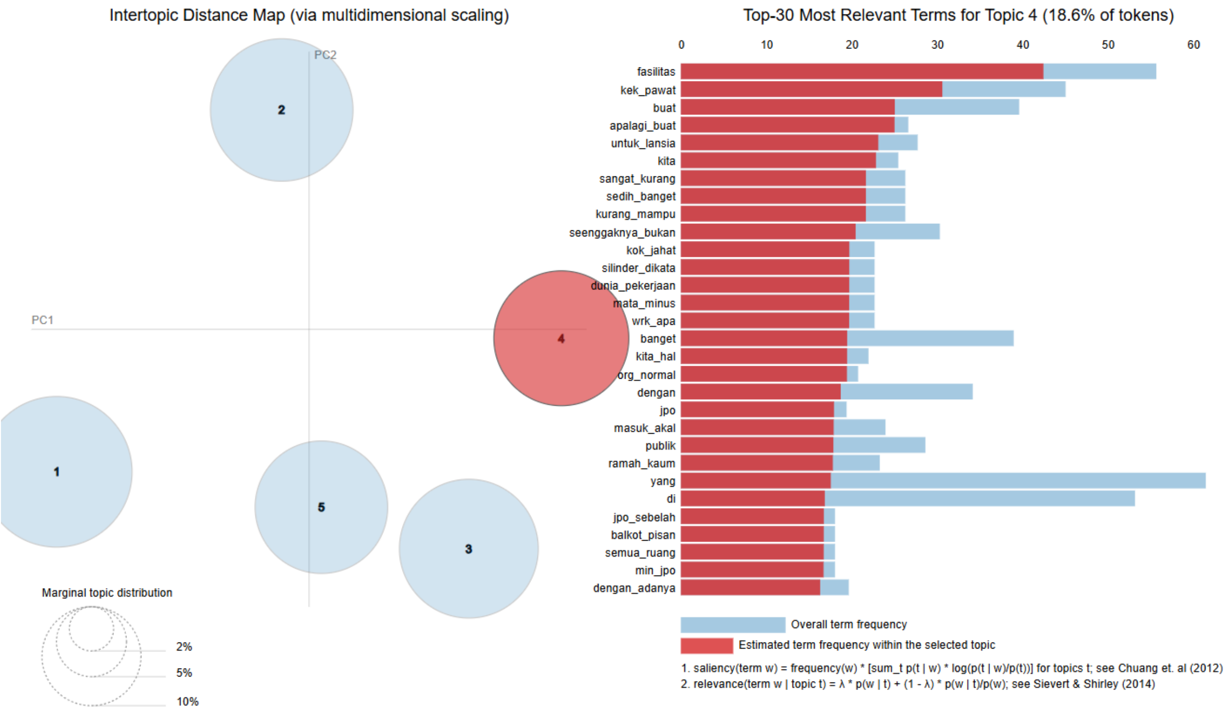

Figure 6. Negative Sentiment

The results of the PyLDAvis diagram also show one of the topics derived from negative sentiment, namely topic 4, with accounts for 18.6% of words relevant to the overall negative sentiment. This topic has several dominant response models, such as what else to do, very lacking, facilities, elderly, underprivileged, and very sad. In addition, there is also terminology related to the description of disabilities that are considered to need care, so the topic that can be taken is the lack of facilities for elderly people with disabilities.

From the topics discussed, the main areas that have been successfully addressed include programs for people with disabilities, as well as the provision of public facilities and services. Then, the topic that is used as material for future improvements is the lack of facilities for elderly people with disabilities, such as the fate of the deaf, bullying of disabled school children, and early marriages that occur.

5 Discussion

The results of the IndoRoBERTa fine-tuning model and model evaluation demonstrate excellent performance in analyzing sentiment, with high accuracy and consistent metric distribution, providing a strong basis for analysis in the following discussion. Additionally, the topics generated are quite diverse, supporting the formulation of public policy analysis.

5.1 Fine-Tuning Analysis

The sentiment analysis in this study employs a fine-tuning approach using the IndoRoBERTa Base Sentiment Classifier model to understand public opinion regarding disability services in Indonesia. The data used in this study comes from 18,242 Twitter posts, collected using keywords such as "disability," "disability services," "disability facilities," and "disability programs" between January 1, 2023, and June 3, 2024. This data is then processed through a pre-processing stage, which involves removing URLs, hashtags, mentions, and special characters, as well as eliminating duplicate data. All text is converted to lowercase to ensure uniformity, resulting in a total of 16,693 data points ready for analysis.

The classification process is used to categorized sentiment into three categories: positive, neutral, and negative. The IndoRoBERTa model is fine-tuned to recognize patterns in the latest data with high accuracy. The evaluation results show that the model's performance is outstanding, with an overall accuracy level reaching 97.42%. For positive sentiment, the model recorded a precision of 93.69%, a recall of 95.50%,

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and an F1-score of 94.59%. Neutral sentiment had a precision of 98.04%, a recall of 98.24%, and an F1-score of 98.14%. Meanwhile, negative sentiment showed the highest precision, at 98.96%, with a recall of 96.95% and an F1-score of 97.94%. These results demonstrate the model's exceptional ability to comprehend and categorized public opinion.

The distribution of sentiment based on keywords provides an interesting picture. The keyword "disability" dominates the data, with 2,485 positive sentiments, 7,820 neutral sentiments, and 3,548 negative sentiments. The keyword "disability services" has 146 positive data points, 455 neutral data points, and 137 negative data points. For "disability facilities," 469 positive data, 1,042 neutral, and 69 negatives were found. Finally, the keyword "disability program" yielded 58 positive data points, 444 neutral ones, and 20 negative ones. Overall, neutral sentiment dominates (9,761 data points), followed by negative sentiment (3,774 data points) and positive sentiment (3,158 data points).

This finding shows that although there are some positive views, many people are neutral or even voice complaints about disability services. The IndoRoBERTa model used can ceffectively apture public sentiment, making it a valuable tool for supporting the formulation of more responsive policies. This provides important input to improve accessibility, reduce discrimination, and provide more inclusive facilities for people with disabilities in Indonesia.

5.2 Model Evaluation Analysis

In this study, the Fine-Tuning IndoRoBERTa model has been evaluated using accuracy, precision, recall, and F1-score metrics. The evaluation results show that this model has a very high level of accuracy, which is 97.42%. This indicates that the model can correctly predict most of the data. In-depth, the analysis of precision, recall, and F1-score metrics provides a more detailed visualization of the model's performance in each sentiment class, ranging from negative to neutral to positive. The highest precision value was recorded for negative sentiment, at 98.96%, indicating the model's ability to provide accurate predictions for negatively labeled data, thereby reducing the number of false positive predictions in this data class. For recall, the highest value is in neutral sentiment, with a figure of 98.24%, reflecting the model's sensitivity in detecting this class, which describes the detection of as much data as possible with a neutral label and can minimize the number of undetected data. Meanwhile, the highest F1-score value, 98.14%, is also found in neutral sentiment, which represents a harmonious combination of precision and recall, achieved by considering the optimal balance between the model's ability to predict correctly and its sensitivity in that class.

For positive sentiment, although precision (93.69%) and recall (95.5%) are lower compared to other classes, the F1-score value of 94.59% indicates that the model still maintains intact performance, albeit with slight weaknesses in detecting positive data compared to other sentiments. Thus, this model demontrates significant advantages in handling negative and neutral sentiments, while its performance in positive sentiment can also be improved through futher optimization. This analysis also demontrates that fine-tuning IndoRoBERTa successfully captures complex patterns in sentimental data, making the model more reliable in its analysis.

5.3 Topic Modelling LDA Analysis

The results of topic modeling generated through sentiment analysis reveal that public services for people with disabilities elicit diverse perceptions, each of which corresponds to a relevant optimal topic. In terms of positive sentiment, there are 15 optimum topics that highlight a deep appreciation for programs that have had a significant impact, such as public facilities, public services, and special programs for people with disabilities that are considered very helpful. One of the dominant topics is evident in the 12th topic, which includes 5.9% of relevant words. These words indicate that the implemented program has succeeded in improving the welfare of people with disabilities and has received a positive response from the community.

In neutral sentiment, there are five optimum topics that do not favor a particular perception but rather reflect administrative and technical issues, such as managing BPJS complaints and providing production equipment for people with disabilities. Topic 1 also includes 32.5% of relevant words, featuring various terms that indicate administrative issues and routine management in the future.

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Finally, negative sentiment is addressed through 5 optimum topics that describe the complaints and challenges still faced by people with disabilities. One of the main topics is Topic 4, which covers 18.6% of relevant words, highlighting the lack of facilities for elderly people with disabilities. The dominant term also reflects a concerning condition and requires special attention, of course, from related parties such as the government and the private sector that oversees it. The visualization results also emphasize that this topic is an important issue that must be addressed inclusively through the implementation of clearer and more assertive public policies.

5.4 Public Policy Analysis

This policy analysis will be crucial in ensuring that policies formulated or implemented are in line with the needs of people with disabilities, thereby making them effective in achieving their goals and overcoming existing challenges.

Based on the positive sentiments related to various programs that have succeeded in helping persons with disabilities, the Indonesian government has launched several initiatives to support individuals with disabilities in community life, including increasing the accessibility of services and information technology, which have shown positive results and can still be expanded. Then, the implementation of inclusive education programs has also shown progress in increasing access to education for children with special needs (Lahesti et al., 2023). In the socio-economic sector, the government has also provided sustainable social assistance programs, and the participation of civil organizations involving people with disabilities must be periodically realized (Julaeha et al., 2022).

Furthermore, based on negative sentiments related to the lack of facilities for elderly people with disabilities, improvements are still needed. The problems that occur include the lack of physical facilities, such as ramps, handrails, and special toilets, which make it difficult for them to carry out activities, so a policy is needed to provide physical facilities in every public place. Then, from the education side, our society still does not understand the needs, especially the elderly with disabilities, where bullying of people with disabilities still occurs. This also indicates that regulations regarding the provision of facilities have not been implemented effectively, resulting in many public services failing to comply with the rules (Hidayah et al., 2024).

With these conditions, a public policy solution is needed that can be proposed, such as increasing physical accessibility by creating comprehensive standards that cover physical services, information, and communication, which must be implemented in public places (Rahadian et al., 2021). Then, periodic audit policies need to be carried out to ensure compliance with the set standards, and the government also needs to educate the public about understanding the needs of people with disabilities to prevent bullying. In addition, educational programs related to life for people with disabilities also need to be implemented to avoid early marriages that are carried out continuously.

6 Conclusion

With the existence of disability service issues and the need for public policy formulation, this study mined online data from Twitter to explore various public opinions related to disability services. The proposed data mining approach utilized Latent Dirichlet Allocation (LDA) for topic modeling and Fine-Tuning IndoRoBERTa for sentiment analysis on 18,242 comments related to four targeted keywords. The textual data modeling successfully identified several key topics from public opinion. Despite existing government programs to support people with disabilities, significant concerns were revealed, particularly regarding physical accessibility, bullying of children with disabilities in schools, and challenges faced by women with disabilities in the workplace.

Based on these findings, the study contributes policy-relevant insights, including the need to enhance physical accessibility through standardized services, provide incentives for disability-friendly private initiatives, strengthen community education to prevent bullying, and promote educational programs for people with disabilities to reduce early marriage. In addition, the evaluation demonstrated a very high performance, with an accuracy of 97.42% and precision, recall, and F1-score values all exceeding 95%. These results confirm the robustness of the proposed approach and highlight its contribution to generating actionable insights for disability-related public policy.

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