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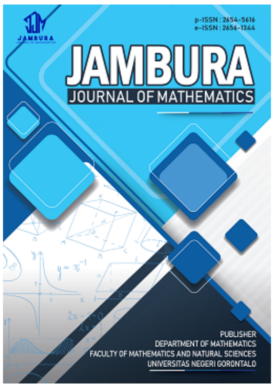

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Research Article

The Childfree Phenomenon in Indonesia: An Analysis of Sentiments on YouTube Video Comments

Amimah Shabrina Putri Prasmono[1] **and Mujiati Dwi Kartikasari**[1,*]

[1]*Department of Statistics, Universitas Islam Indonesia, Indonesia*

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ABSTRACT. *Childfree is a condition in which a person or couple decides not to have children in marriage. Childfree became popular in Indonesia when YouTuber and influencer Gita Savitri uploaded an Instagram story about it. This brought many pros and cons among the people towards the freedom to have children. Many TV broadcasts and YouTube videos cover this phenomenon. Several YouTube channels that broadcast this phenomenon are Menjadi Manusia and Analisa Channel. We collect YouTube comment data using web scraping techniques. From September 2021 to September 2022, 674 sample data points were obtained from two YouTube videos. Data is labelled (positive, negative, and neutral) using the Indonesian language lexicon approach as well as the Support Vector Machine (SVM) and Random Forest algorithms to determine the best model for classifying YouTube comments. The purpose of this research is to understand the public's perception of childfree and to compare the accuracy and AUC values of the two methods. Based on the results of the analysis, 128 comments are classified as positive, the remaining 39 comments are classified as neutral, and 503 comments are classified as negative. This shows that that the commentators on YouTube do not support or give a negative stigma to people who adhere to childfree. The solution to the balanced data problem for each sentiment class uses the random oversampling (ROS) approach. The RBF kernel SVM classification algorithm is a suitable method for classifying commentary data with an accuracy of 98.01% and an AUC of 98.58%, while the Random Forest algorithm only obtains an accuracy of 94.37% and an AUC of 95.87%.*

1. Introduction

The phenomenon of childfree, or the desire not to have children, is currently popular in Indonesia. This phenomenon began to be widely discussed when YouTuber and influencer Gita Savitri posted an Instagram story about childfree on August 14, 2021 [1]. This has sparked many pros and cons in society regarding the freedom to have children.

Childfree is a condition where a person or couple decides not to have children either biologically or by adoption, which is very personal in nature. Even so, this decision is considered taboo in Indonesia. The emergence of the childfree phenomenon has existed for centuries in the United States, Canada, Australia, and Europe. In the early 1500s, European women began delaying marriage at the age of 20. Women at that time were interested in starting independent families because they did not want to live with their in-laws, and work became their main focus to earn money. So, this results in many women not getting married and automatically not having children.

Judging from the results of the study Analysis of the Childfree Phenomenon in Indonesia by Siswanto and Nurhasanah [2], the factors that strengthen someone's decision to choose childfree include being busy with a career, dislike of children, and childhood trauma. But choosing to be childless doesn't mean there are no risks. In the midst of conservative Indonesian society, being childless will receive a negative stigma from the surrounding environment and family environment. Then, based on data from Central Bureau of Statistics regarding the Total Birth Rate in Indonesia and the Population Growth Rate in Indonesia from 2019 to 2022, it continues to decline, so it can be said that Indonesia is experiencing fertilization [3]. This can also be reinforced by several news platforms which state that one of the factors in the decline in birth rates in Indonesia is caused by the childfree phenomenon.

Based on this description, researchers want to find out the truth about the public stigma that considers being childless to be a strange thing to do, and to ensure the truth of news posts which state that childfree is one of the factors that can reduce the birth rate in Indonesia. Therefore, it is necessary to analysis public sentiment towards the childfree phenomenon, and researchers use YouTube comments as a reference for the truth of these negative opinions. Sentiment analysis is the process of automatically understanding, extracting, and processing data in the form of words. It aims to obtain information in a sentence, whether positive, negative, or neutral.

In real cases, the problem that often arises in most sentiment analysis is that most of the comment data are imbalanced datasets in terms of the number of comments per class. In general, machine learning algorithms will produce a model that is less sensitive to minority classes when receiving an imbalanced dataset because this causes poor classification performance for

*Corresponding Author.

Email : *mujiatikartikasari@uii.ac.id* (M. D. Kartikasari)
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sentiment analysis. In this research, the random oversampling (ROS) method is used to handle imbalanced data.

The algorithms that will be used in this research are Support Vector Machine (SVM) and Random Forest. SVM works to find the best hyperplane (separator function between one class and another) among a data set. Meanwhile, Random Forest works by building several decision trees and combining them to get a more accurate prediction classification. The reason for choosing the SVM classification method is that it has good classification accuracy [4] and is able to find the best dividing line, or hyperline [5]. In contrast, the random forest method was chosen because it produces more accurate and stable predictions.

2. Methods

This research consists of several stages. First, the research began by crawling data from YouTube. Then, proceed with data pre-processing. After that, labelling and weighting are carried out. To overcome the data imbalance, oversampling is carried out with ROS. The classification process is carried out after this stage. The research ended by calculating the confusion matrix from the classification results and creating a visualization. Figure 1 shows the research stages in a flowchart.

2.1. Text Mining

Text mining is the process of extracting data in the form of text, where data sources are usually obtained from documents, aiming to find words that can represent the contents of the document so that it can analyze the relationships between documents. Text mining and data mining have different data sources. Text mining is data that is processed from unstructured text data, while data mining is data that has been structured through a warehousing process.

In the text mining process, the documents to be used must first enter the text preprocessing stage. Text preprocessing is used to convert unstructured text data into structured data. This process has several stages, namely case folding, cleaning, translating, filtering, stemming, tokenizing, and normalization.

2.2. Term Frequency

Data that goes through the preprocessing stage must be converted into numbers so that it can be calculated and processed [6]. Word weighting can use the TF algorithm because this algorithm is considered to have accuracy and efficiency. This method finds the TF value for each word in each document. TF is the frequency of occurrence of the word in the document. The more often a word appears (high TF), the greater the similarity value of the word.

2.3. Sentiment Analysis

According to [7], sentiment analysis is a computational study of a person's opinions, characteristics, and emotions about an object. Note that the subject of discussion can be a product, activity, service, or even a topic. In general, sentiment analysis is used to help gather information that will later be used to find positive, negative, and neutral values for a particular topic.

In conducting sentiment analysis, it is divided into three steps: classification, evaluation, and data visualization. The following is a clearer explanation of each of the sentiment analysis steps:

1. Classification
   Classification is divided into three approaches: lexicon-based, machine-learning, and hybrid [8]. The following is an explanation of each classification in sentiment analysis:
   (a) Lexicon-Based Approach
   This approach relies on the sentiment lexicon, which is a collection of known and collected sentiment words. Positive words are represented as (+1), and negative words are represented as (-1). While the neutral class classification is represented by (0) from the calculation of positive and negative scores.
   (b) Machine Learning Approach
   This approach applies machine learning algorithms to analyze text sentiment. Machine learning approaches can be divided into two groups. The first group is features-focused algorithms that use classification methods (such as SVM, Nave Bayes, and others) to propose new features. The second group is model-focused algorithms that propose new classification models, such as probabilistic models combined with regression, applying lexical associations and text distribution analysis to infer sentiment, or others [9].
   (c) Hybrid Approach
   The hybrid approach is an approach that combines the lexicon and machine learning approaches [10]. The advantages of a hybrid approach include symbiosis between lexicon and learning, the ability to detect and measure sentiment at the concept level, and being less sensitive to variations in topic domains. However, this method has the disadvantage that reviews with a lot of noise (words that are not related to the topic of the review) usually get a neutral score because this method cannot detect any sentiment.
2. Evaluation
   The second step is to carry out evaluation matrices such as accuracy, precision, recall, and F1-score with the help of the confusion matrix of the classification algorithm method used.
3. Data visualization
   The third step is to visualize the data using graphics according to the needs of the researcher. Most people generally use familiar techniques such as histograms, pie charts, or matrices.

2.4. Sentiment Lexicon Indonesia

The Indonesian Lexicon is a dictionary that contains opinions in Indonesian that contain opinion words. This research requires two lexicons, namely a positive lexicon and a negative lexicon. A positive lexicon is a dictionary that contains positive words (e.g., *bagus, suka*, and *akur*) in KBBI (*Kamus Besar Bahasa Indonesia*). The negative lexicon is a dictionary containing negative words (e.g., *alibi, acak-acakan, amatir*) in KBBI.

2.5. Imbalance Data

In computing systems, imbalanced data is the process of distributing data that has an unbalanced data class. The number of majority data points is greater than the number of minor-

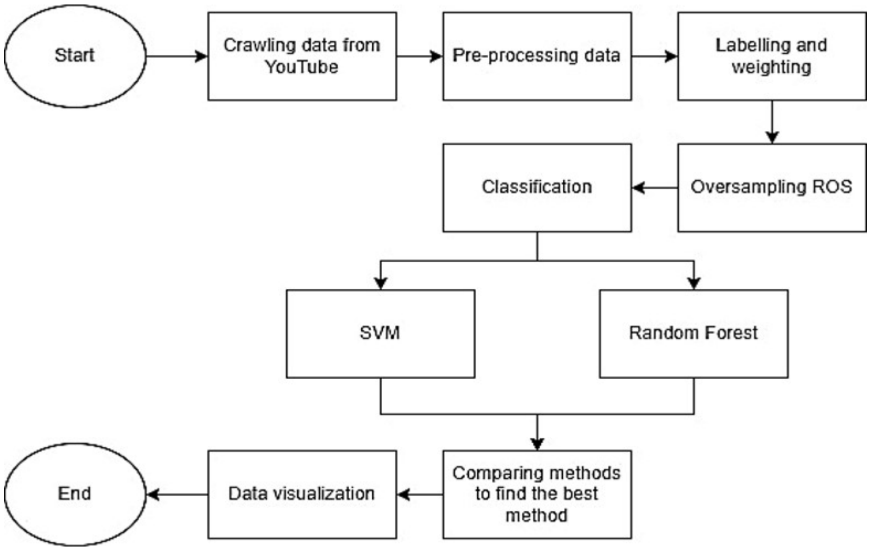

Figure 1. Research flowchart

ity data points. This imbalanced data can cause misclassification events where the classifier is more inclined towards the majority data. Minority data will be considered noise and outliers, which can reduce the performance of the classifier [11].

There are various methods that can be used to overcome problems with the number of imbalanced data classes, including the use of oversampling and undersampling. Oversampling will enlarge the minority class so that it becomes as many as the majority class, while undersampling will reduce the majority class so that it becomes as many as the minority class. The G-means and AUC values can be used to measure how well a classification algorithm performs in situations with imbalanced data. A low G-means number indicates that the classification method performs poorly in a class, and so is the AUC value is low [12]. In this study, the ROS (random oversampling) method was used as an oversampling technique.

2.6. Confusion Matrix

According to [13], the confusion matrix is a matrix that contains information about the actual classification that will be predicted by the classification system. The confusion matrix can be explained by a table containing the amount of testing data that is classified correctly and the data that may also be misclassified. In general, classification performance is measured using a confusion matrix [14]. Table 1 is a 3x3 confusion matrix for multi-class classification [15].

Table 1. Confusion matrix

Prediction	Actual		
	Positive	Neutral	Negative
Positive	True Positive (TP)	False Positive (FP)	False Positive (FP)
Neutral	False Neutral (FN)	True Neutral (TN)	False Neutral (FN)
Negative	False Negative (FN)	False Negative (FN)	True Negative (TN)

There are several formulas that can be used to measure the performance of the classification results, as follows:

1. Accuracy
Accuracy describes how accurately the model correctly classifies.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \times 100. \quad (1)$$

2. Precision
Precision describes the level of accuracy between the requested data and the predictions provided by the model.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100. \quad (2)$$

3. Recall or sensitivity
Recall describes how successful a model is at retrieving information.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100. \quad (3)$$

4. Specificity
Specificity is a system that expects no errors to detect an actual bad but well-predicted location.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100. \quad (4)$$

5. F1-Score
F1-Score is a measure of the balance between precision and recall.

$$\text{F1} - \text{Score} = 2 \times \frac{(\text{recall} \times \text{precision})}{(\text{recall} + \text{precision})}. \quad (5)$$

6. AUC
AUC is used to measure performance in terms of probability estimates from the results of a randomly selected sample from a positive, negative, or neutral population.

$$\text{AUC} = \frac{1}{2}(\text{sensitivity} + \text{specificity}). \quad (6)$$

2.7. Classification

According to [16] , classification is the process of building models or functions that describe and differentiate data classes or concepts with the aim of predicting data classes whose class is unknown. There are two processes for classifying: the training process is used to create a model, and the testing process is used to predict labels.

1. Support Vector Machine (SVM)
   According to [17], SVM is an attempt to find the best hyperplane as a separator between two different classes in the input space. SVM takes the basics of a linear classifier, where classification cases can be separated linearly, and has been further developed so that it can deal with nonlinear problems by combining the kernel trick concept in a high-dimensional workspace. There are types of kernel functions, including linear, polynomial, RBF (Gaussian Radial Basis Function), and sigmoid. There are no special requirements for choosing to use linear and the highest level of accuracy because, usually, the selected kernel does not produce a significantly different level of accuracy [18].
2. Random Forest
   Random forest is a method consisting of a set of structured trees, each of which casts a sound unit for a class and obtains a result based on the most decisions. Random forest is an algorithm used to classify data sets for comments on machine learning results. Then, this algorithm works by building several decision trees and combining them to get more accurate predictions. The basic technique used by Random Forest is a decision tree. In other words, the random forest is a set of decision trees that are used to classify and predict data by entering input into the upper roots and descending to the lower leaves [19].

3. Results and Discussion

3.1. Crawling

This research was conducted to collect data in the form of public perceptions of childfree through comments on a YouTube video. YouTube was used as a platform for data collection because one video provides an explanation or excerpt of the entire conversation about childfree. For this reason, you can be sure that all Indonesian citizens will watch the full discussion about childfree raised by this channel. Thus, it is hoped that there will be no miscommunication in the sources' opinions. A code was obtained from the YouTube Data API v3 on the Google Developer Console. Activating the API is used to confirm to YouTube that it will provide wider access to the data on YouTube. In this research, the API code can be used for the integration process between the YouTube API and Python.

3.2. Data Processing

The data that has been obtained is then processed in order to obtain information from the data. Data processing was carried out in the community towards childfree with a sample of 674. There were two types of data processing carried out, consisting of descriptive analysis and data preprocessing.

1. Preprocessing Data
   The data in this study is comment data from a video taken from the YouTube platform in the form of unstructured text. At the preprocessing stage, using the text mining method to clean text data, the stages include case folding, cleaning, translating, filtering, tokenizing, stemming, and normalization. Table 2 is an example of some of the original data taken from the comment data results of two YouTube videos before data preprocessing was carried out.

   Table 2. Youtube video comments data

No	Author	Text
1	ulatbuluk	*Suka sekali dengan opini para narasumber, juga comment section yang tidak judge mental*
2	Kita Boleh	*Siapa yang selfish? Siapa yg memaksa opini terhadap organ reproduksi sendiri terhadap orang lain? Kamu yang selfish*
3	Dinda D. Syavitri	*@MuhammadFarhan mohon maaf di atas saya komen tentang menghargai keputusan orang lain. bukan tentang childfree nya* ðŸ™□ðŸ™□

   The following are the preprocessing stages:
   (a) Case Folding and Cleaning Text
   Case folding is the stage of changing the capital letters "a-z" into lowercase or uppercase. Cleaning is a step that is carried out to clean the text to reduce noise, such as punctuation, urls, tags, usernames, mentions, hashtags, numbers, single characters, special characters, and so on. The results of case folding and cleaning data are in Table 3.
   (b) Translating
   Translating is a process for language uniformity, because in this study conducting analysis in Indonesian, all comments in foreign languages (English) will be translated into Indonesian using Google Sheets to translate the text. The results of the translating process are in Table 4.
   (c) Filtering, Stemming, Tokenizing, and Normalization
   Filtering is a step to retrieve words that do not have the appropriate meaning in the stop word dictionary, for example, "*yang*", "*dan*", "*ke*", "*oleh*", "*dari*", and so on. Stemming is the stage for changing words that have affixes into basic words. Tokenizing is a step to separate sentences into words per word, also known as a token. Normalisation is a stage for correcting and substituting words that are abbreviated, misspelt, or in slang. For example, the word "*hancur*" has many forms of writing, such as *ancur, ambyar*, and so on. The results of filtering, stemming, tokenizing, and normalisation are in Table 5.
2. Class Weighting and Labelling
   In this study, the data collected has not been labelled with any sentiment class, so a hybrid approach technique is needed, which is a combination of the lexicon and machine learning approaches, where the lexicon helps in labelling the sentiment class, and then a machine learning approach is used to test the performance of the resulting model. Labelling is done with lexicon weighting, which considers sentiment scores automatically. To get the sentiment score by looking for the number of positive words and the number

Table 3. Results of case folding and cleaning process

No.	Text	Case Folding
1	*Suka sekali dengan opini para narasumber, juga comment section yang tidak judge mental*	*suka sekali dengan opini para narasumber juga juga comment section yang tidak judge mental*
2	*Siapa yang selfish? Siapa yg memaksa opini terhadap organ reproduksi sendiri terhadap orang lain? Kamu yg selfish*	*siapa yang selfish siapa yg memaksa opini terhadap organ reproduksi sendiri terhadap orang lain kamu yg selfish*
3	*@MuhammadFarhan mohon maaf di atas saya komen tentang menghargai keputusan orang lain. bukan tentang childfree nya ðŸ™*	*mohon maaf di atas saya komen tentang menghargai keputusan orang lain bukan tentang childfree nya*

Table 4. Results of translating process

No.	Clean Text	Translating
1	*suka sekali dengan opini para narasumber juga comment section yang tidak judge mental*	*suka sekali dengan opini para narasumber bagian komen yang tidak menilai mental*
2	*siapa yang selfish siapa yg memaksa opini terhadap organ reproduksi sendiri terhadap orang lain kamu yg selfish*	*siapa yang egois siapa yg memaksa opini terhadap organ reproduksi sendiri terhadap orang lain kamu yg egois*
3	*mohon maaf di atas saya komen tentang menghargai keputusan orang lain bukan tentang childfree nya*	*mohon maaf di atas saya komen tentang menghargai keputusan orang lain bukan tentang childfree nya*

Table 5. Results of filtering, stemming, tokenizing, and normalization process

No.	Cleaning	Filtering, Stemming, Tokenizing, and Normalization
1	*suka sekali dengan opini para narasumber juga bagian komen yang tidak menilai mental*	[*'suka', 'opini', 'narasumber', 'komen', 'nilai', 'mental'*]
2	*siapa yang egois siapa yg memaksa opini terhadap organ reproduksi sendiri terhadap orang lain kamu yg egois*	[*'egois', 'paksa', 'opini', 'organ','reproduksi','egois'*]
3	*mohon maaf di atas saya komen tentang menghargai keputusan orang lain bukan tentang childfree nya*	[*'maaf', 'komen', 'hargai', 'putus','childfree'*]

of negative words in one comment, the Indonesian Lexicon dictionary is used to determine the class of each word. For future work, apart from using Lexicon, an Indonesian language expert can also be used to label comments, as can an expert who understands childfree. Table 6 shows examples of text results that have been weighed and labelled by the machine sentiment.

Table 6. Results of text weighting and labelling

No.	Text	Compound Score	Klasifikasi
1	*suka opini narasumber komen nilai mental*	7	Positive
2	*egois paksa opini organ reproduksi egois*	-14	Negative
3	*maaf komen harga putus childfree*	0	Neutral

From the results of text data labelling of 670, positive sentiment labelling of 128 comments, negative sentiment labelling of 503 comments, and the remaining neutral sentiment of 39 comments, as shown in Table 7, The results of the sentiment labelling show that negative sentiment towards childlessness is more dominant when compared to other sentiments.

Table 7. Text labelling classification

Amount of Data		
Positive	Negative	Neutral
128	503	39

Figure 2 is a visualization of all positive, negative and neutral sentiment classification results. Figure 2(a) is data that experiences imbalance, so in this case the handling uses the ROS method. The results of the ROS method are shown in Figure 2(b), namely the data is balanced, with each sentiment class obtaining 503 data.

3.3. *Classification*

This study carried out a classification process with two algorithms, namely the support vector machine and the random forest. At this stage, the machine will be taught to understand existing patterns or documents so that it can classify data into three classes, namely positive, negative, and neutral. The data will be divided into two parts, namely training data and testing data. From the total balance of existing ROS data, which is 1509, the researcher will divide using the proportion of 80% for training data and 20% for testing data. The distribution of training and testing data is shown in Table 8.

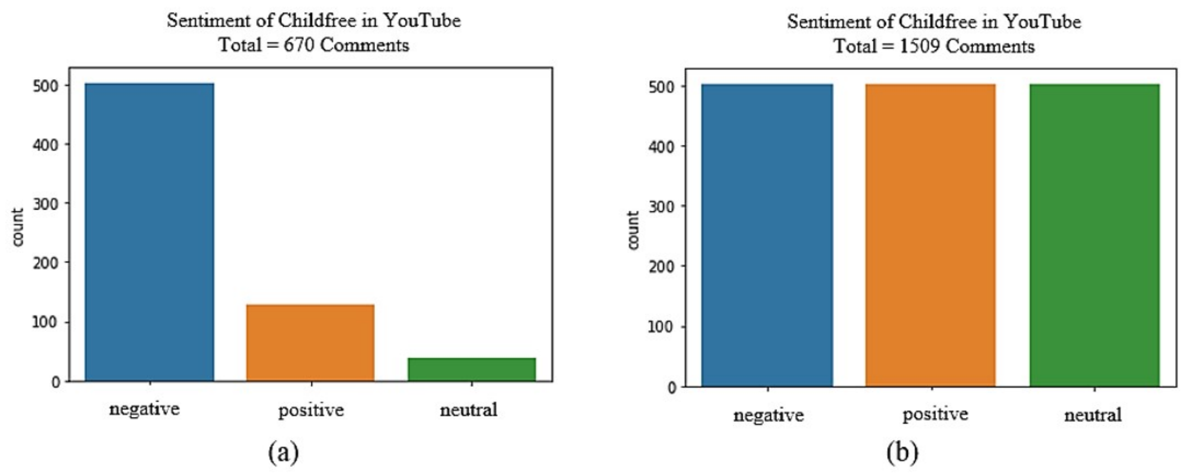

Figure 2. (a) Imbalance dataset, (b) Balance dataset using ROS

Table 8. Distribution of training data and testing data

Training	Testing
80%×503 = 1207	20%×503 = 302

1. Classification of the Support Vector Machine Algorithm
   The first classification stage uses the SVM algorithm by using the Python and RStudio programming languages. Researchers use the RBF kernel to obtain the most accurate classification. Classification accuracy measurement is done by forming a confusion matrix based on the prediction results. The confusion matrix is one of the tools used in the evaluation method used in machine learning, usually producing two or more classes [20]. The confusion matrix describes the rows that contain test data for the actual class, and the columns describe the predicted classes. In the RBF kernel, a gamma value is needed, researchers use a gamma value of 1.0 and C of 1.0 because these two values provide the best SVM accuracy. The results of determining the gamma value on the SVM kernel RBF are in Table 9.

Table 9. Gamma and C-values on the SVM kernel RBF

Gamma	C	Accuracy
0.001	1.0	0.4338
0.01	1.0	0.7053
0.1	1.0	0.9371
1.0	1.0	0.9801

Furthermore, the results of the confusion matrix obtained by the SVM algorithm using the RBF kernel are shown in Table 10.

Table 10. Confusion matrix SVM on balance dataset

Prediction	Actual		
	Positive	Neutral	Negative
Positive	101	0	0
Neutral	0	100	0
Negative	6	0	95

Then the manual testing process is carried out with the confusion matrix value to get the accuracy, precision, recall, specificity, F1-Score, and AUC values of each class.

$$\begin{aligned}\text{Accuracy}_{\text{RBF}} &= \frac{\text{number of correct prediction data}}{\text{total data}}\times 100\% \\ &= \frac{101+100+95}{302}\times 100\% \\ &= 98.01\%\end{aligned}$$

(a) Class Positive

$$\begin{aligned}\text{Precision}_{\text{Positif}} &= \frac{\text{TP}}{\text{TP}+\text{FP}}\times 100\% \\ &= \frac{101}{101+(0+0)}\times 100\% \\ &= 100\%\end{aligned}$$

$$\begin{aligned}\text{Recall}_{\text{Positif}} &= \frac{\text{TP}}{\text{TP}+\text{FN}}\times 100\% \\ &= \frac{101}{101+(0+6)}\times 100\% \\ &= 94.39\%\end{aligned}$$

$$\begin{aligned}\text{Specificity}_{\text{Positif}} &= \frac{\text{TN}}{\text{TN}+\text{FP}}\times 100\% \\ &= \frac{100+95}{(100+95)+(0+0)}\times 100\% \\ &= 100\%.\end{aligned}$$

(b) Class Neutral

$$\begin{aligned}\text{Precision}_{\text{Netral}} &= \frac{\text{TP}}{\text{TP}+\text{FP}}\times 100\% \\ &= \frac{100}{100+(0+0)}\times 100\% \\ &= 100\%\end{aligned}$$

$$\begin{aligned}\text{Recall}_{\text{Netral}} &= \frac{\text{TP}}{\text{TP}+\text{FN}}\times 100\% \\ &= \frac{100}{100+(0+0)}\times 100\% \\ &= 100\%\end{aligned}$$

$$\begin{aligned}\text{Specificity}_{\text{Netral}} &= \frac{\text{TN}}{\text{TN}+\text{FP}}\times 100\% \\ &= \frac{101+95}{(101+95)+(0+0)}\times 100\% \\ &= 100\%.\end{aligned}$$

(c) Class Negative

$$\begin{aligned}\text{Precision}_{\text{Negatif}} &= \frac{\text{TP}}{\text{TP}+\text{FP}}\times 100\% \\ &= \frac{95}{95+(0+6)}\times 100\% \\ &= 94.05\%\end{aligned}$$

$$\begin{aligned}\text{Recall}_{\text{Negatif}} &= \frac{\text{TP}}{\text{TP}+\text{FN}}\times 100\% \\ &= \frac{95}{95+(0+0)}\times 100 \\ &= 100\%\end{aligned}$$

$$\begin{aligned}\text{Specificity}_{\text{Negatif}} &= \frac{\text{TN}}{\text{TN}+\text{FP}}\times 100\% \\ &= \frac{101+100}{(101+100)+(6+0)}\times 100\% \\ &= 97.10\%.\end{aligned}$$

$$\begin{aligned}\text{Precision}_{\text{RBF}} &= \frac{\text{Positif}+\text{Netral}+\text{Negatif}}{\text{total class}}\times 100\% \\ &= \frac{1+1+0.9405}{3}\times 100\% \\ &= 98.01\%\end{aligned}$$

$$\begin{aligned}\text{Recall}_{\text{RBF}} &= \frac{\text{Positif}+\text{Netral}+\text{Negatif}}{\text{total class}}\times 100\% \\ &= \frac{0.\,9439+1+1}{3}\times 100\% \\ &= 98.13\%\end{aligned}$$

$$\begin{aligned}\text{Specificity}_{\text{SVM}} &= \frac{\text{Positif}+\text{Netral}+\text{Negatif}}{\text{total class}}\times 100\% \\ &= \frac{1+1+0.9710}{3}\times 100\% \\ &= 99.03\%\end{aligned}$$

$$\begin{aligned}\text{F1}-\text{Score}_{\text{SVM}} &= 2\times\frac{(\text{recall}\times\text{precision})}{(\text{recall}+\text{precision})} \\ &= 2\times\frac{(98.13\times 98.01)}{(98.13+98.01)} \\ &= 98.07\%\end{aligned}$$

$$\begin{aligned}\text{AUC}_{\text{SVM}} &= \frac{1}{2}(\text{recall}+\text{specificity}) \\ &= \frac{1}{2}(98.13+99.03) \\ &= 98.58\%.\end{aligned}$$

According to the calculation above, in terms of accuracy, it succeeded in predicting 98.01% of positive, neutral, and negative sentiments from all the data. While the precision value is 98.01%, recall is 98.13%, specificity is 99.03%, F1-Score is 98.07%, and AUC is 98.58%, The greater the accuracy and AUC values, the more relevant the method is for classification.

2. Classification of Random Forest Algorithm
   The second classification stage uses the random forest algorithm. The random forest algorithm is a combination of each tree from the decision tree, then combined and combined into a model. The results of the confusion matrix obtained by the random forest algorithm are shown in Table 11.

Table 11. Confusion matrix Random Forest on balance dataset

Prediction	Actual		
	Positive	Neutral	Negative
Positive	88	2	11
Neutral	0	100	0
Negative	4	0	97

Furthermore, the testing process is carried out manually with the value of the confusion matrix to get the accuracy, recall, and precision values of each class.

$$\begin{aligned}\text{Accuracy}_{\text{RF}} &= \frac{\text{number of correct prediction data}}{\text{total data}}\times 100\% \\ &= \frac{88+100+97}{302}\times 100\% \\ &= 94.37\%\end{aligned}$$

(a) Class Positive

$$\begin{aligned}\text{Precision}_{\text{Positif}} &= \frac{\text{TP}}{\text{TP}+\text{FP}}\times 100\% \\ &= \frac{88}{88+(2+11)}\times 100\% \\ &= 87.12\%\end{aligned}$$

$$\begin{aligned}\text{Recall}_{\text{Positif}} &= \frac{\text{TP}}{\text{TP}+\text{FN}}\times 100\% \\ &= \frac{88}{88+(0+4)}\times 100\% \\ &= 95.65\%\end{aligned}$$

$$\begin{aligned}\text{Specificity}_{\text{Positif}} &= \frac{\text{TN}}{\text{TN}+\text{FP}}\times 100\% \\ &= \frac{100+97}{(100+97)+(2+11)}\times 100\% \\ &= 93.80\%.\end{aligned}$$

(b) Class Neutral

$$\begin{aligned}\text{Precision}_{\text{Netral}} &= \frac{\text{TP}}{\text{TP}+\text{FP}}\times 100\% \\ &= \frac{100}{100+(0+0)}\times 100\% \\ &= 100\%\end{aligned}$$

$$\begin{aligned}\text{Recall}_{\text{Netral}} &= \frac{\text{TP}}{\text{TP}+\text{FN}}\times 100\% \\ &= \frac{100}{100+(2+0)}\times 100\% \\ &= 98.03\%\end{aligned}$$

$$\begin{aligned}\text{Specificity}_{\text{Netral}} &= \frac{\text{TN}}{\text{TN}+\text{FP}}\times 100\% \\ &= \frac{88+97}{(88+97)+(0+0)}\times 100\% \\ &= 97.91\%.\end{aligned}$$

(c) Class Negative

$$\begin{aligned}\text{Precision}_{\text{Negatif}} &= \frac{\text{TP}}{\text{TP}+\text{FP}}\times 100\% \\ &= \frac{97}{97+(4+2)}\times 100\% \\ &= 94.17\% \\ \text{Recall}_{\text{Negatif}} &= \frac{\text{TP}}{\text{TP}+\text{FN}}\times 100\% \\ &= \frac{97}{97+(11+0)}\times 100\% \\ &= 89.81\% \\ \text{Specificity}_{\text{Negatif}} &= \frac{\text{TN}}{\text{TN}+\text{FP}}\times 100\% \\ &= \frac{88+100}{(88+100)+(4+0)}\times 100\% \\ &= 97.91\%\end{aligned}$$

$$\begin{aligned}\text{Precision}_{\text{RF}} &= \frac{\text{Positif}+\text{Netral}+\text{Negatif}}{\text{total class}}\times 100\% \\ &= \frac{0.9437+1+0.9417}{3}\times 100\% \\ &= 93.76\% \\ \text{Recall}_{\text{RF}} &= \frac{\text{Positif}+\text{Netral}+\text{Negatif}}{\text{total class}}\times 100\% \\ &= \frac{0.9565+0.9803+0.8981}{3}\times 100\% \\ &= 94.50\% \\ \text{Specificity}_{\text{RF}} &= \frac{\text{Positif}+\text{Netral}+\text{Negatif}}{\text{Jumlah Kelas}}\times 100\% \\ &= \frac{0.9380+0.9791+0.9791}{3}\times 100\% \\ &= 97.24\% \\ \text{F1}-\text{Score}_{\text{RF}} &= 2\times\frac{(\text{recall}\times\text{precision})}{(\text{recall}+\text{precision})} \\ &= 2\times\frac{(94.50\times 93.76)}{(94.50+93.76)} \\ &= 94.13\% \\ \text{AUC}_{\text{RF}} &= \frac{1}{2}(\text{recall}+\text{specificity}) \\ &= \frac{1}{2}(94.50+97.24) \\ &= 95.87\%.\end{aligned}$$

According to the calculation above, in terms of accuracy, it succeeded in predicting 94.37% of positive, neutral, and negative sentiments from all the data. While the precision value is 93.76%, recall is 94.50%, specificity is 97.24%, F1-Score is 94.13%, and AUC is 95.87%, The greater the accuracy and AUC values, the more relevant the method is for classification.

3.4. Data Visualization

Visualization is done for each category of sentiment class. Visualization is carried out to provide an overview of information, topics, and discussions that are often discussed about childlessness, so that from the many existing commentary texts, information that is considered important can be retrieved and searched for associations between words that appear most frequently together, so as to strengthen the achievement of that information.

1. Positive Comments
   The extraction of information on positive comments is done repeatedly to get information about positive comments about childlessness, which are most often discussed. Figure 3 is a visualization of the results of information extraction obtained from positive comments.

Figure 3. Word cloud of positive data

In Figure 3, there is a set of positive words that are often used to discuss the topic of childlessness in two research YouTube videos. The larger the word size in the word cloud, the higher the frequency of the word, meaning that the word is often used as a topic of conversation in positive comments. Furthermore, a search for associations between words that are related to words that often appear together is carried out, and the following results are in Table 12.

Table 12. Positive word associations

Keyword	Word Association	Skor
Islam	*Paham*	0.68
	Kontra	0.22
	Publik	0.18
Hidup	*Bahagia*	0.45
	Tuju	0.30
	Pikir	0.22

Based on the association value obtained on the positive sentiment associated with the word "*islam*", one of the words is "*paham*". It is possible that the word Islam is associated with understanding before choosing to be childless or not requiring understanding from an Islamic point of view. And maybe the word life associated with happiness means that the presence of children does not guarantee you will live happily ever after.

2. Negative Comments
   The extraction of information on negative comments is done repeatedly to get information about negative comments about childlessness, which are most often discussed. Figure 4 is a visualization of the results of information extraction obtained from negative comments.

Figure 4. Word cloud of negative data

In Figure 4, there is a set of negative words that are often used to discuss the topic of childlessness in two research YouTube videos. The larger the word size in the word cloud, the higher the frequency of the word, meaning that the word is often used as a topic of conversation in positive comments. Furthermore, a search for associations between words that are related to words that often appear together is carried out, and the following results are in Table 13.

Table 13. Negative word associations

Keyword	Word Association	Skor
	Pasang	0.37
Nikah	*Komunikasi*	0.25
	Cerai	0.21
	Hubung	0.32
Manusia	*Jahat*	0.31
	Komitmen	0.20

Based on the association value obtained from the negative comments, some information was obtained, including whether the child is childless or not, which is a choice that must be carefully considered. Because marriage is something that is binding, do not let decisions that are independent of women imprison the wishes of men, or vice versa. Miscommunication from the start ended badly for the marriage, such as an affair that ended in divorce. And maybe today you are planning to be childless, but in the future, you may not be able to consistently keep your commitments. Humans only plan to lower their minds and passions but forget that God is the Supreme Planner.

3. Neutral Comments
   The extraction of information on neutral comments is done repeatedly to get information about neutral comments about childlessness, which are most often discussed. Figure 5 is a visualization of the results of information extraction obtained from neutral comments.

Figure 5. Word cloud of neutral data

In Figure 5, there is a set of neutral words that are often used to discuss the topic of childlessness in two research YouTube videos. The larger the word size in the word cloud, the higher the frequency of the word, meaning that the word is often used as a topic of conversation in positive comments. Furthermore, a search for associations between words that are related to words that often appear together is carried out, and the following results are in Table 14.

Table 14. Neutral word associations

Keyword	Word Association	Skor
	Komitmen	0.56
Tanggung	*Suara*	0.56
	Tuju	0.37
	Trauma	0.56
Didik	*Ilmu*	0.49
	Wawas	0.37

Based on the association value obtained on neutral sentiment associated with the word "*tanggung jawab*", one of them is "*komitmen*". It is possible that the word responsibility associated with commitment means that both partners must be responsible for their commitment to choosing to be childless or not. And the possibility of students associated with trauma learning from childhood trauma to educate children.

4. Conclusion

The results of sentiment analysis using the Indonesian language lexicon labelling produced 670 comments, including 128 comments classified as positive, the remaining 39 comments classified as neutral, and 503 comments classified as negative. Thus, it can be concluded that the commentators on YouTube do not support or give a negative stigma to people who adhere to childfree. So, childfree does not affect the birth rate in Indonesia. This research provides information to the government and society that currently childfree is not a big concern. From the results of the comparison of algorithmic methods, it is known that SVM is a suitable method for word classification in commentary data, with a model accuracy of 98.01% and an AUC of 98.58%. While the accuracy value for the Random Forest method in the model is only 94.37% and the AUC is 95.87%. For future researchers, it is hoped that they will use an Indonesian language expert in labelling comments and an expert who understands childfree. As well as being able to expand the time period or select other videos in obtaining data to make it more varied and use other algorithmic methods, so that more specific classification results are obtained.

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