International Journal of Engineering and Computer Science Applications (IJECSA)
Vol. 4, No. 2, September 2025, pp. 71∼80
ISSN: 2828-5611
DOI: doi.org/10.30812/ijecsa.v4i2.4980

Assessing Twitter User Sentiment Regarding Divorce Issues Using the Random Forest Method

Muhamad Azwar, I Putu Hariyadi, Raisul Azhar
Universitas Bumigora, Mataram, Indonesia

Article Info

Article history:

Received March 12, 2025
Revised April 21, 2025
Accepted May 20, 2025

Keywords:

Confusion Matrix
Divorce
Random Forest
Sentiment Analysis

ABSTRACT

The issue of divorce remains a complex and sensitive topic within Indonesian society, influenced by various factors such as repeated disputes, domestic violence, lack of harmony, financial difficulties, and other socio-cultural aspects. With the rise of social media, particularly Twitter, public discussions regarding divorce have become more widespread, allowing individuals to express their opinions and sentiments on the subject. These diverse perspectives create a wealth of sentiment data that can be analyzed to understand public perception and societal trends related to divorce. **This study aims** to classify public sentiment on divorce-related discussions using the Random Forest algorithm, providing insight into how people perceive and react to divorce issues. **The research adopts a quantitative** approach with a case study framework. The methodology involves data collection through web scraping techniques to gather approximately 1500 tweets containing discussions on divorce. The collected data is then preprocessed, including text cleaning, tokenization, and feature extraction, before being used to train and evaluate the Random Forest model. Sentiments are classified into three categories: negative, neutral, and positive. The classification model's performance is assessed using accuracy and F1-score metrics derived from the confusion matrix to determine its effectiveness in categorizing sentiments. **Experimental results** indicate that the Random Forest algorithm achieves an accuracy of 70%. The relatively low accuracy is attributed to the imbalance in sentiment class distribution, where negative sentiments dominate while positive sentiments are underrepresented. This imbalance affects the model's ability to predict positive sentiments effectively. **The implications of this research contribute** to a better understanding of public sentiment dynamics regarding divorce, which can be beneficial for policymakers, psychologists, and social researchers in analyzing societal attitudes towards marital dissolution.

Corresponding Author:

Muhamad Azwar,
Universitas Bumigora, Mataram, Indonesia,
Email: azwar@universitasbumigora.ac.id

How to Cite: M. Azwar, I. P. Hariyadi, & R. Azhar, "Assessing Twitter User Sentiment Regarding Divorce Issues Using the Random Forest Method," *International Journal of Engineering and Computer Science Applications (IJECSA)*, vol. 4, no. 2, pp. 71-80, Sep. 2025. doi: 10.30812/ijecsa.v4i2.4980..

1. INTRODUCTION

Divorce is a complex and sensitive social issue in Indonesia. Various factors, such as recurring disputes, domestic violence, disharmony in relationships, economic problems, and third-party interference, can trigger divorce cases. According to the 2023 Indonesian Statistics Report, the number of divorce cases in Indonesia reached 516,334 cases in 2022, an increase of 15.31% compared to the previous year, which recorded 447,743 cases. This figure shows a significant upward trend over the past six years and has become a concern for various stakeholders [1]. In the digital era, social media, particularly Twitter, has become a primary platform for individuals to express their opinions and experiences regarding various issues, including divorce. The diverse sentiments expressed on Twitter can serve as an indicator of public perception toward this phenomenon. Sentiment analysis, also known as opinion mining, is a technique used to identify and classify public opinions on a specific topic based on textual data available on social media. By analyzing public sentiment regarding divorce, governments, academics, and social practitioners can gain insights into societal views and the potential impacts of this issue [2]. Previous research has applied various methods to sentiment analysis on social media. Study [3] examined sentiment analysis on the development of Artificial Intelligence (AI) using the Random Forest method, achieving an accuracy of 57.8%. This study highlighted that class imbalance significantly affects model performance. Study [4] compared the Random Forest and K-Nearest Neighbors (K-NN) methods for sentiment analysis on Twitter, where Random Forest achieved 39.74% accuracy, while K-NN performed better in certain cases. Study [5] applied Random Forest for sentiment analysis of digital wallet services, achieving an accuracy of 60%, but still faced challenges related to class imbalance.

Although various studies have been conducted in the field of sentiment analysis using Random Forest, several challenges remain unresolved. Most previous studies have focused on general sentiment analysis on Twitter, covering topics such as product reviews, public policies, or emerging technologies, but have rarely explored public sentiment toward divorce [6]. Divorce, as a socially and emotionally charged issue, generates diverse reactions, making it a unique case for sentiment analysis [7]. Additionally, sentiment classification on divorce-related discussions presents distinct challenges, such as the subjectivity of opinions, variations in linguistic expressions, and the influence of cultural and societal norms. These factors can significantly affect the reliability of sentiment classification models and require specialized preprocessing techniques to enhance accuracy [8]. Another key challenge in sentiment analysis is class imbalance, where the distribution of positive, negative, and neutral sentiments is often uneven. This imbalance can significantly affect model performance, resulting in biased classification outcomes. Prior studies on sentiment analysis, particularly those focused on controversial topics like divorce, have frequently overlooked this issue, leading to underrepresentation of minority sentiment classes and reduced overall accuracy. Moreover, many existing approaches rely on traditional machine learning techniques without exploring the comparative potential of ensemble methods. What remains underexplored is how ensemble-based classifiers like Random Forest can enhance the accuracy and robustness of sentiment classification in the context of emotionally charged social media discussions.

To bridge this gap, this study proposes a novel application of the Random Forest algorithm for sentiment analysis on Twitter data related to divorce. Unlike earlier works, this research emphasizes balancing the sentiment classes and incorporating advanced feature processing techniques, thereby offering a more comprehensive and effective solution. The proposed model aims to produce a more accurate, balanced, and representative public sentiment classification, which contributes methodologically and empirically to the field. This research aims to classify public sentiment toward divorce (positive, negative, or neutral) and evaluate factors affecting model performance, such as data balance and text preprocessing techniques. By addressing these challenges, **this study aims** to provide deeper insights into public opinions on divorce and enhance sentiment analysis accuracy in the social domain. To achieve these objectives, this study employs the Random Forest method with an optimized text preprocessing approach, including stemming, stopword removal, and feature selection. The model will be evaluated based on accuracy, precision, recall, and F1-score to ensure reliable sentiment classification. The results of this study will not only **contribute** to academic literature on sentiment analysis but also serve as a reference for policymakers and social practitioners in understanding public opinions on divorce in Indonesia.

2. RESEARCH METHOD

A flowchart is used to illustrate the occurrence of a process, making it easier to understand the ongoing process [9]. This research can be categorized as an implementative study because it implements the Random Forest algorithm to analyze public sentiment toward the issue of divorce in Indonesia. The methodological steps taken to achieve the objectives of this study are depicted in the flowchart as shown in *Figure 1* [10]. This research begins with a literature study to identify the problems to be solved using technology. This is followed by a needs analysis during the research process and data collection based on the chosen topic. Data preprocessing is first conducted in the model development stage, followed by creating a classification model using a machine learning algorithm. At the end of the research, testing will be carried out on the model's results based on a designed scenario.

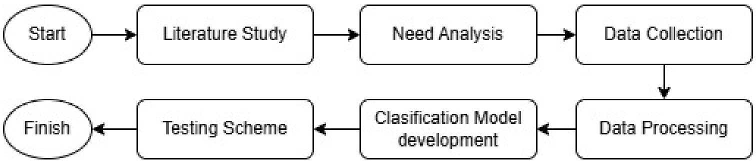

Figure 1. Research step

2.1. Literature Study

The literature study is conducted by collecting relevant sources of information based on the selected topic. The reference sources used as the foundation for this research include books, theses, research papers, journals, scientific works, dissertations, and internet sources. The references used are related to sentiment analysis, the application of the Random Forest algorithm, and other topics that support the objectives of this research.

2.2. Needs Analysis

The needs analysis stage includes data requirements analysis and software & hardware requirements to ensure the research runs as expected. The data required for this study consists of tweets from the social media platform Twitter related to the issue of divorce in Indonesia. The data collection period is limited from November 29, 2024, to December 13, 2024. This research requires both software and hardware to support the study's success. A high-performance laptop with 16 GB of RAM and an 8-core CPU is used. The software utilized includes a web browser for running programs, Jupyter Notebook, and the Python programming language.

2.3. Data Collection

The data collection stage aims to obtain as much raw data as possible while considering the keywords used and the time frame limitations. This stage includes an explanation of data sources and the initial design of the data structure. This research utilizes secondary data obtained from Twitter through the Twitter API, collecting all tweets related to public opinions on the issue of divorce in Indonesia. The collected tweets are filtered to be in the Indonesian language and contain the keyword "divorce" ("perceraian"). The tweets are collected from January 29, 2024, to December 13, 2024.

2.4. Data Processing

The collected Twitter dataset related to divorce issues is processed using Python 3.11 (64-bit). Before classification using machine learning algorithms, preprocessing is conducted to remove potential issues that may interfere with the classification process. Next, automatic labeling is performed to determine whether the sentiment of each tweet is positive, neutral, or negative. The process continues with dataset visualization and calculations using the feature extraction method. The research data preprocessing steps are shown in *Figure 2*.

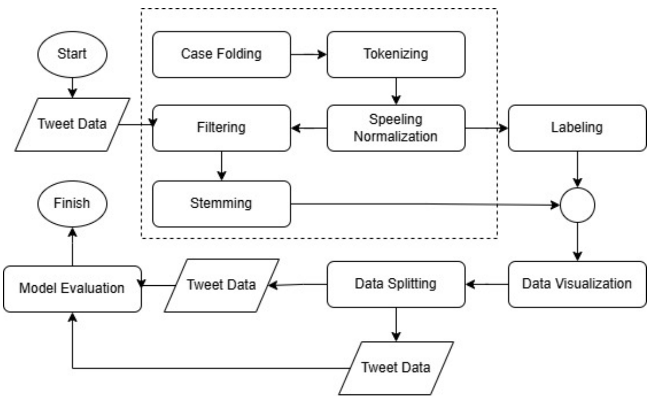

Figure 2. Flowchart of Data Processing Method

Using tweet data obtained through crawling and scraping on the Twitter social media platform via the open-access Twitter API (Application Programming Interface) based on the selected topic [11]. Data preprocessing includes case folding, which converts all uppercase letters in the document into lowercase and removes punctuation, links, numbers, and special characters [12]. Tokenizing is performed to break sentences into word groups known as tokens. Spelling normalization is applied to convert non-standard words in tweets into standard words [13]. Filtering or stopword removal eliminates unimportant words (stoplist) while retaining meaningful words (wordlist). Stemming is conducted to convert affixed words into their root forms [14]. Each tweet is labeled as positive, negative, or neutral using the Python package transformers with a fine-tuned model [15]. Tweet data visualization, including graphs and word clouds, uses Python's matplotlib, seaborn, and wordcloud packages. The tweet dataset is then split into training and testing data with a certain ratio, which will be used as input for the classification model. Finally, model evaluation is performed to assess how well the model predicts sentiment in the divorce-related dataset [16].

2.5. Classification Model Development

After preprocessing and labeling the dataset, classification is performed using the Random Forest machine learning algorithm to evaluate model performance. The best model is then selected to classify new tweet data. The classification process begins by utilizing feature-extracted tweet data, consisting of training and testing datasets loaded from a pickle-formatted data file. A Random Forest classification model is then developed by determining the number of trees for each classification model. The dataset sample for each tree is created from the total training data using bootstrapping or random sampling. The number of randomly selected features or attributes as splitting points is then defined among the total available features. The classification calculation is performed for each tree by first selecting the root node with the smallest splitting value in the training data. The calculation is repeated to form internal nodes until the node contains a homogeneous class or no additional attributes with splitting criteria exist. This process is applied to each tree, resulting in different internal splitting nodes and tree depths. Majority voting is used on classification results from all trees to obtain the final classification output as a predicted class. This process is called debugging.

2.6. Model Evaluation Development

Model evaluation is conducted using a confusion matrix to measure the performance of the classification model on the test dataset. The confusion matrix consists of four main components: True Positive (TP), which indicates the number of cases correctly predicted as positive; True Negative (TN), for cases correctly predicted as negative; False Positive (FP), for negative cases incorrectly predicted as positive; and False Negative (FN), for positive cases incorrectly predicted as negative. Based on this matrix, several key evaluation metrics are calculated. Precision is used to measure how accurately the model predicts positive cases, with the formula Precision = TP / (TP + FP). Recall, also known as sensitivity, measures the model's ability to identify all actual positive cases, with the formula Recall = TP / (TP + FN). To obtain a more balanced performance measure, the F1-Score is used, which is the harmonic mean of precision and recall, calculated using the formula F1-Score = 2 $\times$ (Precision $\times$ Recall) / (Precision + Recall). These three metrics are used to comprehensively understand the model's effectiveness, particularly in sentiment analysis tasks where class imbalance is a common challenge.

3. RESULT AND ANALYSIS

The results and discussion cover the implementation of a sentiment analysis program using the Random Forest machine learning algorithm on Twitter social media platform data related to the issue of divorce in Indonesia.

3.1. Data Collection

This is the initial stage of the research, aimed at obtaining as much dataset as possible in the form of Twitter text tweets related to the issue of divorce in Indonesia. Data collection consists of data crawling and data scraping. The data crawling stage aims to retrieve tweet link data from each indexed page on Twitter based on keyword parameters. Data crawling utilizes a GitHub repository developed by Helmi Satria. The keywords used are entered as a combination of queries, which can include a phrase or individual words appearing in a sentence. This study uses the phrase keyword "perceraian" (divorce). The collected data consists of tweets in Indonesian within a specified time range. A total of approximately 1500 tweet link data points were obtained and stored in a CSV-formatted file. The process of crawling and saving data into a CSV file is performed using Python's Pandas library.

3.2. Preprocessing

The collected Twitter tweet data is unstructured, requiring a text mining preprocessing process to improve classification accuracy. The preprocessing steps include case folding, tokenizing, spelling normalization, filtering, and stemming. Case folding aims to standardize letter formats and remove unnecessary numbers and punctuation marks. This process consists of several steps: converting all uppercase letters to lowercase, removing spaces at the beginning and end of sentences, eliminating tabs, new lines, and backslashes, removing non-ASCII characters, mentions, and hashtags, deleting URLs, punctuation marks, and numbers, converting double spaces into single spaces, and removing single characters. Case folding results are shown in *Table 1*.

Table 1. Case folding data tweet

Original Tweet	Clean Text
kehidupan pasca perceraian https://t.co/9TJhxA1n4d	kehidupan pasca perceraian
@tanyarlfes Polisi Benarkan Ammar Zoni Dtangkap Lagi Terkait Narkoba" untung gue ngga nonton ampe abis podcast'a dia sama deddy, tadi'a gue kasian pas d cerai Irish Bella. Tp seperti'a keputusan irish tepat, atau gara2 perceraian'a maka'a ammar "make" lagi? Ah gue nonton debat capres ajalah"	polisi benarkan ammar zoni dtangkap lagi terkait narkoba untung gue ngga nonton ampe abis podcast dia sama deddy tadi gue kasian pas cerai irish bella tp seperti keputusan irish tepat atau gara perceraian maka ammar make lagi ah gue nonton debat capres ajalah
@milkywaygyal @18fesss Sekarang kl kasus si sender, dia rugi ga menurutmu? Dan kl ga ada jalan keluar (si sender sudah mengajak ngobrol tp ga ada ngaruhnya), dan berujung ke perceraian...rugi ga menurutmu?	sekarang kl kasus si sender dia rugi ga menurutmu dan kl ga ada jalan keluar si sender sudah mengajak ngobrol tp ga ada ngaruhnya dan berujung ke perceraian rugi ga menurutmu

The tokenizing process is carried out after the tweet data has been standardized through case-folding. Tokenizing aims to separate each word using spaces as delimiters. Each separated word is called a token. Tokens will serve as variables with specific values. Below is an example of the tokenizing result. Tokenizing results are shown in *Table 2*. Spelling normalization is the process of correcting misspelled or non-standard words into their proper form based on the Indonesian Dictionary (KBBI). A dataset or dictionary containing incorrect words and their corrections is required to correct word spelling. The file normalization_resource2.csv contains thousands of corrected Indonesian words, which can be found in the appendix. Each tweet sentence is then iterated to match every word with the spelling normalization dictionary. Below is the result of the normalization implementation. Spelling normalization results are shown in *Table 3*.

Table 2. Tokenizing data tweet

Clean Text	Tokenize Text
kehidupan pasca perceraian	['kehidupan', 'pasca', 'perceraian']
polisi benarkan ammar zoni dtangkap lagi terkait narkoba untung gue ngga nonton ampe abis podcast dia sama deddy tadi gue kasian pas cerai irish bella tp seperti keputusan irish tepat atau gara perceraian maka ammar make lagi ah gue nonton debat capres ajalah	['polisi', 'benarkan', 'ammar', 'zoni', 'dtangkap', 'lagi', 'terkait', 'narkoba', 'untung', 'gue', 'ngga', 'nonton', 'ampe', 'abis', 'podcast', 'dia', 'sama', 'deddy', 'tadi', 'gue', 'kasian', 'pas', 'cerai', 'irish', 'bella', 'tp', 'seperti', 'keputusan', 'irish', 'tepat', 'atau', 'gara', 'perceraian', 'maka', 'ammar', 'make', 'lagi', 'ah', 'gue', 'nonton', 'debat', 'capres', 'ajalah']
sekarang kl kasus si sender dia rugi ga menurutmu dan kl ga ada jalan keluar si sender sudah mengajak ngobrol tp ga ada ngaruhnya dan berujung ke perceraian rugi ga menurutmu	['sekarang', 'kl', 'kasus', 'si', 'sender', 'dia', 'rugi', 'ga', 'menurutmu', 'dan', 'kl', 'ga', 'ada', 'jalan', 'keluar', 'si', 'sender', 'sudah', 'mengajak', 'ngobrol', 'tp', 'ga', 'ada', 'ngaruhnya', 'dan', 'berujung', 'ke', 'perceraian', 'rugi', 'ga', 'menurutmu']

Table 3. Spelling Normalization Data Tweet

Tokenize Text	Spelling Normalization
['kehidupan', 'pasca', 'perceraian']	['kehidupan', 'pasca', 'perceraian']

Tokenize Text	Spelling Normalization
['polisi', 'benarkan', 'ammar', 'zoni', 'dtangkap', 'lagi', 'terkait', 'narkoba', 'untung', 'gue', 'ngga', 'nonton', 'ampe', 'abis', 'podcast', 'dia', 'sama', 'deddy', 'tadi', 'gue', 'kasian', 'pas', 'cerai', 'irish', 'bella', 'tp', 'seperti', 'keputusan', 'irish', 'tepat', 'atau', 'gara', 'perceraian', 'maka', 'ammar', 'make', 'lagi', 'ah', 'gue', 'nonton', 'debat', 'capres', 'ajalah']	['polisi', 'benarkan', 'ammar', 'zoni', 'ditangkap', 'lagi', 'terkait', 'narkoba', 'untung', 'gue', 'enggak', 'menonton', 'sampai', 'habis', 'podcast', 'dia', 'sama', 'deddy', 'tadi', 'gue', 'kasihan', 'pas', 'cerai', 'irish', 'bella', 'tapi', 'seperti', 'keputusan', 'irish', 'tepat', 'atau', 'gara', 'perceraian', 'maka', 'ammar', 'memakai', 'lagi', 'ah', 'gue', 'menonton', 'debat', 'capres', 'ajalah']
['sekarang', 'kl', 'kasus', 'si', 'sender', 'dia', 'rugi', 'ga', 'menurutmu', 'dan', 'kl', 'ga', 'ada', 'jalan', 'keluar', 'si', 'sender', 'sudah', 'mengajak', 'ngobrol', 'tp', 'ga', 'ada', 'ngaruhnya', 'dan', 'berujung', 'ke', 'perceraian', 'rugi', 'ga', 'menurutmu']	['sekarang', 'kalo', 'kasus', 'sih', 'sender', 'dia', 'rugi', 'enggak', 'menurutmu', 'dan', 'kalo', 'enggak', 'ada', 'jalan', 'keluar', 'sih', 'sender', 'sudah', 'mengajak', 'mengobrol', 'tapi', 'enggak', 'ada', 'ngaruhnya', 'dan', 'berujung', 'ke', 'perceraian', 'rugi', 'enggak', 'menurutmu']

Filtering is performed by retaining tokens from the spelling normalization process with meaningful significance and removing those without. This process involves eliminating stopwords such as "untuk," "juga," "perlu," "di," and others. Below is the result of the filtering implementation. The filtering data results are shown in *Table 4*. The stemming stage aims to convert words with affixes into their root forms. The affixes removed include prefixes and suffixes from a word. Below is the result of the stemming implementation. Stemming results are shown in *Table 5*.

Table 4. Filtering Data Tweet

Spelling Normalization	Filtered Text
['kehidupan', 'pasca', 'perceraian']	['kehidupan', 'pasca', 'perceraian']
['polisi', 'benarkan', 'ammar', 'zoni', 'ditangkap', 'lagi', 'terkait', 'narkoba', 'untung', 'gue', 'enggak', 'menonton', 'sampai', 'habis', 'podcast', 'dia', 'sama', 'deddy', 'tadi', 'gue', 'kasihan', 'pas', 'cerai', 'irish', 'bella', 'tapi', 'seperti', 'keputusan', 'irish', 'tepat', 'atau', 'gara', 'perceraian', 'maka', 'ammar', 'memakai', 'lagi', 'ah', 'gue', 'menonton', 'debat', 'capres', 'ajalah']	['polisi', 'benarkan', 'ammar', 'zoni', 'dtangkap', 'terkait', 'narkoba', 'untung', 'gue', 'menonton', 'habis', 'podcast', 'deddy', 'gue', 'kasihan', 'pas', 'cerai', 'irish', 'bella', 'keputusan', 'irish', 'gara', 'perceraian', 'ammar', 'memakai', 'ah', 'gue', 'menonton', 'debat', 'capres', 'ajalah']
['sekarang', 'kalo', 'kasus', 'sih', 'sender', 'dia', 'rugi', 'enggak', 'menurutmu', 'dan', 'kalo', 'enggak', 'ada', 'jalan', 'keluar', 'sih', 'sender', 'sudah', 'mengajak', 'mengobrol', 'tapi', 'enggak', 'ada', 'ngaruhnya', 'dan', 'berujung', 'ke', 'perceraian', 'rugi', 'enggak', 'menurutmu']	['kalo', 'sih', 'sender', 'rugi', 'menurutmu', 'kalo', 'jalan', 'sih', 'sender', 'mengajak', 'mengobrol', 'ngaruhnya', 'berujung', 'perceraian', 'rugi', 'menurutmu']

Table 5. Stemming data from tweet

Filtered Text	Stemmed Text
['kehidupan', 'pasca', 'perceraian']	['hidup', 'pasca', 'cerai']
['polisi', 'benarkan', 'ammar', 'zoni', 'dtangkap', 'terkait', 'narkoba', 'untung', 'gue', 'menonton', 'habis', 'podcast', 'deddy', 'gue', 'kasihan', 'pas', 'cerai', 'irish', 'bella', 'keputusan', 'irish', 'gara', 'perceraian', 'ammar', 'memakai', 'ah', 'gue', 'menonton', 'debat', 'capres', 'ajalah']	['polisi', 'benar', 'ammar', 'zoni', 'dtangkap', 'kait', 'narkoba', 'untung', 'gue', 'tonton', 'habis', 'podcast', 'deddy', 'gue', 'kasihan', 'pas', 'cerai', 'irish', 'bella', 'putus', 'irish', 'gara', 'cerai', 'ammar', 'pakai', 'ah', 'gue', 'tonton', 'debat', 'capres', 'aja']
['kalo', 'sih', 'sender', 'rugi', 'menurutmu', 'kalo', 'jalan', 'sih', 'sender', 'mengajak', 'mengobrol', 'ngaruhnya', 'berujung', 'perceraian', 'rugi', 'menurutmu']	['kalo', 'sih', 'sender', 'rugi', 'turut', 'kalo', 'jalan', 'sih', 'sender', 'ajak', 'obrol', 'ngaruhnya', 'ujung', 'cerai', 'rugi', 'turut']

Labeling is performed on the data after spelling normalization and before the filtering process to retain the context of the sentences. The labeling process for 1,500 data entries is not conducted manually but utilizes a fine-tuned model from a pretrained model. The labeling results in three classes: positive, negative, and neutral. Below is the result of the dataset labeling. The labeling results are shown in *Table 6*.

Table 6. Labeling data tweet

Normalize Text	Sentiment
[’kehidupan’, ’pasca’, ’perceraian’]	Positive
[’polisi’, ’benarkan’, ’ammar’, ’zoni’, ’ditangkap’, ’lagi’, ’terkait’, ’narkoba’, ’untung’, ’gue’, ’enggak’, ’menonton’, ’sampai’, ’habis’, ’podcast’, ’dia’, ’sama’, ’deddy’, ’tadi’, ’gue’, ’kasihan’, ’pas’, ’cerai’, ’irish’, ’bella’, ’tapi’, ’seperti’, ’keputusan’, ’irish’, ’tepat’, ’atau’, ’gara’, ’perceraian’, ’maka’, ’ammar’, ’memakai’, ’lagi’, ’ah’, ’gue’, ’menonton’, ’debat’, ’capres’, ’ajalah’]	negative
[’sekarang’, ’kalo’, ’kasus’, ’sih’, ’sender’, ’dia’, ’rugi’, ’enggak’, ’menurutmu’, ’dan’, ’kalo’, ’enggak’, ’ada’, ’jalan’, ’keluar’, ’sih’, ’sender’, ’sudah’, ’mengajak’, ’mengobrol’, ’tapi’, ’enggak’, ’ada’, ’ngaruhnya’, ’dan’, ’berujung’, ’ke’, ’perceraian’, ’rugi’, ’enggak’, ’menurutmu’]	negative

3.3. Dataset Visualization

The dataset can also be used to group frequently occurring words, illustrated through word cloud visualization. Visualizing word occurrences helps facilitate the analysis of features or words that may influence classification results. *Figure 3* below displays the word cloud visualization of the dataset.

Figure 3. Word Cloud of Data Frequency

3.4. Data Splitting

Before proceeding with the classification model development using machine learning algorithms, the dataset is first split into training and testing data based on a predetermined ratio. The data splitting process is performed using a library that provides a data splitting function, namely the sklearn library. The largest portion of the split is used for model training, while the remaining portion is used for testing. The author uses a 70:30 ratio in this study, with 70% allocated for training data and 30% for testing data.

3.5. Feature Extraction

After the dataset has undergone preprocessing and splitting into training and testing data, the next step is assigning weights to each word to generate word features. This process is known as word embedding or can also be referred to as feature extraction. The method used for feature extraction is the Document-Term Matrix, implemented using the CountVectorizer() function from the sklearn library. The extracted feature values represent discrete numerical values indicating the frequency of word occurrences in each data row or tweet sentence. These values serve as input for the classification model, which will categorize sentiment into positive, negative, or neutral. The classification of sentiments is determined based on the obtained weights or the significance of each variable.

3.6. Data Classification

After undergoing preprocessing, data splitting, and word embedding, the dataset proceeds to the data classification stage. The data used for classification is divided into two categories: training data and testing data. This study evaluates the classification model's accuracy based on variations in data splitting ratios as part of the testing scenario. For instance, if a 70:30 ratio is used, then 70% of the data is used for training, consisting of 1,059 tweets, while the remaining 30% is used for testing, consisting of 454 tweets.

3.7. Model Evaluation

At this stage, the Random Forest algorithm's accuracy is evaluated, with an 80% accuracy for training data and 70% accuracy for testing data. To further assess the model's ability to classify data, the author utilizes a confusion matrix to evaluate model performance. The following confusion matrix represents the results obtained.

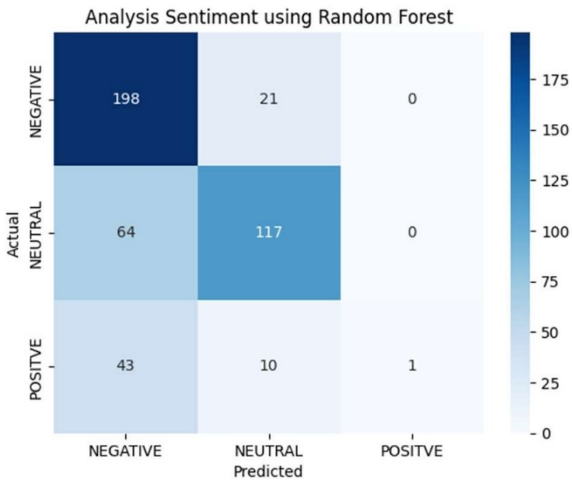

Figure 4. Confusion Matrix of the Random Forest Model

Figure 4 shows that the model successfully predicts data in the negative class and performs fairly well in predicting data in the neutral class. However, it struggles with data in the positive class. For positive-class data, the model tends to misclassify them as negative, as evidenced by a total of 43 misclassified instances. From the confusion matrix, as shown in Figure 4, we can extract several key metrics, including precision, recall, and F1-score, as shown in *Table 7*.

Table 7. Confusion Matrix of Random Forest

Class	Precision	Recall	F1 Score
Negative	0.65	0.90	0.76
Neutral	0.80	0.66	0.73
Positive	1.00	0.22	0.04

The findings of this study are that the performance of the Random Forest method in classifying three sentiment classes (Negative, Neutral, and Positive) shows varying results for each class, based on the Precision, Recall, and F1 Score metrics, as shown in *Table 7*. Explicitly: The Negative class has high Recall (0.90) and moderate Precision (0.65), resulting in an F1 Score of 0.76, indicating that the model is quite good at detecting the Negative class. However, there are still errors in false-positive predictions. The Neutral class shows the second highest Precision (0.80) but a lower Recall (0.66), with an F1 Score of 0.73, indicating that the model is quite reliable in recognizing Neutral data. Still, some neutral data fails to be recognized. The Positive class shows perfect Precision (1.00), but very low Recall (0.22), resulting in a very low F1 Score (0.04). This indicates that although every prediction for the Positive class is correct (no false positive errors), the model rarely predicts the Positive class, so many Positive class data points are undetected. The Random Forest model tends to exclude the Positive class, which may be due to data imbalance or lack of feature representation that distinguishes the Positive class [17]. Therefore, improving the model or handling class imbalance is necessary to improve classification performance, especially in the Positive class.

Table 7 shows that the model performs reasonably well in predicting the negative and neutral classes, with F1-scores of 0.76 and 0.73, respectively. However, the performance on the positive class is significantly low, with an F1-score of only 0.04. This indicates that the model has difficulty identifying and correctly classifying positive sentiments. Further analysis reveals that the class distribution plays a major role in the model's prediction ability. The negative class contains 743 instances, the neutral class 578 instances, and the positive class only 192 instances. This class imbalance is the main factor contributing to the poor performance in predicting positive sentiments. To provide a broader context, the results of this study are compared with previous research that also applied sentiment analysis on Twitter data using machine learning approaches, as shown in *Table 8*.

Table 8. Comparison with Previous Studies

Research	Method	Positive Precision	Positive Recall	Positive F1-Score
This Research	Random Forest	1.00	0.22	0.04
[18]	SVM	0.78	0.65	0.71
[19]	Naïve Bayes	0.79	0.69	0.74

The comparison *Table 8* shows that the positive class F1-score in this study is significantly lower than in the previous studies. This suggests that although Random Forest may perform well in certain scenarios, class imbalance can severely hinder its effectiveness, especially in detecting minority sentiment classes. **Earlier studies support these findings** [18, 20, 21], which highlighted that imbalanced class distributions often cause models to underperform in identifying minority classes. Therefore, future work should consider implementing data balancing techniques, such as oversampling, undersampling, or SMOTE, to improve the model's performance in underrepresented classes.

4. CONCLUSION

Based on the Twitter user sentiment analysis research regarding divorce issues in Indonesia, this study concludes that the Random Forest algorithm can be effectively applied for sentiment classification. Using a dataset of 1,500 entries, the model achieved an accuracy of 70%. One of the key findings is that the model performs well in classifying negative and neutral sentiments but struggles significantly with positive sentiments. This performance discrepancy is largely due to class imbalance, where the positive class was underrepresented compared to the negative and neutral classes.

These findings align with the research objective of evaluating the effectiveness of the Random Forest algorithm in handling real-world, imbalanced sentiment data related to sensitive social issues like divorce. The study also highlights the importance of addressing class imbalance to enhance model performance. For future research, it is recommended to apply data balancing techniques such as SMOTE, oversampling, or ensemble methods to improve the detection of minority sentiment classes. Additionally, comparing the performance of Random Forest with other machine learning or deep learning models could offer deeper insights into the most suitable methods for sentiment analysis in similar contexts. Further exploration into topic modeling and temporal sentiment trends may also enrich the understanding of public discourse on divorce over time.

ACKNOWLEDGEMENTS

The author expresses gratitude to all parties who have supported and contributed to completing this research. In particular, appreciation is extended to Universitas Bumigora for the academic support and facilities provided throughout the research process. The author also sincerely thanks both parents for their financial support, which has greatly contributed to the smooth progress of this research. Additionally, appreciation is given to colleagues and respondents who participated in data collection, enabling the successful completion of this study. It is hoped that the findings of this research will be beneficial for the advancement of knowledge, especially in sentiment analysis using the Random Forest algorithm.

REFERENCES

[1] Q. Ainiyah and I. Muslih, "Dilema Hukum Keluarga di Indonesia (Studi Analisis Kasus Perceraian di Indonesia)," *Jurnal Istiqro*, vol. 6, no. 1, pp. 73–81, Jul. 2020. DOI: 10.30739/istiqro.v6i1.560.

[2] R. Puspita and A. Widodo, "Analisis Sentimen terhadap Layanan Indihome di Twitter dengan Metode Machine Learning," *Jurnal Informatika Universitas Pamulang*, vol. 6, no. 4, pp. 759–766, 2021. DOI: 10.32493/informatika.v6i4.13247.

[3] S. M. Fani, R. Santoso, and S. Suparti, "Penerapan Text Mining untuk Melakukan Clustering Data Tweet Akun Blibli pada Media Sosial Twitter Menggunakan K-Means Clustering," *Jurnal Gaussian*, vol. 10, no. 4, pp. 583–593, Dec. 2021. DOI: 10.14710/j.gauss.v10i4.30409.

[4] M. R. Santoso and P. Musa, "Rekomendasi Kesehatan Janin dengan Penerapan Algoritma C5.0 Menggunakan Classifying Cardiotocography Dataset," *Jurnal Simantec*, vol. 9, no. 2, pp. 65–76, Jun. 2021. DOI: 10.21107/simantec.v9i2.10730.

[5] A. N. Nurkalyisah, A. Triayudi, and I. D. Sholihati, "Analisis Sentimen pada Twitter Berbahasa Indonesia Terhadap Penurunan Performa Layanan Indihome dan Telkomsel," *Jurnal Sistem dan Teknologi Informasi (JustIN)*, vol. 10, no. 4, pp. 387–394, Dec. 2022. DOI: 10.26418/justin.v10i4.50858.

[6] A. R. Dewi *et al.*, "Sentimen Analisis terhadap Puan Maharani sebagai Kandidat Calon Presiden 2024 Berdasarkan Opini Twitter Menggunakan Metode Naive Bayes dan Adaboost," *JSiI (Jurnal Sistem Informasi)*, vol. 10, no. 1, pp. 75–80, Mar. 2023. DOI: 10.30656/jsii.v10i1.5785.

[7] K. E. Linadi, "Pelatihan Pembelajaran Interaktif untuk Pelaksana Kelas Persiapan Pernikahan di Kecamatan Sambi Boyolali," *Indonesian Journal of Community Dedication in Health (IJCDH)*, vol. 3, no. 2, pp. 54–60, Aug. 2023. DOI: 10.30587/ijcdh.v3i02.4956.

[8] U. Indahyanti, N. L. Azizah, and H. Setiawan, "Pendekatan Ensemble Learning untuk Meningkatkan Akurasi Prediksi Kinerja Akademik Mahasiswa," *Jurnal Sains dan Informatika*, vol. 8, no. 2, pp. 160–169, Dec. 2022. DOI: 10.34128/jsi.v8i2.459.

[9] Y. Tambing, "Prototype Sistem Kontrol Lampu Berbasis Internet of Things (IoT) Menggunakan Nodemcu," *Jurnal Informatika dan Teknik Elektro Terapan*, vol. 12, no. 1, pp. 266–274, Jan. 2024. DOI: 10.23960/jitet.v12i1.3702.

[10] G. Tamboto, Q. C. Kainde, and V. P. Rantung, "Aplikasi Reservasi Layanan Rumah Sakit Berbasis Android Menggunakan Metode Spiral," *Jurnal Indonesia Sosial Teknologi*, vol. 4, no. 5, pp. 556–569, May 2023. DOI: 10.59141/jist.v4i5.616.

[11] Y. Mz *et al.*, "Analisis Sentimen Terhadap Layanan Tokopedia Berdasarkan Twitter dengan Metode Klasifikasi Support Vector Machine," *Smart Comp: Jurnalnya Orang Pintar Komputer*, vol. 12, no. 1, Jan. 2023. DOI: 10.30591/smartcomp.v12i1.4591.

[12] D. S. Prasetyo, K. Auliasari, and M. R. P. Syalabi, "Klasifikasi Serangan Jaringan Menggunakan Metode K-Nearest Neighbour pada Data Riwayat Jaringan," *Prosiding SENIATI*, vol. 7, no. 1, pp. 63–71, Dec. 2023. DOI: 10.36040/seniati.v7i1.7874.

[13] R. Kosasih and A. Alberto, "Sentiment analysis of game product on shopee using the TF-IDF method and naive bayes classifier," *ILKOM Jurnal Ilmiah*, vol. 13, no. 2, pp. 101–109, Aug. 2021. DOI: 10.33096/ilkom.v13i2.721.101-109.

[14] X. Shi *et al.*, "Experiment Study of Stemming Length and Stemming Material Impact on Rock Fragmentation and Dynamic Strain," *Sustainability*, vol. 15, no. 17, pp. 1–20, Aug. 2023. DOI: 10.3390/su151713024.

[15] Rianto *et al.*, "Improving the accuracy of text classification using stemming method, a case of non-formal Indonesian conversation," *Journal of Big Data*, vol. 8, no. 1, pp. 1–16, Dec. 2021. DOI: 10.1186/s40537-021-00413-1.

[16] Pratibha *et al.*, "Multimodal Hinglish Tweet Dataset for Deep Pragmatic Analysis," *Data*, vol. 9, no. 2, p. 38, Feb. 2024. DOI: 10.3390/data9020038.

[17] C. M. Lauw *et al.*, "Combination of Smote and Random Forest Methods for Lung Cancer Classification," *International Journal of Engineering and Computer Science Applications (IJECSA)*, vol. 2, no. 2, pp. 59–64, Sep. 2023. DOI: 10.30812/ijecsa.v2i2.3333.

[18] A. Ahmad and W. Gata, "Sentimen Analisis Masyarakat Indonesia di Twitter Terkait Metaverse dengan Algoritma Support Vector Machine," *Jurnal JTIK (Jurnal Teknologi Informasi dan Komunikasi)*, vol. 6, no. 4, pp. 548–555, Mar. 2022. DOI: 10.35870/jtik.v6i4.569.

[19] O. P. Zusrotun, A. C. Murti, and R. Fiati, "Analisis Sentimen Terhadap Belajar Online pada Media Sosial Twitter Menggunakan Algoritma Naive Bayes," *Jurnal Nasional Pendidikan Teknik Informatika (JANAPATI)*, vol. 11, no. 3, pp. 310–319, Dec. 2022. DOI: 10.23887/janapati.v11i3.49160.

[20] I. N. Switrayana *et al.*, "Sentiment Analysis and Topic Modeling of Kitabisa Applications using Support Vector Machine (SVM) and Smote-Tomek Links Methods," *International Journal of Engineering and Computer Science Applications (IJECSA)*, vol. 2, no. 2, pp. 81–91, Sep. 2023. DOI: 10.30812/ijecsa.v2i2.3406.

[21] H. Hairani *et al.*, "Thesis Topic Modeling Study: Latent Dirichlet Allocation (LDA) and Machine Learning Approach," *International Journal of Engineering and Computer Science Applications (IJECSA)*, vol. 3, no. 2, pp. 51–60, Sep. 2024. DOI: 10.30812/ijecsa.v3i2.4375.