Aspect-based Sentiment Analysis and Topic Modelling of International Media on Indonesia Tourism Sector Recovery

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ABSTRACT

The international world's perception of a country is essential. In 2022, Indonesia attracted international media attention, which can form the nation's image of Indonesia in the international public perception. Therefore, this study analyses international media, online news, and social media Twitter perceptions towards Indonesia. For the news, aspect-based sentiment analysis is carried out, and for Twitter opinion, sentiment classification using multiple classification algorithms, and topic modeling related to these sentiments are carried out. Furthermore, this research classifies news sentiment based on aspects of forming the country's image, such as tourism, exports, diplomacy, government policies, and people's behavior. It was obtained that aspects of people, policy, and tourism, besides being classified as "none" class, mostly classified in negative sentiment. While diplomacy and export are mostly positive sentiment. One limitation of this classifier is the insufficient number of cases in the training data, which led to relatively low accuracy and precision in this study. On Twitter opinion, it was found that Twitter's positive sentiment about Indonesia is associated with tourism recovery. The topic modeling of positive tweets highlighted international interest in Indonesia's tourism. This study's findings can provide valuable insights for the government on boosting foreign tourism to support economic growth. Additionally, policymakers should focus on addressing issues that attract foreign media attention. By effectively managing these concerns, Indonesia's branding can be enhanced, potentially leading to an increase in tourist arrivals.

Keywords: International Media; Nation's Image; Sentiment Analysis; Topic Modelling; Tourism Recovery

ABSTRAK

Persepsi dunia internasional terhadap suatu negara sangat penting. Pada tahun 2022, Indonesia menarik perhatian media internasional, yang dapat membentuk citra negara Indonesia di persepsi publik internasional. Oleh karena itu, penelitian ini menganalisis persepsi media internasional, yaitu berita daring, dan media sosial Twitter terhadap Indonesia. Untuk berita, dilakukan analisis sentimen berbasis aspek, sementara untuk opini Twitter dilakukan klasifikasi sentimen menggunakan berbagai algoritma klasifikasi dan *topic modelling* terkait sentimen tersebut. Selain itu, penelitian ini mengklasifikasikan sentimen berita berdasarkan aspek yang membentuk citra negara, seperti pariwisata, ekspor, diplomasi, kebijakan pemerintah, dan perilaku masyarakat.

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Hasil penelitian didapatkan bahwa aspek masyarakat, kebijakan, dan pariwisata, selain diklasifikasikan sebagai kelas "none", sebagian besar diklasifikasikan dalam sentimen negatif. Sementara itu, diplomasi dan ekspor sebagian besar berada diklasifikasikan sebagai sentimen positif. Salah satu keterbatasan dari pengklasifikasi ini adalah jumlah kasus yang tidak cukup dalam data pelatihan, dan berpengaruh pada akurasi dan presisi yang relatif rendah dalam penelitian ini. Pada opini Twitter, ditemukan bahwa sentimen positif Twitter tentang Indonesia memiliki korelasi dengan pemulihan pariwisata. *Topic modelling* dari *tweet* positif menyoroti minat internasional terhadap pariwisata Indonesia. Temuan penelitian ini dapat memberikan referensi kepada pemerintah dalam meningkatkan pariwisata asing untuk mendukung pertumbuhan ekonomi. Selain itu, pembuat kebijakan juga harus fokus untuk menangani isu-isu yang menarik perhatian media asing secara efektif sehingga citra Indonesia dapat ditingkatkan, dan berpotensi meningkatkan jumlah kedatangan wisatawan.

Kata Kunci: Media Internasional; Citra Negara; Analisis Sentimen; Topik Modeling; Pemulihan Pariwisata.

1. Introduction

The international world's perception of a country's government is essential to constructing foreign policy and public diplomacy (Anholt, 2008; Wang, 2006a). According to Wang (2006b), a country's reputation is essential because it affects a country's ability to achieve international political goals, attracts foreign investment and tourism, and influences consumer perceptions in buying domestic products. The image of a country is indirectly formed from the following activities, some of which are tourism promotion, exported goods and services, government policy decisions, and people's behavior in that country (Anholt, 2008). In addition, according to some practitioners, diplomacy also forms the image of a country as a branding technique (Szondi, 2008). According to Wang (2006b), one way to see a country's reputation is to look at foreign public opinion about that country.

Data is an essential resource for modern society (Jacobson et al., 2018). Big data analysis is also starting to be used in various sectors. One sector that massively utilises big data analysis is the economic sector. In addition, big data analysis has also begun to be used frequently in the international relations sector and diplomatic negotiations, which are then called data diplomacy (Jacobson et al., 2018). International courts are implementing data diplomacy using digital footprints to assist international law. Some examples of implementing data diplomacy include analysing and evaluating economic diplomacy and monitoring policy implementation, such as the Sustainable Development Goals (SDGs). Data diplomacy can also be applied to understand opinions regarding public diplomacy services, such as sentiment analysis (Jacobson et al., 2018).

Economic diplomacy, based on the Ministry of Foreign Affairs' Strategic Plan (Renstra Kemlu) 2015-2019, is defined as a way to achieve economic goals by utilising international relations resources (Muhibat & Intan, 2020). Economic diplomacy has three elements: investment, exports, and tourism. One of the roles of tourism in the economic sector is as a source of foreign exchange income (Badan Pusat Statistik, 2018; Jain & Winner, 2013). Jain and Winner's (2013) research shows the importance of a country's reputation to the economy, one of which is through the tourism sector. The study states that the reputation received by a government has a significant relationship with the number of tourists.

During 2022, there were news and events in Indonesia that caught the attention of the international media. One is the incident at the beginning of October 2022, the Kanjuruhan tragedy. CNN reported several things highlighted by international media regarding the tragedy, such as the number of children who died and the public's distrust of the Indonesian National Police (Polri/Kepolisian Republik Indonesia) (CNN Indonesia, 2022). The word "Indonesia" in international media is associated with the words "dead," "stampede," and "killed," which can build a negative perception of the international public towards Indonesia.

In 2022, there will also be an essential moment for Indonesia, specifically the Group of Twenty (G20) presidency, where the leadership of the G20 is currently held by Indonesia (Kementerian Keuangan, 2022b). This moment can build a positive perception of the international public towards Indonesia. One of the benefits of the G20 presidency is the increase in foreign tourists (Kementerian Keuangan, 2022a). Observing Indonesia post-pandemic with a gradually improving economy, as evidenced by several international events held in the country, such as the G20 Summit, the author aims to conduct a study based on the research Jain & Winner (2013) to examine Indonesia's tourism recovery through the lens of international media. This international media consists of global news outlets and tweets from the international community. The study seeks to answer the question of how Indonesia's branding is perceived by international media through sentiment analysis and its correlation with tourism recovery.

2. Literature Review

Diplomacy is recognized as a key method for implementing foreign policy (Barston, 2014; Robert & Feilleux, 2009). Barston (2014) categorizes the functions of diplomacy into six distinct areas: ceremonial, management, information/communication, international negotiation, protection, and normative/legal functions. Szondi (2008) explores the relationship between diplomacy and a state's image, asserting that some practitioners view diplomacy as integral to a state's branding, serving as a strategy to shape national identity. This theoretical perspective underpins the selection of specific aspects in aspect-based sentiment analysis of online news.

Data plays a crucial role in influencing diplomatic processes and can occasionally catalyze diplomatic actions. As a tool, data aids in informing foreign policy decisions, measuring both domestic and international public sentiment, providing early warnings, managing consular affairs, mapping bilateral relations, resolving multilateral issues, and monitoring the Ministry of Foreign Affairs (MFA) network. Furthermore, it can be utilized to observe emergent crisis situations (Jacobson, Höne, & Kurbalija, 2018). From a marketing and branding perspective, national image holds significant importance. Stock (2009) outlines four primary reasons for the critical nature of a country's image: attracting tourists, adding value to domestic products, attracting foreign investment, and luring talented individuals. In this regard, the tourism sector exerts the most substantial influence on a nation's image, as Anholt (2007) said that tourism can directly contribute to shaping a country's identity through interactions between tourists and the local population. Tourists often relay their experiences to others, thereby influencing perceptions of the country. Effective tourism promotion can cultivate a positive image of the nation among the international community (Anholt, 2007).

The research by Seyfi et al. (2021) explores how cognitive destination images, shaped by media, influence behavioral intentions during times of crisis. It highlights that prospective tourists' perceptions of a destination and the knowledge gained from media regarding crisis management, healthcare systems, solidarity, and destination marketing are key components of the cognitive destination image. These factors, in turn, impact future travel intentions, particularly in the post-pandemic era. Similarly, Park (2015) the study emphasizes the influence of different media types on tourist behavioral intentions. Notably, electronic media has a strong effect on interpersonal influence, often in the form of word-of-mouth, which is the most significant source of information when consumers make purchasing decisions, and consumers' willingness to pay more. This aligns with Solomon et al. (2012) the social media life effect on consumer behavior, which posits that social media platforms allow for free interaction among users, enabling them to share content such as reviews, ratings, photos, and stories. The culture fostered on these platforms can significantly affect an individual's decision to purchase or consume a product or, in this context, choose to travel to a specific destination.

Previously, Jain & Winner (2013) sentiment analysis was explored regarding the relationship between US public opinion about other foreign countries and their relationship with the economy of these countries. Public opinion was taken from 30 countries' press releases and news articles, and public opinion was taken from Anholt's Nation Brand Index (NBI) data in 2009. The study shows that the reputation received by a country has a significant relationship with many tourists. In addition, Jain and Winner (2013) also show that a country's media coverage is related to people's decisions to travel and invest in a country, where positive media coverage has a positive relationship with the number of tourists.

Sentiment analysis on Twitter has emerged as one of the most extensively researched areas (Giachanou & Crestani, 2016). In their study, Neethu & Rajasree (2013) conducted sentiment analysis at the sentence level on Twitter data. Among the three machine learning algorithms, all demonstrated comparable performance in identifying the sentiment of Twitter data, although Naïve Bayes exhibited superior precision. Leelawat et al. (2022) focused on sentiment analysis of Twitter posts regarding the COVID-19 pandemic in Thailand. In their study, three algorithms—Support Vector Machine (SVM), Random Forest, and Decision Tree—were tested, with SVM emerging as the most effective model for sentiment analysis. While sentiment analysis has been widely explored, ongoing research continues to examine this field. Bahri & Suadaa (2023) conducted aspect-based sentiment analysis on 30 Indonesian tourism reviews sourced from the Google Maps platform. The findings indicated that the optimal method for sentiment analysis was transfer learning utilizing the pre-trained IndoBERT model, which is the Indonesian variant of the pre-trained BERT model.

Raj P. M. & Sai D. (2021) explored sentiment analysis, opinion mining, and topic modeling using Latent Dirichlet Allocation (LDA) on storybook data. Furthermore, Xie et al. (2021) performed sentiment analysis and topic modeling on COVID-19-related data obtained from Weibo. Their topic modeling results identified themes such as prevention, stay-at-home orders, treatment, and economic impacts. The sentiment analysis revealed that posts with positive sentiment outnumbered those with negative sentiment.

Akmalia (2019) examines tourist perceptions of Indonesia's tourism destinations using sentiment analysis and topic modeling. The study concludes that topic modeling reveals that the most frequently discussed topics are scenery, services, and activities, with scenery being a prominent feature across nearly all destinations. The topics identified related to tourist attractions can serve as valuable information for evaluating these destinations, helping to identify areas of interest and concern for each location. Sentiment analysis of the data indicated a predominantly positive sentiment, or "joy," regarding Indonesia's tourism attractions. While Ganguly (2025) research further explores the impact of social media on travel and tourism-related decisions, noting that tweets with negative language amplified negative emotions, while positive tweets generated positive emotions, ultimately influencing travel-related decisions. Additionally, the study found that exposure to a diverse range of tweets related to the pandemic significantly affected the emotions of different groups of people and contributed to shifts in travel plans and preferences.

3. Method

The data sources used are the five most frequently visited international news websites in English, such as bbc.com, cnn.com, dailymail.co.uk, cnbc.com, and Reuters (Majid, 2017). Only five data sources were chosen for analysis in this study because of the lack of sufficient resources. In this case, time, availability of particular datasets, and computing power were the primary restrictions. In spite of the small scope of sources, the data obtained were considered to be enough to answer the research question without compromising on relevance and reliability. The analysis was limited to news content, and the keyword used to scrap the news was "Indonesia." The data collected are the title, date, news link, and news content. News data is collected by web scraping using Selenium and BeautifulSoup in Python. Before scraping the contents and titles, news links are retrieved with the keyword "Indonesia." After that, by accessing the links that have been retrieved, news content, title, and news date are retrieved using BeautifulSoup.

Besides news, another data source used is social media Twitter, where the tweets used are only located outside Indonesia and are in English. Tweets are collected with Snscrape and the keyword "Indonesia." After the data is collected, tweet filters are used to reduce the possibility that the tweets taken are from Indonesians. The filter process follows the research of van der Veen et al. (2015), which states the features that can be used in determining the origin country of Twitter users are timezone, user location, and user language. To avoid the opinions of Indonesians who speak English is by filtering accounts from Indonesian government accounts that always send tweets in English, such as the accounts of the Ministry of Foreign Affairs of the Republic of Indonesia (Kemlu RI), Embassy of the Republic of Indonesia (KBRI), Consulate General of the Republic of Indonesia (KJRI), Permanent Mission of the Republic of Indonesia (PTRI), and Consulate of the Republic of Indonesia (KRI).

3.1. Aspect-based Sentiment Analysis

On news data, an aspect-based analysis will be carried out. The aspects used can build the country's image, which are tourism, exports, diplomacy, government policies, and the behavior of the Indonesian people (Anholt, 2020); Szondi, 2008). Each aspect is classified into "positive," negative," and "neutral" sentiments, and also "none." "None" means that the news does not contain the five aspects that were previously mentioned.

To train the classifier, it is necessary to do labeling by human annotators. The human annotators employed are trained annotators with at least a high school education, proficiency in English, and a solid understanding of sentiment analysis. The data that has been labeled is then trained so that the classifier can classify the actual data. Three human annotators do labeling to avoid subjectivity. After that, majority voting was carried out to choose the sentiment class the annotators are most chosen. The data will be deleted if there is no agreement between the annotators. Then inter-rater reliability test was carried out.

Based on Krippendorff (2004), if Krippendorf's alpha value is more than 0.667, it can be said that the label between annotators is reliable. Apart from the Krippendorf test, another inter-rater reliability test is Fleiss Kappa. In Fleiss Kappa, the threshold used is if the kappa value is less than 0 means there is no agreement between annotators, between 0.01 and 0.2 means there is almost no agreement, then 0.21 to 0.4 means mediocre, 0. 41 to 0.6 means moderate inter-annotator agreement, then 0.61 to 0.8 substantial, and 0.81 to 1 means almost perfect inter-annotator agreement.

These are annotators' guides for classifying sentiments for each news aspect. For tourism, it discusses sentiments about tourism in Indonesia, such as Bali, Labuan Bajo, Komodo Island, etc. The second aspect discusses export products from Indonesia, such as palm oil, nickel, etc. The third aspect is Indonesia's diplomacy with other countries and the private sector. This diplomacy means communication carried out by Indonesia with other countries and other individual parties (Barston, 2014). The fourth aspect is the Indonesian government's policies, such as prohibiting sexual intercourse outside marriage for local residents and foreign tourists. The last aspect is the behavior of the Indonesian people, such as the behavior of the Indonesian people towards tourists or the criminal acts committed by the Indonesian people. An example of labelling carried out by the annotator can be seen in Figure 1.

Aspect-based sentiment analysis in the news uses the transfer learning method from the pre-trained Bidirectional Encoder Representations from Transformers (BERT) model. Based on research by Bahri & Suadaa (2023) the best model for classifying aspect-based sentiments is transfer learning from the BERT pre-trained model compared to machine learning. Therefore, the method used in the aspect-based sentiment analysis will use the BERT pre-trained model. In this research, we tried bert-base-cased and bert-base-uncased. The difference is that the bert-base-uncased model is not case-sensitive. In BERT, news data is divided into five folds, with 60% training data and 20% valid and test data. Then the model is trained with ten epochs.

Figure 1. An Example of Aspect-based Sentiment Labelling in News by Human Annotator

News				
Cars park side by side in a vacant lot in the center of Kuta, Bali, near a sign that implores passersby not to urinate there. **It was here 10 years ago that a bomb tore through the Sari Club**, for a split second silencing the crowd of revelers as they chatted, drank and danced on a typical Saturday night out. Phil Britten was there with his team mates from the Kingsley Cats, Australian rules football players on an end of season trip from Perth, on the country's west coast. In his book "Undefeated," Britten, who received burns to 60% of his body, describes the stench and burning in his throat from the bomb, before his hearing kicked in and the screams rang out. "It started really softly, a moaning or whimpering, then grew louder and louder. It was piercing. It sounded unnatural, as if it was part of a horror movie, and it was terrifying," he wrote. Britten is back in Bali this week for memorial events to mark the 10-year anniversary of the bombing. Two hundred and two people were killed; 88 Australians, 38 Indonesians, 24 Britons, seven Americans and 30 others from a number of European countries. New Zealand, Brazil, Canada and Japan also lost citizens, as did South Africa, South Korea and Ecuador. **The attack was blamed on Jemaah Islamiyah (JI), a South East Asian militant group with links to al Qaeda**. Since the attack, **Indonesia has tried and executed three perpetrators and killed other key conspirators in police raids**. The last man to stand trial over the blasts, Umar Patek, was jailed for 20 years in June for helping to assemble the bombs. The Bali bombings, he wrote, "set off a series of critical chain reactions. Indonesia developed a highly skilled and dedicated police anti-terror unit. And an international campaign was launched to restore the image of Indonesia as a peaceful tourist destination. Today, tourism in Bali has exceeded pre-attack figures."				
Aspect				
Tourism	Export	Diplomacy	Policy	People
Negative	None	None	Neutral	Negative

3.2. Sentiment Analysis with Machine Learning

Twitter data was also labelled by three human annotators, then majority voting was carried out, and the inter-rater reliability test was carried out. An example of labelling carried out by the annotator can be seen in Table 1.

Table 1. Example of Sentiment Labelling for tweets by Human Annotators

Tweet	Label
Murder and torture of Australians by Indonesia covered up by our corrupt politicians and bureaucrats	Negative
I bet she knows a few stories about war crimes cover up with Indonesia	Negative
Indonesia changes quarantine norms for certain travellers	Neutral
Naturally beautiful... Tanzania, Indonesia, named Most Beautiful Countries by UK survey	Positive

Sentiment analysis on tweets about Indonesia is carried out using a machine learning approach. Several algorithms used in sentiment analysis include Support Vector Machine (SVM), Naïve Bayes, and Logistic Regression. In machine learning, preprocessing must first be done, including tokenising, lemmatisation, removing stopwords, feature extraction, and deleting emoji, mentions, and links for tweets. Feature extraction aims to convert text data into a mathematical representation. TF-IDF usually performs better in machine learning models (Huilgol, 2020). The TF-IDF mathematical representation is information on words that are more important and less important in documents (Huilgol, 2020). If a word occurs frequently, then that word is essential. In this research, sentiment analysis with machine learning uses the TF-IDF feature extraction.

The performance of sentiment analysis using machine learning and transfer learning is measured by accuracy, precision, recall, and f1-score. The calculation of each formula is based on the components of the confusion matrix, where there is a TP (True Positive) or the number of positive data correctly classified in the positive class, TN (True Negative) or the amount of negative data that is correctly classified in the negative class, FP (False Positive)) or the number of negative data classified in the positive class, and FN (False Negative) or the number of positive data classified in the negative class. Then there is also a total of all data whose actual class is positive P and negative N. The formula for each score is as follows:

$$Accuracy = \frac{TP+TN}{P+N} \quad (1)$$

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

$$Recall = \frac{TP}{TP+FP} \quad (3)$$

$$F1 - Score = 2 \times \frac{precision \times recall}{precision + recall} \quad (4)$$

3.3. Methods to Overcome Imbalance

If the data train is imbalanced, it is necessary to do some treatment. Several ways to deal with imbalanced data are by resampling. There are two resampling that are oversampling, or adding data to train data that has a minority class, and undersampling, or reducing data in train data that has a majority class (Nanni, Fantozzi, & Lazzarini, 2015). This research used random oversampling and random undersampling. Nanni et al. (2015) said the random oversampling algorithm picks random data classified into minority classes and duplicates it until the amount of data matches the amount of majority class data. In contrast, random undersampling is randomly choosing data in the majority class and then erasing it until the amount of data matches the minority class. Oversampling can make the classifier overfitted when the classifier works well in the training data but poorly in the test data (Liu, 2004; Zheng, Cai, & Li, 2015). Undersampling affects the loss of information in the training data. The classifier may lose an important feature of classifying data (Hasanin & Khoshgoftaar, 2018; Liu, 2004).

Another way is to give weight to the small amount of data. This study also includes other algorithms with class_weight methods to provide weights, namely Random Forest, Decision Tree, and Stochastic Gradient Descent (SGD). There is a parameter in the class_weight method called "balanced," which will give more weight to classes with small data and less weight to the majority class. The purpose is to tell the classifier which class is more important (see Scikit Learn Developers).

In the BERT classifier, resampling cannot be carried out because there will be a meaning mismatch in the resampling results. This can be a problem because the BERT classifier uses transformers to contextualize the relationship between words (Sabharwal & Agrawal, 2021). Therefore, one way to overcome imbalanced data is to perform data augmentation. Data augmentation can be done by duplicating random data by swapping or inserting synonyms into the duplicated text data classified in the minority class, so that the number of the minority class's data will increase (Li, Hou, & Che, 2022).

3.4. Topic Modelling

Topic Modeling performs topic grouping from a series of topics contained in a document (Yi & Allan, 2009). Topic modeling can be used to describe the content of a document. Topic modeling is done for tweets that identify negative and positive sentiments. Topic modelling will identify topics for tweets from those sentiments, so that topics related to negative and positive sentiments can be identified. Latent Dirichlet Allocation (LDA) is often used in topic modeling. In implementing LDA, it is necessary to identify the number of topics to be assigned to the dataset, or it will create a number of topics that are too large and cannot be interpreted (Syed & Spruit, 2017). The number of topics is determined using the coherence score matrix (Nair, 2012). The coherence score measures words' similarity on each topic using semantic values (Syed & Spruit, 2017).

3.5. Spearman Correlation

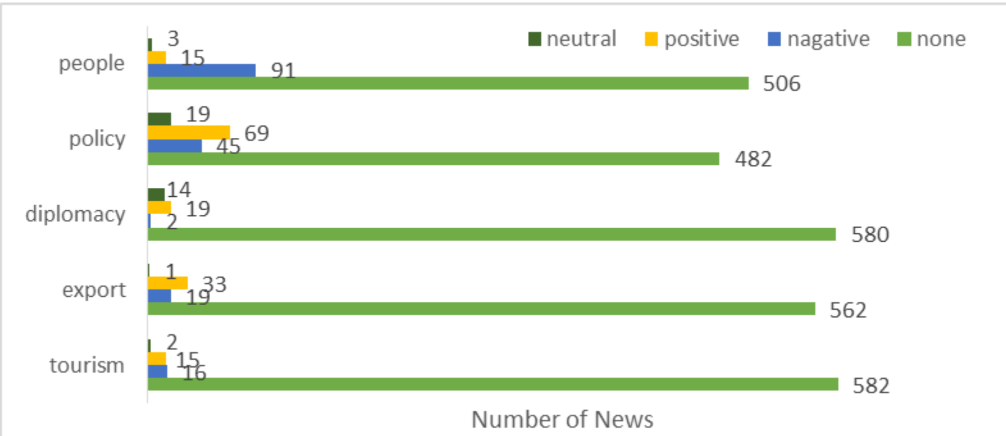
The Spearman correlation test is carried out to analyze the relationship between sentiment and tourism. The data is the proportion of tweet data about Indonesia with positive sentiments and the total number of foreign tourists monthly. The null hypothesis is that there is no correlation between tweets with positive sentiments and the number of foreign tourists. α used is 0.05. The scores from the Spearman correlation are in the range of -1 to +1. Prion & Haerling (2014) use a rule of thumb to determine the threshold of the Spearman correlation score, that is 0 to ± 0.20 means there is no relationship between data, ±0.21 to ±0.4 means the relationship between data is weak, ±0.41 to ±0.6 means the relationship between the data is moderate if score from ±0.61 to ± 0.8, the correlation is strong. From ± 0.81 to ±1, the relationship between the data is powerful.

4. Results

4.1. Aspect-based Sentiment Analysis About Indonesia on Online News

After news data collection, deletion of news data that did not contain news content, and deletion of news that was not published during the 2018-2022 period, the BBC obtained 98 news, CNBC obtained 206 news, CNN obtained 1,007 news, Dailymail obtained 21,077 news, and Reuters obtained as many as 2,756 news. Because the BBC only has 98 data points, all BBC news data is labelled by human annotators. Meanwhile, the news from other sources is taken as a sample for labelling.

Figure 2. Bar Chart of the Amount of News for Aspect-based Sentiment Analysis Data Train



Source: Authors primary data, 2024

After fine-tuning or adjusting the case classification on the data train to the pre-trained BERT model classifiers, namely, bert-base-cased and bert-base-uncased, the accuracy, f1-score, recall, and precision results are shown in Table 2. Both models have high accuracy but low F1-score values. This is due to an imbalanced dataset. Accuracy only focuses on data that is classified correctly but ignores misclassified data. For imbalanced data, looking at model performance based solely on accuracy is not recommended. The reason for the high accuracy in this dataset is that the model can only correctly classify data into the majority class, that is, the "none" class. In contrast to accuracy, the F1-score calculates misclassified data in the minority class. Table 2 shows a low F1-score. This indicates that the model has poor performance in classifying the minority class.

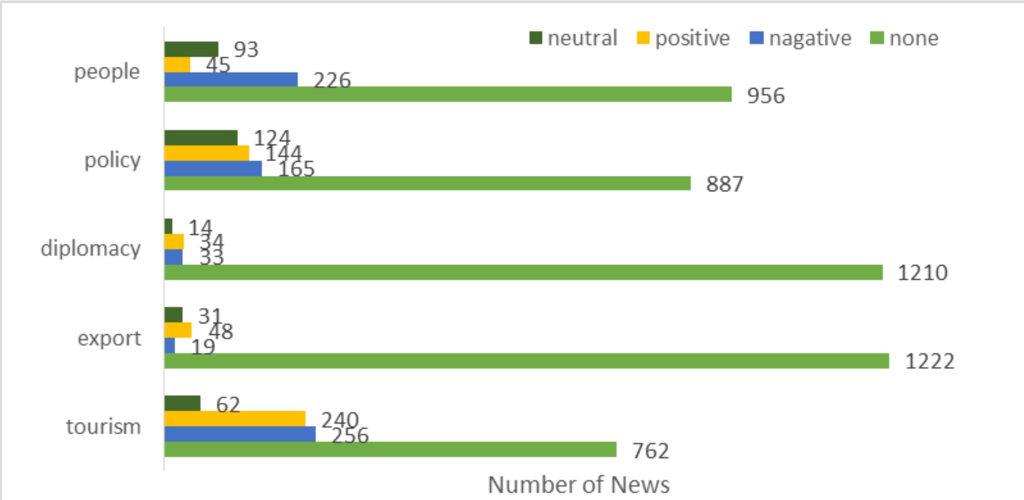
Table 2. Classifier Performance on Aspect-based Sentiment Analysis on Online News

Model	Accuracy	F1-score	Recall	Precision
bert-base-cased	0.898	0.408	0.400	0.508
bert-base-uncased	0.890	0.402	0.376	0.514

Source: Authors primary data, 2024

To overcome the low F1-score on imbalanced data in BERT classifiers, data augmentation is carried out using the "insert" method. The results of data augmentation can be seen in Figure 3. In this figure, it can be seen that some labels have increased in number compared to Figure 2. Figure 3 demonstrates that the majority of the news articles analyzed are classified as "none," indicating the absence of sentiment in each aspect of the news. However, it is evident that the aspects of people, policy, and tourism, in addition to being classified as "none," are predominantly categorized under negative sentiment. In contrast, the aspects of diplomacy and export tend to lean towards positive sentiment, although in the diplomacy aspect, there is no significant difference between the number of positive and negative sentiments. Additionally, Figure 3 reveals that the diplomacy and export aspects are the least likely to be classified as neutral, positive, or negative compared to the other aspects. This suggests the possibility of bias in the classifier, which may struggle to categorize these aspects into clear sentiment categories.

Figure 3. Bar Chart of the Amount of News for Aspect-based Sentiment Analysis Train Data After Data Augmentation



Source: Authors primary data, 2024

On the augmented data, fine-tuning is carried out, and the model performance is obtained, as shown in Table 3. The table shows that the model's performance has increased compared to before the augmentation, especially the F1-score value on the bert-base-cased model. The bert-base-cased model, after the augmentation, also performs better than the bert-base-uncased model. So, the model that will be used to classify news is bert-base-cased.

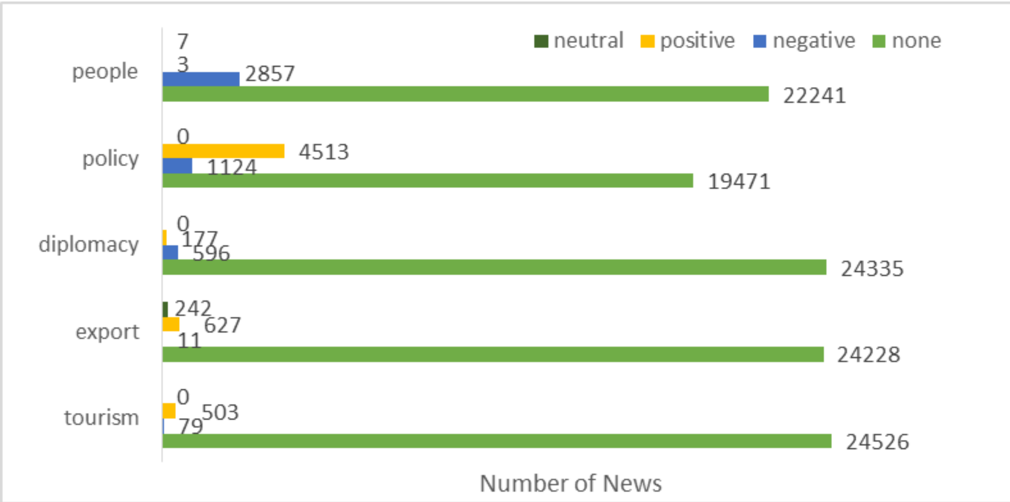
Table 3. Classifier Performance on Aspect-based Sentiment Analysis on Online News After Data Augmentation

Model	Accuracy	F1-score	Recall	Precision
bert-base-cased	0.894	0.474	0.451	0.574
bert-base-uncased	0.893	0.456	0.437	0.532

Source: Authors primary data, 2024

The prediction results can be seen in Figure 4. The figure shows that the majority of the data is classified into the "none" class in every aspect. This is because the "none" class is still the majority class even though the data has been augmented. However, it can be seen in Figure 4 that the model can classify each aspect into a class other than "none," even though only a few news articles are classified into positive, negative, and neutral sentiments. This is also due to the small train dataset. Besides, the proportion of predicted sentiment classes in each aspect matches the proportion in Figure 4.

Figure 4. Graph of The Amount of Classification Result Data of Aspect-based Sentiment Analysis on News



Source: Authors primary data, 2024

Figures 5 and 6 compare classification results between the classifier, bert-base-cased, and human annotators in aspect-based sentiment analysis. Figure 5 is news about the COVID-19 vaccination policy. Both human annotators and the classifier have the same results, where the policy aspect has positive sentiments. Figure 5 shows that Indonesia is facing the COVID-19 pandemic "relatively well" compared to other countries. Figure 5 shows that Indonesia is facing the COVID-19 pandemic "relatively well" compared to other countries. This shows that the Indonesian government's policies during the COVID-19 pandemic have been able to maintain the economy despite having considerable geographical challenges.

Figure 5. The Comparison of News Aspect-based Sentiment Classification Results by Classifier and Annotater

News				
Indonesia will take at least a year before a sufficient portion of its population becomes immune to Covid-19, the country's Finance Minister Sri Mulyani Indrawati told CNBC and stressed the need for the government to keep spending to support the economy. Indonesia launched its Covid-19 vaccination program earlier this month after approving for emergency use the vaccine developed by China's Sinovac Biotech. Sri Mulyani said conservative estimates by experts showed Indonesia needs about 15 months to vaccinate around 180 million people in order to reach "herd immunity" That occurs when enough people in a population develop protection against a disease such that it can no longer spread easily. But President Joko Widodo wants to "accelerate" that process to achieve herd immunity within 12 months — which is a "daunting task" given the country's geographic spread, said Sri Mulyani. Indonesia is the world's largest archipelago nation, with its roughly 250 million population spreading across thousands of islands. Sri Mulyani said Indonesia will prioritize spending on vaccines, as well as continued support for low-income households and small businesses. She added that the government has targeted a budget deficit of 5.7% of gross domestic product this year, lower than last year's shortfall of 6.1% of GDP. The Indonesian finance minister said her country has weathered the economic hit from the pandemic "relatively well" compared to many countries in the region and among the G-20 group of economies. The economy is expected to contract around 2.2% "at the deepest" in 2020, before rebounding to a growth of around 5% this year, she added.				
Prediction Results of Aspect-Based Sentiment Classification with bert-base-cased				
Tourism	Export	Diplomacy	Policy	People
None	None	None	Positive	None
Aspect-Based Sentiment Classification by Annotater				
Tourism	Export	Diplomacy	Policy	People
None	None	None	Positive	None

Source: Authors primary data, 2024

Figure 6 is online news regarding species discovery in Indonesia with labels from the predicted models and labels from the labelling results by annotators. The figure shows that the model and the annotator classify these aspects into the same class: "none." In Figure 5, it can also be seen that there are no aspects of positive, negative, or neutral sentiment in the news.

Figure 6. The Comparison of News Aspect-based Sentiment Classification Results by Classifier and Annotator

News				
Fourteen new species of shrew have been discovered on the Indonesian island of Sulawesi, a new study reveals. The creatures, found following a decade-long survey on Sulawesi, are confirmed as new species based on physical characteristics and DNA sequences. It marks the largest number of new mammals described in a scientific paper for 90 years, since 1931, according to researchers. Shrews are a diverse group of mammals " 461 species have been identified so far" and they have a nearly global distribution. These small insectivorous animals are closer relatives to hedgehogs and moles than to any other mammals Crocidura pallida (pictured) is one of the 14 new shrew species discovered by a team led by Jake Esselstyn at Louisiana State University The discovery was made by group of scientists led by Louisiana State University mammologist Jake Esselstyn.'It's an exciting discovery, but was frustrating at times,' said Esselstyn, curator of mammals at the LSU Museum of Natural Science and associate professor in the Department of Biological Sciences. 'Usually, we discover one new species at a time, and there is a big thrill that comes from it. Fourteen new species of shrew have been discovered on the Indonesian island of Sulawesi, the eleventh-largest island on Earth Crocidura pallida, one of the new species Mount Bawakaraeng in south Sulawesi, Indonesia. It's the third-highest peak on the Indonesian island The researchers say: 'The species-level diversity of Crocidura on Sulawesi is nearly three times the known diversity of any other insular shrew fauna'. After catching several specimens for further study, the team said the Somali elephant shrew survives after fears it had gone extinct. The insect-eating creature is neither an elephant nor a shrew, although it's more closely related to the former. Also known as a sengi, it's a distant relation to aardvarks and manatees as well as elephants, despite being the size of a mouse. Since being lost to science, just 39 preserved specimens held in the world's natural history museums was the only physical evidence that it ever existed.The Global Wildlife Conservation group even included it on its '25 most wanted lost species' list. Read more:Â Elusive elephant shrew spotted in Africa.				
Prediction Results of Aspect-Based Sentiment Classification with bert-base-cased				
Tourism	Export	Diplomacy	Policy	People
None	None	None	None	None
Aspect-Based Sentiment Classification by Annotater				
Tourism	Export	Diplomacy	Policy	People
None	None	None	None	None

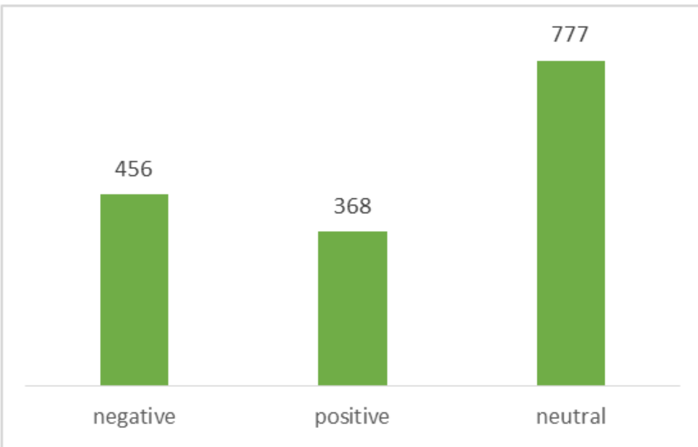
Source: Authors primary data, 2024

4.2. Sentiment Analysis About Indonesia on Tweets

The results after scraping tweets from 2018 to December 2022 are 7,588,632 tweets. After removing duplicates, tweets that are not in English, user locations that are not from Indonesia, and tweets from Indonesian Embassy accounts and Indonesian government representative offices abroad, the total Twitter data is 5,486,229 tweets.

Furthermore, the inter-rater reliability test was conducted on the Twitter data label between three annotators. It got 0.453 for Krippendorff's alpha, which means that the label results from the three annotators are unreliable. Then we tried to do another inter-rater reliability test with Fleiss kappa, and we got a kappa of 0.452, which means that the agreement between the annotators was moderate. Figure 7 shows the number of tweets after majority voting between three annotators. It shows that neutral sentiment is almost twice the amount of positive sentiment, which means there is an imbalanced dataset to train the classifier.

Figure 7. Bar Chart of the Number of Tweets for Sentiment Analysis Train Data



Source: Authors primary data, 2024

To train the dataset, we have to do feature selection to reduce the data dimension and make the classifier know which words should be prioritized for each sentiment. After that, we try three machine learning algorithms: Logistic Regression, SVM, and Naïve Bayes Multinomial. Table 6 shows sentiment classification results on tweets from those three machine learning models. In the table, the performance of each algorithm is still relatively low. This is because the training data is imbalanced, and there is little data to train.

Table 6. Classifier Performance on Sentiment Analysis on Tweets

Model	Accuracy	F1-score	Recall	Precision
Logistic Regression	0.55	0.36	0.42	0.49
SVM	0.54	0.35	0.41	0.48
MultinomialNB*	0.56	0.38	0.43	0.46

*MultinomialNB: Naïve Bayes Multinomial

Source: Authors primary data, 2024

Several ways can be used to handle imbalanced data, one of which is resampling. On Twitter data, oversampling (ros) and undersampling (rus) are tried, and the performance is obtained as in Table 7. The table shows that the best model is logistic regression, which has been done with oversampling, and SVM, which has been done with undersampling.

Table 7. Classifier Performance on Sentiment Analysis on Tweets After Resampling

Model	Accuracy		F1-Score		Recall		Precision	
	Ros	Rus	Ros	Rus	Ros	Rus	Ros	Rus
Logistic Regression	0.62	0.62	0.54	0.53	0.53	0.53	0.60	0.61
SVM	0.40	0.62	0.40	0.54	0.50	0.53	0.58	0.61
MultinomialNB	0.62	0.33	0.52	0.28	0.51	0.38	0.65	0.47

Note: Ros means Random Over Sampling
Rus means Random Under Sampling.

Source: Authors primary data, 2024

Another method to handle imbalanced data is assigning weights. Therefore, training on machine learning models with a method for using weights, namely the class_weight method, was also carried out. These are Logistic Regression, SVM, Random Forest, Decision Tree, and Stochastic Gradient Descent (SGD). The results are shown in Table 8. The table shows each model's performance before and after assigning weight. The table shows that the resampling and assigning weight methods perform almost the same. However, the Random Forest method that has given weight produces higher precision than other methods, so the model to be used is Random Forest with weight.

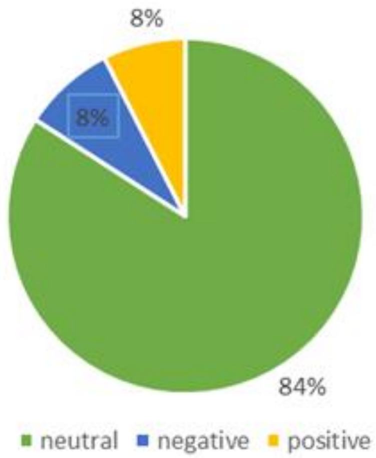
Table 8. Classifier Performance on Sentiment Analysis on Tweets Before and After Assigning Weight

Model	Accuracy		F1-Score		Recall		Precision	
	Before	After	Before	After	Before	After	Before	After
Logistic Regression	0.55	0.62	0.36	0.54	0.42	0.53	0.49	0.61
SVM	0.54	0.60	0.35	0.52	0.41	0.52	0.48	0.59
Decision Tree	0.55	0.61	0.45	0.54	0.46	0.53	0.59	0.62
Random Forest	0.61	0.62	0.53	0.54	0.53	0.53	0.62	0.63
SGDClassifier	0.54	0.62	0.45	0.54	0.45	0.53	0.57	0.61

Source: Authors primary data, 2024

In the results of Twitter sentiment prediction, the number of predicted classes is obtained in Figure 8, where most data is classified into neutral sentiment, from 5,486,229 tweets, 84% classified as neutral sentiment. It is due to most of the train data being classified as neutral sentiment.

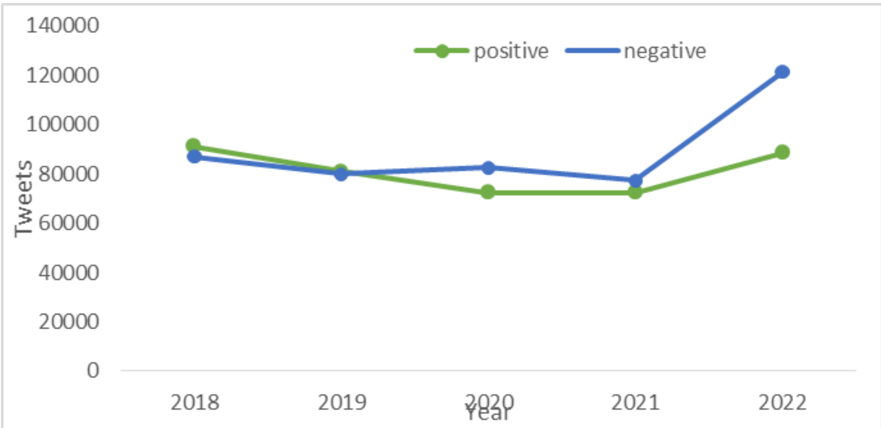
Figure 8. Pie Chart of Number of Tweets from Sentiment Analysis Result



Source: Authors primary data, 2024

Figure 9 shows the frequency of tweets for positive and negative sentiments per year. The figure shows that tweets with negative sentiments have a higher frequency increase than positive sentiments from 2021 to 2022.

Figure 9. Number of Positive and Negative Tweets Yearly from 2018 to 2022



Source: Authors primary data, 2024

The classification results also obtained words related to positive and negative sentiments, which can be seen in Figure 10 and Figure 11 In positive sentiments, it can be seen in Figure 10 that some of the top words related to positive sentiments about Indonesia include “Bali,” “thank,” “Lombok,” and “travel.”

Figure 10. Top 10 Words About Positive Sentiment

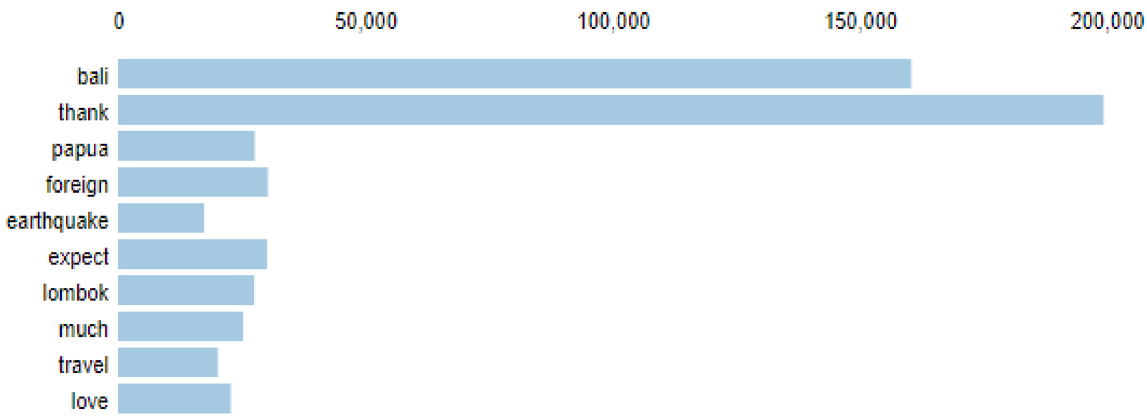


Figure 11 shows the ten most prominent negative words about Indonesia. Those are "people," "refugee," "flood," "Papua," and "kill."

Figure 11. Top 10 Words About Negative Sentiment

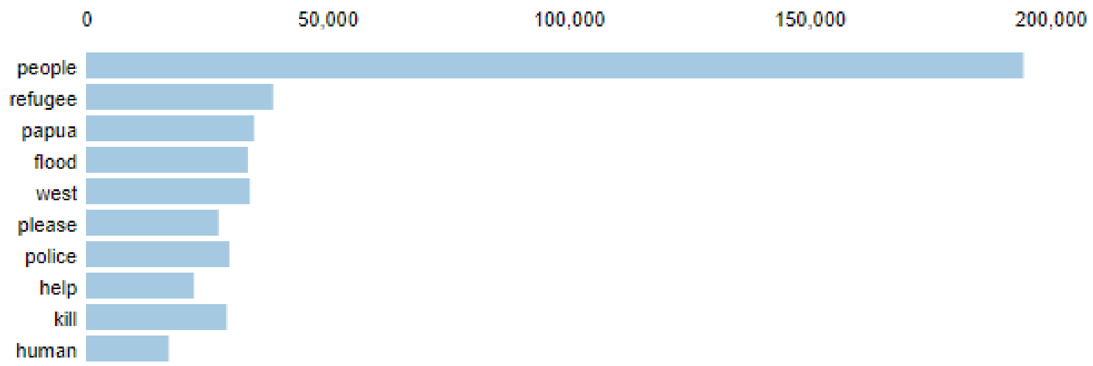


Table 9 compares the tweets' sentiment prediction results with the classifier and the labelling results by human annotators. The table shows some tweets match sentiment between classifiers and human annotators.

Table 9. Sentiment Analysis's Comparison of Classifiers and Human Annotators

Tweet	Classifier	Annotator
Tokopedia is the $7B E-commerce marketplace startup you've never heard of from Indonesia, built by a factory worker's son	Neutral	Neutral
You know you're doing a great job when the client you are consulting for offers you the COO role of the organization. Blessed to explore the opportunities that beautiful #Indonesia has to offer!	Neutral	Positive
Aiding and abetting a foreign military Indonesia who commits war crimes in West Papua New guinea and covers it up is a crime against humanity and Commonwealth law UN charter	Negative	Negative
Nearly 100 refugee children at a learning centre in Indonesia were given playing cards illustrated with people in a boat on heavy seas and stamped with the Australian government coat of arms, staff claim [FREE TO READ] #auspol	Negative	Positive
But if I'm using Indonesia's Paypal, does it work ? Because it must be using Indonesia's currency and Youtube will know it that I'm not from United States, what do you think? Thank you	Positive	Neutral
We are committed to increasing our trade and investment ties, and we are working towards a comprehensive economic partnership between Indonesia and Australia.	Positive	Positive

Source: Authors primary data, 2024

There are some areas for improvement in building a classifier to discover sentiments about Indonesia in English tweets. Although the classifier can classify sentiment, it is not necessarily the classification result that the user wants. This is due to the small number of training datasets. Especially on Twitter, about five million tweets from 2018-2022 about Indonesia, but the training dataset used is only about 1000. This significant difference is undoubtedly a shortcoming in this research. It is feared that the small train dataset cannot capture all the important features useful for classifying sentiment in tweets.

4.3. Topic Modelling on Tweets Sentiment About Indonesia

In determining the number of topics, the coherence score is calculated to select the topics with high sentence similarity in each topic. From the number of topics 2 to 10, the highest coherence score in positive sentiment is 0.47 with six topics and 0.48 with five topics in negative sentiment. After topic modelling, the word representing the topic is obtained to interpret topics in negative and positive sentiment.

Table 10 shows words representing each topic for tweets in each tweet with positive sentiment about Indonesia. Topic-1 in positive sentiment is related to the relationship between Indonesia and other countries. Topic 2 is related to Indonesian government policies related to COVID and investment. Topic 3 is related to Indonesian society. Then, topic 4 is related to the military in Indonesia. Topic 5 relates to Indonesian tourism, and Topic 6 relates to tourists' impressions while visiting Indonesia.

Table 10. Topics and Words that Represent Each Topic on Positive Tweets About Indonesia

Topic	Words that represent the topic
1	Week, new, world, last, Australia, special, south, Philippine, bring
2	Foreign, expect, covid, minister, year, meet, million, policy, high, investment
3	Thank, one, help, need, people, make, support take, Indonesian, please
4	Papua, earthquake, Lombok, military, south, new_guinea, region, time, aid, kill
5	Bali, travel, Lombok, island, day, place, go, visit, tourist, trip
6	Thank, much, love, come, happy, always, make, please, hope, good

Source: Authors primary data, 2024

Table 11 shows words that represent five topics in negative tweets about Indonesia. Topic 1 relates to the request to stop crimes against black people in Indonesia. Topic 2 relates to the human rights of refugees in Indonesia. Topic 3 relates to war crimes committed by police in Indonesia. Topic 4 relates to war and trade. Topic 5 is about natural disasters in Indonesia.

Table 11. Topics and Words that Represent Each Topic on Negative Tweets About Indonesia

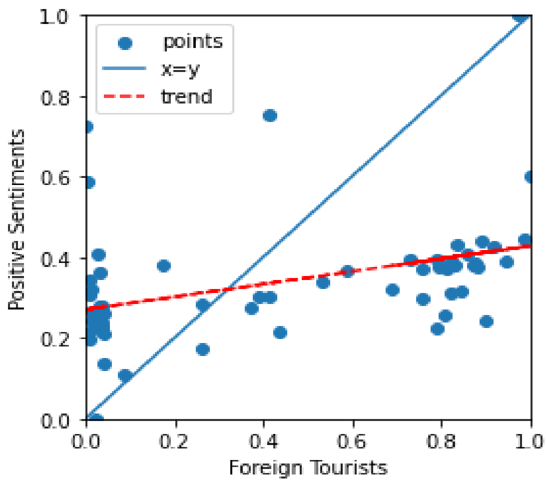
Topic	Words that represent the topic
1	People, stop, black, make, go, good, one, new, cover, Australian
2	Refugee, please, help, human, right, year, life, need, forget, safe
3	People, west, police, war, cover, Australian, fire, Australian, Indonesia, crime
4	People, war, stop, world, Australia, million, Iran, year, trade, go.
5	People, flood, kill, least, earthquake, Jakarta, dead, tsunami, die, island.

Source: Authors primary data, 2024

4.4. Correlation Between Positive Tweets About Indonesia and the Tourism Sector

Spearman correlation is used to see the relationship between foreign tourists and tweets about Indonesia with positive sentiments. The small number of classification results for positive sentiments in online news is a consideration for not testing the correlation between positive news about Indonesia and the tourism sector, because it is feared that there is not enough information to conduct the correlation.

Figure 12. Scatter plot of Standardized Number of Foreign Tourists and Proportion of Positive Tweets



Source: Authors primary data, 2024

The Spearman correlation for positive tweets and foreign tourists is 0.468, and the p-value is 0.00016. These results show that the p-value is less than α, which is 0.05, so it can be concluded that there is sufficient evidence that positive tweets about Indonesia are associated with the tourism sector. Based on the rules of thumb regarding the Spearman correlation threshold, the correlation between the number of foreign tourists and the number of tweets about Indonesia with positive sentiments has a moderate correlation (Prion & Haerling, 2014).

Figure 12 is a scatter plot of the number of tourists with the proportion of positive tweets with a linear line x=y (45 degrees), where x represents the standardised number of foreign tourists, and y is the proportion of tweets with standardised positive sentiment. If positive sentiment and foreign tourists have a positive relationship, the scatter plot will follow the 45-degree line. Figure 12 shows that the trend line of the scatter plot tends to follow the 45-degree line and indicates a positive relationship between positive sentiment tweets and foreign tourists. That means an increase in positive perceptions of Indonesia is positively correlated with a rise in the number of foreign tourists. This is in accordance with Jain & Winner (2013) the fact that the reputation received by a country has a significant relationship to the number of tourists.

5. Discussion

In the findings of this study, a classifier was developed to predict sentiment categorization from news and tweets concerning Indonesia. This achievement is the result of a comprehensive process that includes the creation of training data, the training of the classifier, and the assessment of the classifier's accuracy and precision based on its training outcomes. The accuracy and precision of the classifier improve as more data is incorporated into the training process. One limitation of this classifier is the insufficient number of cases in the training data, which led to relatively low accuracy and precision in this study. Therefore, it is anticipated that future research will address this limitation by expanding the training dataset to enhance the classifier's performance. Additionally, despite relying on five international news sources due to resource constraints, we hope that future research will also explore a broader range of international news sources.

Additionally, this study revealed a positive correlation between tweets about Indonesia, which were categorized as positive, and the number of foreign tourists visiting the country. This finding supports the research by Jain & Winner's (2013), which demonstrated that a country's perception is linked to the number of tourists visiting it. Hence, it can be concluded that there exists a positive relationship between foreigners' perceptions of Indonesia and the number of foreign tourists visiting the country, with the influx of tourists being a contributing factor to the nation's economic growth. An increase in positive perceptions of Indonesia is positively correlated with a rise in the number of foreign tourists.

6. Conclusions

In this research, the best model was obtained to classify Twitter sentiment, namely Random Forest, and obtained a percentage of sentiment on Twitter, most of which had neutral sentiments. On the news, an analysis is carried out based on aspects that shape Indonesia's image, namely tourism, exports, diplomacy, government policies, and public behavior, with BERT. In each aspect, the majority has a sentiment of "none" because the "none" class is the majority class in the training data, but the model can classify news into other classes besides "none." However, we can see that aspects of people, policy, and tourism, besides being classified as "none" class, are mostly classified as negative sentiment. While diplomacy and export mostly have positive sentiment, in the diplomacy aspect, there is no significant difference in the number of positive and negative sentiments.

On both positive and negative sentiments on Twitter, topic modelling has been done to get topics related to the sentiment. In positive sentiment, there are six topics, namely Indonesian government policies related to COVID and investment, topics about Indonesian people, the military in Indonesia, Indonesian tourism, and tourist impressions while visiting Indonesia. In the negative sentiment, five topics were obtained, namely the topic of requests to stop crimes against black people in Indonesia, the human rights of refugees in Indonesia, war crimes committed by the police in Indonesia, topics regarding war and trade, and topics regarding natural disasters in Indonesia. A Spearman correlation was conducted between foreign tourists and tweets about Indonesia with positive sentiments. It can be concluded that there is a moderate and positive relationship between foreign tourists and positive sentiment tweets.

The results of this study can serve as a reference for the government on how to increase the number of foreign tourists to support the country's economic growth, such as by promoting tourist destinations, particularly those that attract foreign visitors. This is also supported by the research findings, where aspect-based sentiment analysis identified tourism as one of the key areas of media focus, and topic modeling of tweets highlighted international interest in Indonesia's tourism. Additionally, several issues were identified that generate negative sentiment towards Indonesia, such as racism, human rights violations concerning refugees, and other related issues. These findings should draw the attention of policymakers to address issues that attract foreign media attention and work towards resolving them. By doing so, Indonesia's branding can be better managed, which could correlate with increasing the number of tourists visiting the country.

7. Funding

This research received no external funding.

8. Conflicts of Interest

The author(s) declare no conflict of interest.

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