CHAPTER II
LITERATURE REVIEW

2.1. Theoretical Framework

2.1.1. National Defense Concept: Information Warfare

According to (Kovacich & Jones, 2006) Information warfare, as defined by the US Defense Information Systems Agency (DISA), is a series of actions undertaken to achieve information superiority in support of national military strategy by influencing an opponent's information and information systems, while exploiting and protecting our own information and information systems. system. The goal is to establish dominance in the acquisition, use, and protection of information. In an effort to achieve information superiority, a series of actions are carried out to influence the information and information systems owned by the opposing party. Actions in information warfare can include a variety of things, such as the conduct of cyber operations to hack or disrupt an opponent's information systems, the dissemination of propaganda to influence an opponent's public opinion, or even intelligence gathering involving the acquisition of classified data from a country. against. All of this is done with the aim that the parties involved in the information war can dominate the information arena which can have a major impact on national military strategy..

The media has an important role in information warfare which is carried out either directly or indirectly to manipulate, eliminate, disrupt or even destroy information and information systems belonging to opposing parties (Lesmana et al., 2018). Information warfare can occur either in peace situations, crises, or even in the context of war involving various aspects, such as social, economic, industrial, or military electronic information systems. Media is a very important tool in disseminating information and influencing public opinion. Various media such as newspapers, television, radio and the internet are used as a forum for disseminating messages that support information warfare objectives. In today's digital era, social media plays an important role in information warfare. Social media platforms allow information and messages to spread quickly, creating new challenges in managing correct and accurate information.

Republic of Indonesia Law Number 3 of 2002 concerning National Defense states that national defense aims to maintain and protect the sovereignty of the country, the territorial integrity of the Unitary State of the Republic of Indonesia (NKRI) and the safety of the entire nation from all forms of threats, both military and non-military threats (Republik Indonesia, 2002). Non-military threats, especially in cyberspace, have become the main focus in modern state defense in the form of information warfare. Information war has a serious impact on national security with the rapid spread of information which can create instability in society.

In facing the threat of information warfare, effective and fast early detection efforts are needed by state intelligence so that it does not further develop and disrupt the stability of national security (Prananda et al., 2021). Intelligence has an important responsibility in collecting, analyzing, and interpreting information related to cyber threats. In the current era of information technology, the role of state intelligence is not only limited to the physical world but must also expand into the cyber world. State intelligence must be able to adapt to technological developments in collecting and analyzing all intelligence data. According to (Kejaksaan Republik Indonesia, 2021) Intelligence data is a record of a collection of facts or descriptions in the form of numbers, characters, symbols, pictures, maps, signs, signals, writing, sounds and/or sounds that represent the actual situation or show ideas, objects, conditions or situations of activities or operations Intelligence that can be used as material to produce Intelligence Information.

Meanwhile, Intelligence Information is the result of processing intelligence data through a data management system and intelligence information in the form of intelligence reports as input for leaders/users in the context of both preventive and repressive law enforcement. Therefore, it is necessary to use appropriate and up-to-date technology in collecting intelligence data to detect it quickly so that information war does not develop further and disrupt the stability of national security.

The popularity of social media has become one of the places for state intelligence to collect data related to information currently circulating in the public. On social media, people are free to express their opinions through comments. This can be used by certain parties to carry out propaganda or mobilize opinions for certain purposes. According to (Wadjdi & Sianturi, 2018) Public opinion can influence people's views about a particular policy or issue and can even disrupt national security stability. (Wadjdi & Sianturi, 2018) explains that forming opinions or framing with positive attributes has a tendency to get a positive response from the public. Public views reported can be influenced based on the framing of the information disseminated to create public opinion. The presence of state intelligence needs to adapt to changes in the threat environment in the formation of public opinion which can become a potential information war that can disrupt national security stability.

The formation of public opinion that develops on social media can be seen through the sentiment generated. Positive sentiment can be interpreted as a supportive community response to developing issues and information. Meanwhile, negative sentiment can be interpreted as a public response that rejects these issues and information. Information warfare carries out propaganda through the formation or framing of opinions on social media. Assessment of public opinion formed in the media in the information war can be done using Sentiment Analysis. So Intelligence needs to have a mechanism for assessing trends in public opinion or sentiment analysis of opinions formed on certain issues or information. The use of the latest technology such as Artificial Intelligence (AI) can help make it easier and faster to assess sentiment on social media.

2.1.2. Sentiment Analysis

Sentiment Analysis is Natural Language Processing (NLP) which identifies and extracts subjective information in text then classifies it into positive and negative. For example, in the sentence "The food was delicious, but the service was too slow," the expected sentiment polarity of the 'food' aspect is positive, while that of the 'service' aspect is negative. Data for this analysis can be extracted from various sources such as websites, newspapers or social media. Sentiment analysis can be used to monitor public opinion on important issues. Sentiment analysis can be used to evaluate the effectiveness of information messages, measure the level of support or opposition to certain policies, and even predict trends or changes in public perception. For example, in a political context, sentiment analysis can provide insight into how well a leader or political party is received by society, which can influence election outcomes.

Sentiment Analysis classifies text based on sentiment or opinion, not based on topic. Topic-based analysis is carried out to identify the main subject or topic being discussed in the text. For example, if a text discusses technology, topic-based analysis will attempt to identify key words or concepts related to technology. Meanwhile, in Sentiment Analysis, the focus is on understanding and classifying feelings or opinions contained in text, whether text that has positive, negative or neutral feelings towards a particular subject or topic. For example, in a product review, Sentiment Analysis will try to determine whether the review expresses satisfaction (positive sentiment), dissatisfaction (negative sentiment), or no strong feelings (neutral sentiment) towards the product..

According to (Sharma et al., 2020) Sentiment analysis methods can be divided into three main categories: machine learning-based, lexicon-based, and hybrid methods. In machine learning-based methods, the sentiment analysis process uses datasets that have been labeled according to their polarity (for example: positive and negative). From this dataset, the model will extract features that are useful for classifying the polarity of sentences in each data. This machine learning-based method itself is divided into two main categories, namely Unsupervised Learning and Supervised Learning according to the following chart:

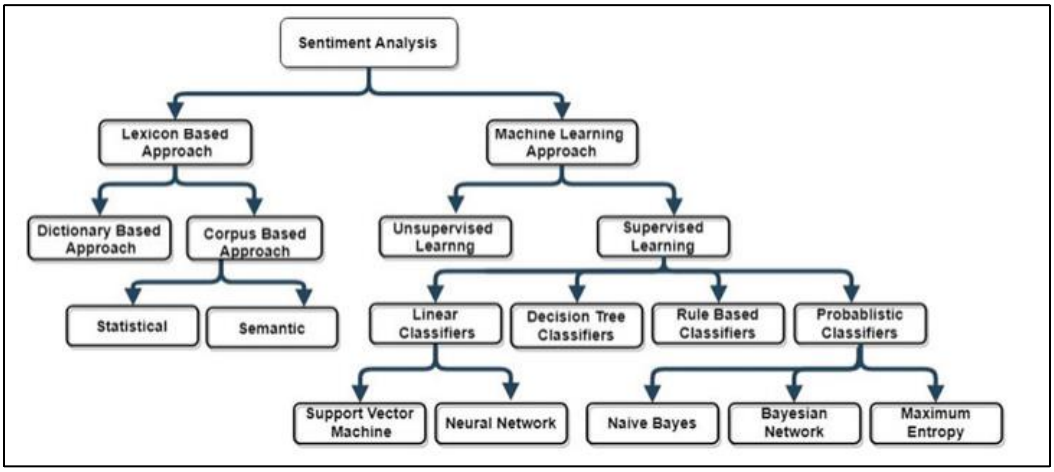


Chart 1. Sentiment Analysis Method

Supervised Learning uses a data set that already has labels to train a model. Meanwhile, Unsupervised Learning does not require labels on the dataset because it groups data into groups that have similarities based on patterns contained in the data itself.

Bidirectional Long Short Term Memory (Bi-LSTM) has the ability to identify dependencies in two directions at once. So BiLSTM can understand the relationship between words in a text not only from left to right (for example understanding words after a certain word), but also from right to left (for example understanding words before a certain word). This makes BiLSTM very useful in tasks such as text comprehension and language translation. In addition, BiLSTM is a model that provides better results than other methods in language processing and related tasks (Wankhade et al., 2022).

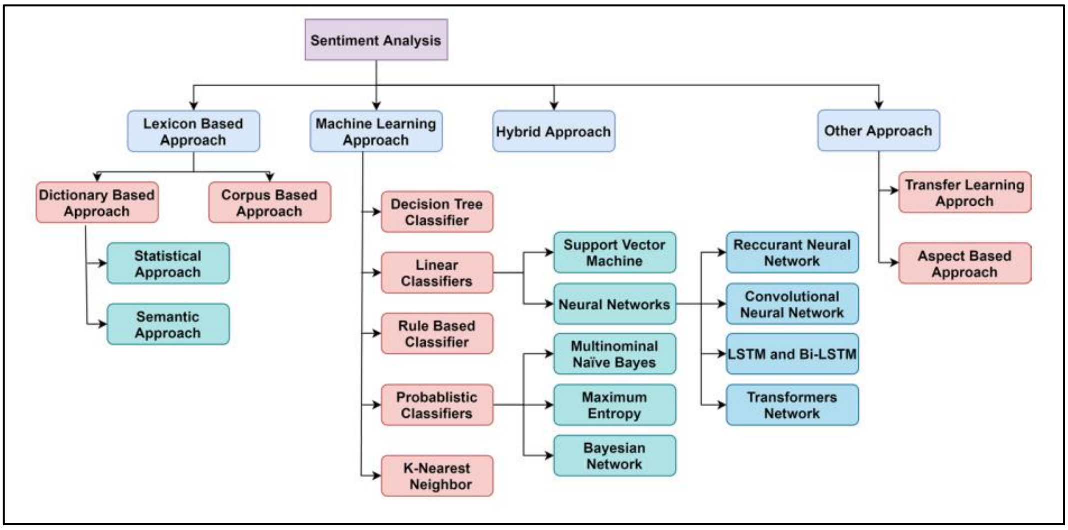


Chart 2. Bi-LSTM on Sentiment Analysis

Sentiment Analysis includes the use of information retrieval techniques, Natural Language Processing (NLP), data collection, and information mining. The stages in Sentiment Analysis are as follows:

1. Data collection

Data collection is an important factor in Sentiment Analysis modeling because the quality and amount of data collected will affect the accuracy and relevance of the analysis results. The more representative and varied the data collected, the better the understanding obtained regarding the sentiments and opinions contained in the text. The data collected should reflect the true diversity of opinions and feelings within the population being represented. The better this representation, the more accurate the resulting sentiment analysis results will be. By collecting varied data, sentiment analysis can more precisely identify and classify positive, negative, or neutral sentiment in text. In sentiment analysis, it is important to minimize biases that may appear in the data collected. This can happen if the data only comes from one particular source or group. By collecting diverse data, sentiment analysis becomes more objective and free from unwanted bias.

Collecting varied data also allows sentiment analysis to better understand the nuances of feelings and opinions expressed in text. Data that is relevant to the context or purpose of the analysis will produce more relevant understanding. For example, if the goal of the analysis is to understand consumer opinions about a particular product, collecting product reviews from multiple sources will provide more relevant results than simply collecting random text.

2. Data Preprocessing

Data preprocessing is carried out on datasets as preparation before further processing in data processing procedures in training machine learning models and AI models. Data preprocessing converts data into a format that is easier and more effective to process in learning AI models to ensure accurate results. Data preprocessing can improve data quality, reduce noise, and prepare data in a way that allows machine learning algorithms and AI models to perform better. By using data preprocessing, AI modeling results become more reliable and accurate in prediction, classification, pattern recognition, and more.

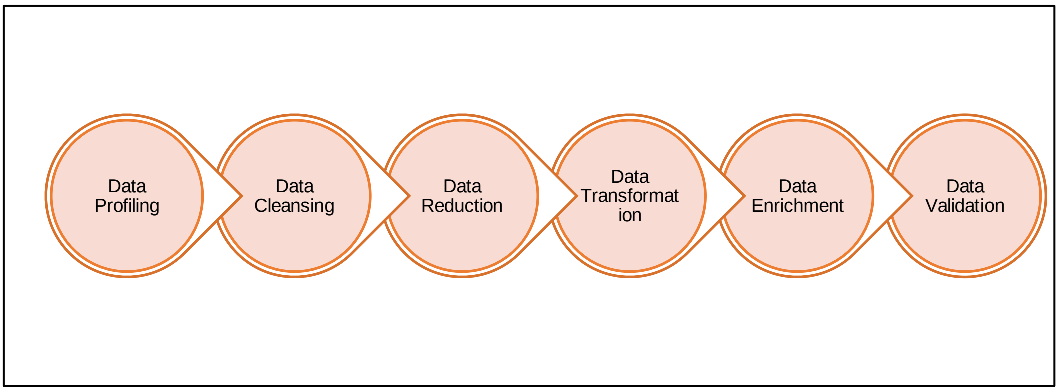


Figure 2. Data Pre-Processing Step

In carrying out data preprocessing, several stages are required in order to produce good data for training machine learning models and AI models. The purpose of data processing is to improve data quality, reduce noise, and prepare data before the training process is carried out on the AI model. The data preprocessing stages are as follows:

a. Data profiling

Data profiling is the process of examining, analyzing, and reviewing data to gather statistics about its quality through surveys of existing data and its characteristics. Data is collected based on datasets relevant to the problem at hand, inventorying significant attributes, and forming hypotheses about features that may be relevant for the proposed analytical or machine learning task..

b. Data cleansing

Data Cleansing is an important step because text that is clean and free from irrelevant elements allows sentiment analysis to run more effectively and accurately. Without proper data cleaning, noise or irrelevant information can affect the analysis results, resulting in an inaccurate understanding of the sentiment in the text. With text that has been cleaned, Sentiment Analysis can focus more on the core content that contains the sentiment or opinion that you want to analyze, thus producing more valuable results in understanding the feelings and views contained in the text data.

c. Data reduction

Datasets often include redundant data that arises from characterizing phenomena in different ways or data that is not relevant for a particular ML, AI, or analytics task. Data reduction uses techniques such as principal component analysis to transform raw data into a simpler form suitable for a particular use case.

d. Data transformation

Data transformation is carried out to change data into a form that is more appropriate to analysis or modeling needs. Data transformation helps improve the relevance, accuracy and effectiveness of data analysis. One of the tasks often carried out in data transformation is organizing or changing unstructured data into a more structured format. Unstructured data usually does not have a clear format, such as free text or unorganized data. To get data that is more structured and easy to process, this can be done by tokenization (breaking the text into words or tokens), lemmatization (changing words to their basic form), or stopwords (removing connecting words).

e. Data enrichment

Data enrichment is used to find a balance between improving data quality and maintaining computing performance. Appropriate transformations at this stage can affect the accuracy and efficiency of the model that will be built in the next step in the data analysis process. One important aspect of data embedding is selecting the most relevant and informative features or variables for a particular task. Selecting a subset of all available features to focus on more efficient analysis or modeling can help reduce model complexity.

f. Data validation

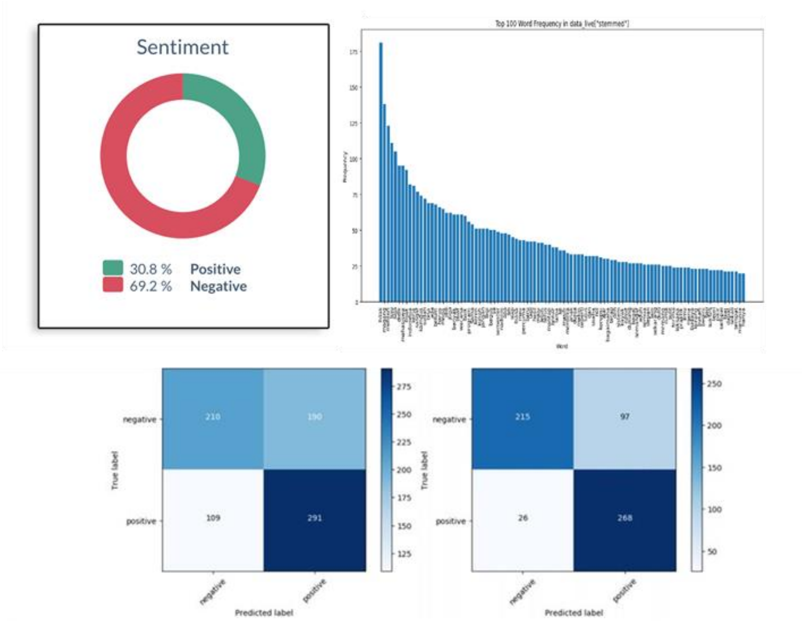
Data validation is an important stage in the data analysis process in machine learning or deep learning to determine the accuracy of AI model predictions. At this stage, the data that has been prepared and processed first is divided into two separate data sets, namely Training Data and Test Data. Data Training is used to train machine learning or deep learning models and to understand patterns and relationships in data, so that they can make predictions or take action based on the data provided. Meanwhile, Data Testing is used to measure the accuracy and strength of the model that has been trained. The goal of data testing is to evaluate the extent to which the model can make accurate and consistent predictions on unknown data.

3. Keyword Analysis

Keyword analysis is carried out to identify and classify feelings or opinions contained in the text into appropriate categories, such as positive, negative, or neutral. The process is carried out by identifying key words or phrases that express feelings or opinions. For example, words like “good,” “beautiful,” or “satisfied” are often used in positive contexts, whereas words like “bad,” “disappointing,” or “dislike” tend to be associated with negative sentiments. In addition, the context of words or phrases in the text is also analyzed. The same word can have different meanings depending on the context. For example, the word "hot" can refer to hot weather (positive) or food that is too hot (negative).

4. Sentiment Classification

Once sentiment keywords or phrases have been identified, the next step is to classify the sentiment into one of the appropriate sentiment categories. Sentiment classification aims to determine the sentiment category that best suits the expression of feelings or opinions contained in the text. Grouping sentiments into categories that reflect the nuance or intensity of the feelings expressed, whether positive, negative, or neutral. Sentiment classification can be done automatically using machine learning and deep learning algorithms that have been trained on train data containing text examples with certain sentiment labels.



SWN, NP

	precision	recall	f1-score	support
negative	0.66	0.53	0.58	400
positive	0.60	0.73	0.66	400
avg / total	0.63	0.63	0.62	800

SS, NP

	precision	recall	f1-score	support
negative	0.89	0.69	0.78	312
positive	0.73	0.91	0.81	294
avg / total	0.82	0.80	0.79	606

Figure 3. Sentiment Analysis Result Example

Figure 3 shows an example of the results of the sentiment classification process using machine learning with the resulting output in the form of positive or negative sentiment. This evaluation is carried out by comparing the model prediction results with the actual data contained in the dataset used. This evaluation aims to measure the model's accuracy in recognizing true sentiment in the text or data provided.

2.1.3. Youtube Social Media

YouTube has become one of the largest websites on the internet, with more than 2 billion active users every month. This platform is known for allowing users to upload, watch and share videos for free. In Indonesia, YouTube shows extraordinary popularity, based on (We Are Social & Meltwater, 2023) Youtube users in Indonesia are registered at more than 129 million active users. Meanwhile, the YouTube site is ranked second as the most frequently visited website in Indonesia. One of YouTube's main features is its ability to allow anyone to become a content creator. With simple tools, anyone can make videos about almost any topic they like. This has created a new phenomenon known as “YouTubers” or “content creators,” where individuals or groups create video content that can entertain, educate, or inspire millions of people around the world. Apart from that, YouTube is also a place where various organizations and companies share their content, ranging from product advertisements to educational videos. This has created huge opportunities for marketing and promotion.

The use of YouTube is also used for propaganda with many active users as a potential place for various parties to convey messages, influence public opinion, and build positive or negative images related to various issues or brands. According to research conducted by (Akmal et al., 2020), The use of propaganda techniques in advertising on YouTube has proven to be a success factor for the Traveloka company. One aspect that stands out is Traveloka's ability to create advertisements that are not only able to attract the attention of the audience, but also make YouTube users feel emotionally connected to the Traveloka brand. Traveloka's YouTube advertisements are well designed, using a variety of propaganda techniques to communicate their message. These techniques include the use of strong narratives, compelling visuals, and moving music. These advertisements often depict positive travel experiences and invite the audience to experience them for themselves. This creates an emotional bond between the Traveloka brand and YouTube users. Traveloka's success in utilizing propaganda techniques on YouTube is also reflected in the growing number of subscribers to Traveloka's YouTube channel. In other words, Traveloka has succeeded in building a strong fan base on this platform. Subscribers to the Traveloka YouTube channel not only see advertisements as a means of promotion, but also as entertainment and a source of inspiration. They actively follow Traveloka content, such as travel vlogs, hotel reviews, and travel tips, which are all part of the brand's marketing strategy.

Apart from that, Traveloka also takes advantage of various interactive features offered by YouTube, such as comments columns and live chat during live broadcasts. This allows Traveloka to interact directly with their fans, answer questions and listen to their feedback. These interactions create a stronger sense of ownership and engagement among YouTube users, which in turn contributes to an enhanced positive brand image. The use of propaganda techniques in YouTube advertising has become an effective strategy for the Traveloka company in achieving their marketing goals. They not only focus on promoting their products or services, but also on building relationships with the audience. Traveloka has succeeded in creating a positive experience for YouTube users, making them feel connected, entertained and inspired by the brand.

2.1.4. Data Scraping on Youtube Comments

The YouTube API is a tool provided by YouTube to enable developers and researchers to access comment data from YouTube videos and various other functionalities (Google API, 2023). By using the YouTube API, users can access comments left by users on videos on the platform. This allows for deeper data analysis of users' views of content, as well as the sentiment associated with a particular video. This comment data can be used for a variety of purposes, including scientific research, trend analysis, understanding public opinion, and developing YouTube-based applications.

Figure 4. Scraping Comments Process on Youtube
Source : (Pokharel & Bhatta, 2021)

YouTube Data API is used for authentication and comment access on videos. This API is used for authentication, and then the obtained credentials are fed into the comment extractor. The comment extractor then performs comment retrieval by scrolling through all the comments and loading them dynamically. The image above shows the process of retrieving

Youtube Comments data using the Youtube API. The data retrieval process begins with the use of the YouTube Data API for authentication. After successful authentication, we use this API to access comments on the video. The authentication credentials we obtain from the API are used by our comment extractor to collect comments. This extractor works by scrolling through the comments, thus ensuring the retrieval of all available comments. Next, we chose to extract comments from videos uploaded on YouTube. Videos on the YouTuber platform have various comments, ranging from questions, responses, to in-depth discussions about the topics discussed in the video.

2.1.5. Public Dataset

The dataset used in this research comes from sources that can be accessed by the public in accordance with research conducted by (Zhafira et al., 2021). The data collection process in this research was carried out using a scraping technique which took information from the YouTube platform, especially videos related to the Independent Campus Policy. The total dataset collected was 1000 comment data with a balanced composition of positive and negative sentiment. This allows research to produce more objective and comprehensive results related to community responses to the Independent Campus Policy.

According to (Tenopir et al., 2020) The use of public datasets in research has many advantages, not only influencing the scientific community and society, but also having a positive impact on authors and is generally considered positive among researchers. Then research from (Sielemann et al., 2020) also explained that reusing public data has more advantages than disadvantages, such as reducing research time and costs, availability of large data and various types, can be used to check and challenge previous research, can find new information or patterns that were not seen before so that has the potential to discover novelties in research. Additionally, with public datasets, researchers can combine and analyze results from several studies to gain a more comprehensive understanding. Then with the use of public datasets Authors of these public datasets can benefit from data reuse through increased reputation and acceptance in the scientific community. Continued contributions in data sharing can also increase the visibility and impact of research.

Next, the labeling process is carried out (Zhafira et al., 2021) This dataset was carried out manually in this research, assisted by three actors who have different field backgrounds, but are still related to the Independent Campus Policy. This approach was chosen to ensure that each comment is labeled with sentiment with high accuracy and in a relevant context. The involvement of three actors with diverse backgrounds also helps reduce bias in the labeling process.

The use of public datasets in this research ensures that the model to be built has strong validity. When the results of the model to be developed can be compared with other models that also use the same dataset, the modeling accuracy becomes more valid. This allows researchers to measure the extent to which the developed model can compete or even surpass other existing models in terms of sentiment analysis. By using the same public dataset used by other models, researchers can more easily evaluate the extent to which the model developed is successful in classifying data correctly and analyzing the sentiment contained in the dataset. So, it can be seen whether the model is effective in understanding and analyzing the opinions and sentiments contained in it. In addition, the use of public datasets also helps ensure that research results are trustworthy and can be used as a reference in sentiment analysis of the same dataset in the future. Thus, public datasets become an approach to evaluate and measure the quality of sentiment models developed in research. The distribution of the public dataset obtained from (Zhafira et al.,

2021) is divided into two labels, namely positive and negative. The number of sentences or texts in each data set is as follows:

Table 1. Public Dataset

No	Sentiment Type	Total
1	Positive	500
2	Negative	500

Source : (Zhafira et al., 2021)

The sentiment classification process in research (Zhafira et al., 2021) uses the Multinomial Naive Bayes Classifier method by carrying out text preprocessing and using the TF-IDF (Term Frequency-Inverse Document Frequency) method. This research obtained test results with an average accuracy value of 91.8%, with a precision value of 90.35%, recall of 93.6%, and f1-score of 91.95%.

2.1.6. Word2Vec Embedding

Word2Vec is a technique in natural language processing (NLP) that is used to convert words into distributed numerical representations as word vectors or word embeddings. This word vector reflects the features of words in the language used in the training dataset. These features include words that describe the context of individual words in our vocabulary. Word2Vec aims to describe words in vector form so that words that have similar or related meanings in context will have closer vectors in the vector space. Word2Vec helps in recognizing and understanding associations between words in text, such as if two words have similar vectors, they tend to have similar meanings or contexts.

For example, in the Word2Vec representation, the words "cat" and "dog" will probably have vectors that are closer to each other than the words "cat" and "computer." This reflects that in many contexts, “cat” and “dog” are often used together or have related meanings, while “cat” and “computer” have very different meanings and tend to be used in different contexts. Or in the Word2Vec representation, the words "man" and "woman" will probably have vectors that are closer to each other than the words "man" and "king." This reflects that in many contexts, "man" and "woman" are often used together or have related meanings, while "man" and "king" have very different meanings and tend to be used in different contexts. In this case, Word2Vec helps the computer recognize the association between the words "man" and "woman" as words related to sex or gender.

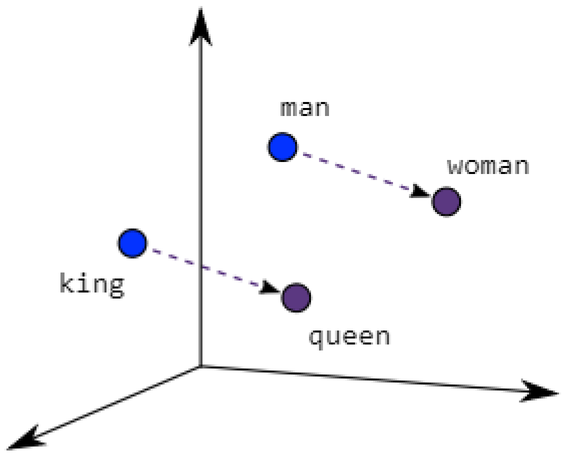


Figure 5. NLP Semmantic

The advantage of using Word2Vec in NLP is to help computers to understand the meaning of words in text, even if the computer does not have human-like understanding. Word2Vec allows computers to work with text more intelligently and deeply.

To train Word2Vec in Indonesian, you need a lot of Indonesian texts, one of which uses the Wikipedia corpus. The learning model in Word2Vec can use the gensim library. Gensim was used to perform preprocessing, streaming the Wikipedia corpus and training the Word2Vec model. Gensim performs preprocessing by tokenizing (breaking the text into words), removing special characters, changing all words to lowercase, and removing irrelevant words (stop words) and creating a streaming corpus. Gensim will map the words in the text into numerical vectors that represent the meaning of the words and organize them using Continuous Bag of Word (CBOW) or Skip-gram.

In Skip-gram architecture it is used to understand how words are related to each other in a text around a given word (current word) in the text. So the Skip-gram model in predicting will consider two words before and two words after the current word (Mikolov et al., 2013). Skip-gram architecture can describe the relationship between words in a sentence by predicting the current word based on its context. It then classifies the current word based on other words in the same sentence to identify words that appear within a certain range before and after the current word.

For example, the training data is in the form of the sentence " Ibu kota Negara Indonesia adalah Jakarta" with window dimensions 2. Next, each word in the sentence is converted into a one-hot encoded vector representation, where each word is represented as a binary vector where only one vector element has the value 1. identify the word.

```
ibu                         :[1,0,0,0,0,0]
kota                        :[0,1,0,0,0,0]
negara                      :[0,0,1,0,0,0]
indonesia                   :[0,0,0,1,0,0]
adalah                      :[0,0,0,0,1,0]
jakarta                     :[0,0,0,0,0,1]
```

For example, the word we want to predict the context of is "Indonesia". So in the Skip-gram method, weighting of the matrices w and w' is carried out.

w has size V x N, and w' has size N x V, where V is the number of words in the vocabulary and N is the dimension of the representation vector.

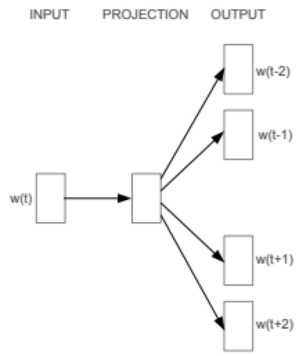


Figure 6. Word2Vec Skip-gram Method

The dimension used to predict the vector of the sentence " Ibu kota Negara Indonesia adalah Jakarta" is 2, so it will consider the two words before and the two words after the current word, namely "Indonesia". So the words "kota", "negara", "adalah", "jakarta".

```
ibu                         :[0,0,0,0,0,0]
kota                        :[0,1,0,0,0,0]
negara                      :[0,0,1,0,0,0]
indonesia                   :[0,0,0,1,0,0]
adalah                      :[0,0,0,0,1,0]
jakarta                     :[0,0,0,0,0,1]
```

This skip-gram will produce a word vector representation that has high similarity between words that often appear together in various contexts. The representation vector for "Indonesia" will be close to the representation vector for the word "Negara" and the word "adalah" because these words often appear together in the same sentence. Word2Vec using Skip-gram architecture will produce vector representations of words that allow to identify semantic and contextual relationships between words in a text corpus, and words that have similar contexts will have representation vectors that are close to each other in vector space.

2.1.7. Bi-Directional Long Short-Term Memory

Bidirectional Long Short-Term Memory (Bi-LSTM) is an LSTM with two processing paths at once, namely the forward path which processes the data sequence from beginning to end, then the backward path which processes data from end to beginning (Ertugrul & Karagoz, 2018). In this way, Bi-LSTM “sees” data sequences from both directions, allowing it to combine information from the past and future in data analysis. Bi-LSTM is able to capture relationships between sentences well because it can access information from both directions. So with Bi-LSTM you can understand deeper meaning and context in the text and improve the quality of sentiment analysis results. Bi-LSTM's ability to perform parallel computing also enables faster model training. Bi-LSTM's ability to process context from both directions makes it very effective in tasks that require a strong understanding of context, such as natural language processing (NLP) (Isnain et al., 2020). For example, in sentiment analysis tasks, Bi-LSTM can understand sentence context better because it can access words around the target word from both directions.

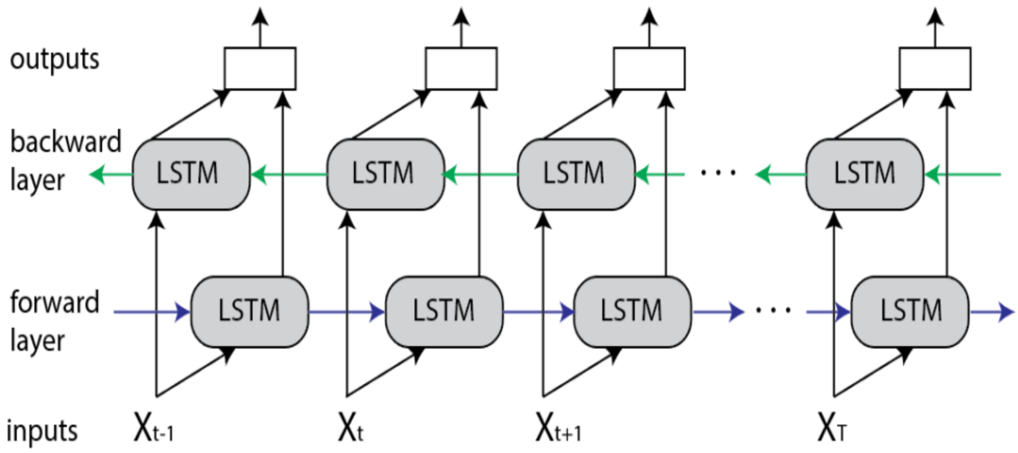


Figure 7. Bi-LSTM Architecture

The combination of two layers (forward and backward) makes Bi-LSTM so powerful in understanding context in sequence data. When data is processed by both layers simultaneously, Bi-LSTM has the ability to "see" the data sequence from both directions. So that Bi-LSTM has an understanding of the context that includes previous tokens and future tokens. In other words, Bi-LSTM can better capture dependencies in data sequences because it incorporates future information in the current data processing. The forward layer starts with the first token in the sequence and moves forward one by one to the next token that can remember the information in the sequence. Meanwhile, the backward layer starts with the last token in the sequence and moves backwards one by one by remembering the information in that sequence in the internal memory cells. This research utilizes the Keras-TensorFlow library which is available in the Python programming language (Chollet & others, 2015).

2.1.8. Accuracy Evaluation Model

Model accuracy evaluation is carried out to measure how well the machine learning model can correctly predict positive, negative and neutral sentiment classification values (Mantoro et al., 2020). Accuracy is one of the simplest and most commonly used evaluation metrics. By using accuracy metrics, you can compare the performance of different models or algorithms for the same task. This helps in selecting the best model. Next, you can use the Confusion matrix which can calculate various evaluation metrics, including accuracy, precision, recall, and F1-score. The following is the formula for measuring the accuracy of a model:

$$Level\ of\ Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \tag{1}$$

Where:

- True Positive (TP): The number of positive cases that were actually predicted correctly by the model.

– True Negative (TN): The number of negative cases that the model actually predicted correctly.
– False Positive (FP): The number of negative cases that were incorrectly predicted as positive by the model.
– False Negative (FN): The number of positive cases that were incorrectly predicted as negative by the model.

Next is measuring precision, where precision is used to measure the extent to which the model's positive predictions are correct. The following is the formula for measuring precision:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Then, to measure the extent to which the model is able to detect all actual positive cases, the Recall measurement is used with the following formula:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

To provide a balance between these two metrics, between precision and recall, the F1-Score measurement is used with the following formula:

$$F1 - Score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \tag{4}$$

2.1.9. Pancagatra News Articles Dataset

Pancagatra includes ideology, politics, economics, socio-culture, defense and security (Utami et al., 2018). Pancasila as the ideology of the Indonesian nation is a fundamental value for the government and society in achieving national goals. Political stability that reflects a harmonious relationship between government and society can create an environment of support and trust from society in efforts to achieve national goals. A healthy and strong economic sustainability will support national resilience by providing the resources needed to protect and defend the region. In Indonesia, diverse socio-cultural conditions, with various ethnicities and cultures, are a valuable asset in maintaining national resilience. Tolerance and mutual cooperation between people are values that must be maintained, so as to avoid internal conflicts that can weaken the country. Furthermore, regional defense and security is another important element in creating national resilience. An area that is safe and free from disturbances or threats is an important factor in creating a calm and peaceful community life. The community must unite and actively participate in maintaining the security of their region.

Pancagatra News Articles Dataset is a collection of data in the analysis of important words related to Pancagatra (ideology, politics, economy, socio-culture, defense and security). This dataset contains thousands of news articles that have been collected from various online news media sources using Google Search with keywords for each pancagatra. These articles cover various topics relevant to Pancagatra, from political policies to economic trends, emerging socio-cultural issues, as well as the latest developments in defense and security. The media used in collecting Pancagatra data is online news media in Indonesia, namely:

1. detik.com
2. tribunnews.com
3. kompas.com
4. cnnindonesia.com
5. liputan6.com
6. suara.com
7. okezone.com
8. sindonews.com
9. kumparan.com
10. merdeka.com

11. idntimes.com
12. jawapos.com
13. pikiran-rakyat.com
14. bisnis.com
15. mediaindonesia.com,

This dataset is used to identify key words in texts related to Pancagatra which form a word dictionary or lexicon for topic categorization. Each word contained in this dataset provides an overview of certain aspects or topics that are considered significant in the context of Pancagatra news. The word dictionary or lexicon produced from the dataset becomes a dictionary that includes key Pancagatra words, and this lexicon then functions as a guide for grouping the topics discussed in a text. By using this lexicon, texts related to Pancagatra can be grouped based on topics or aspects identified by key words.

2.1.10. Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) is a probabilistic model used to determine the topic of a document based on the words contained in it with a three-level hierarchical Bayesian approach (Mutiah et al., 2022). In LDA, each text document has a different topic, and each word in the document is associated with a particular topic. Additionally, each corpus (collection of documents) is associated with a predefined set of topics. LDA has the ability to generate a weighted list of topics for each document. The LDA work process is based on the corpus in each document. LDA also helps in identifying relationships between similar documents, allowing clustering of documents based on the same or similar topics.

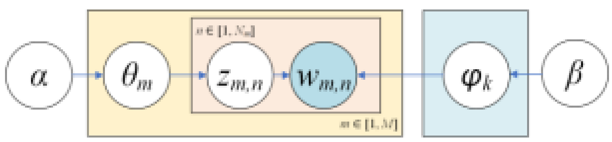


Chart 4. Graphical LDA Model

Where:

K : Number of topics

m : Number of words in the document

n : Number of documents for analysis

$\varphi(k)$: Probability of words per topic

$\Theta(m)$: Probability of the topic of per document

$Z(i,j)$: Topic assignment of $W(i,j)$

$W(i,j)$: Word on j in document i

These variables are used in calculating the Latent Dirichlet Allocation (LDA) model to analyze topics in a collection of documents or text (Anwar et al., 2022).

1. K (Number of Topics): K is the number of topics you want to identify in the document set. This is the first step in LDA, where you have to decide how many topics you want to search in the documents.
2. N (Number of Words in Document): N is the number of words in one particular document in a document set. In LDA, we need to understand how these words relate to the topics to be identified.
3. m (Number of Documents Analyzed): m is the total number of documents in the collection that you will analyze using LDA. LDA will attempt to find topics that are common across these collections of documents.
4. $\varphi(k)$ (Probabilitas Kata per Topik): $\varphi(k)$ adalah probabilitas distribusi kata-kata dalam setiap topik k. Ini mencerminkan seberapa mungkin suatu kata akan muncul dalam topik tertentu. Dalam LDA, kita akan mencoba untuk memperkirakan probabilitas ini saat model diperbaharui.
5. $\Theta(i)$ (Topic Probability per Document): $\Theta(i)$ is the probability distribution of topics in one document i. It describes how likely each topic will appear

in a particular document. LDA will try to estimate this probability for each document.

6. Z(i,j) (Topic Assignment to W(i,j)): Z(i,j) is the topic assigned to the jth word (W(i,j)) in document i. These are hidden variables in LDA that we try to discover through iteration.
7. W(i,j) (jth word in Document i): W(i,j) is the jth word in document i. In LDA, we want to understand how these words are connected to the topics to be identified.

LDA steps involve an iterative process that attempts to identify hidden topics in a collection of documents. During iteration, the model will attempt to estimate probabilities φ(k) and Θ(i), and also determine the topic assignment Z(i,j) for each word W(i,j). The goal is to construct a probability distribution of words in each topic and a probability distribution of topics in each document that can explain how words are related to these topics in the documents. To facilitate LDA model calculations, this research utilizes the Scikit-Learn (sklearn) library which is available in the Python programming language. Selection of Scikit-Learn as the main tool for implementing Latent Dirichlet Allocation (LDA) in data processing and machine learning. The Scikit-Learn library provides a variety of algorithms and functions that support a variety of data analysis tasks, including LDA, which is used in the context of text topic analysis.

Furthermore, the Python programming language has easy-to-understand syntax and many libraries and modules that support text processing, data processing, visualization, and statistical analysis. Therefore, Python becomes an ideal language to implement LDA algorithms and perform in-depth data exploration. This makes it easier to identify and understand hidden topics in a collection of documents or text. Scikit-Learn makes this task easier by providing ready-to-use functions for training LDA models, processing text, and evaluating the results..

2.2. Previous Research

The results of previous research are a summary and analysis of various research or literature that is relevant to the topic or problem related to this research. The goal is to provide a solid knowledge base and context for the research being conducted. There are several previous studies that were used as references and rationale for this research, namely:

No.	Author	Subject	Description	Relevance	Difference
1	(Zhafira et al., 2021)	*Analisis Sentimen Kebijakan Kampus Merdeka Menggunakan Naive Bayes dan Pembobotan TF-IDF Berdasarkan Komentar pada Youtube*	This paper carries out the data collection process through a scraping technique that takes information from the YouTube platform, especially videos related to the Independent Campus Policy. The total dataset collected was 1000 comment data with a balanced composition of positive and negative sentiment. This allows research to produce more objective and comprehensive results related to	Based on the dataset used and publicly accessible in this research, this dataset can be used as a dataset in this research so that it can be used as comparative data. The use of public datasets in this research ensures that the model built has strong validity. When the results of the model developed can be compared with other	This paper uses the Multinomial Naïve Bayes method to analyze sentiment on existing datasets.

No.	Author	Subject	Description	Relevance	Difference
			community responses to the Independent Campus Policy. Furthermore, the labeling process for this dataset was carried out manually in this research, assisted by three actors who had different field backgrounds, but were still related to the Independent Campus Policy. This approach was chosen to ensure that each comment is labeled with sentiment with high accuracy and in a relevant context. The involvement of three actors with diverse backgrounds also helps reduce bias in the labeling process. The model used is	models that also use the same dataset, the modeling accuracy becomes more valid.	

No.	Author	Subject	Description	Relevance	Difference
			Multinomial Naïve Bayes with an average accuracy of 91.8%.		
2	(Röchert et al., 2020)	Identifying Political Sentiments on YouTube: A Systematic Comparison Regarding the Accuracy of Recurrent Neural Network and Machine Learning Models	This paper examines sentiment analysis on YouTube comments using Word2Vec with RNN compared to SVM and Logistic Regression. Furthermore, this paper also compares other models with other word embeddings, namely Fasttext.	This paper strengthens the idea that the use of Word2Vec word embedding will increase the accuracy of AI models with a Neural Network approach compared to classical or probabilistic machine learning approaches	This paper uses an English language dataset and uses an RNN model
3	(Purwarianti & Crisdayanti, 2019)	Improving Bi-LSTM Performance for Indonesian Sentiment Analysis	Bi-LSTM sentiment prediction is influenced by the order of words, and the first or last phrase in the text tends to have stronger features than other phrases.	The model used is BiLSTM which is combined with Paragraph Vector to transform text into vector form and produces a very	The dataset used is a combination of various platforms, namely Twitter, Zomato, TripAdvisor, Facebook, Instagram,

No.	Author	Subject	Description	Relevance	Difference
		Using Paragraph Vector	However, within the scope of Indonesian sentiment analysis problems, phrases that express the sentiment of a document may not appear in the first or last part of the document, which may result in incorrect sentiment classification. This paper uses word embedding in the form of "paragraph vector" as an additional input feature for Bi-LSTM. This vector provides context document information for each processing sequence. This paragraph vector is simply combined with every word vector in the document. Combining the two methods has shown	high increase in accuracy. Thus strengthening the idea that the use of the BiLSTM model combined with word embedding techniques can increase the accuracy of Sentiment Analysis	Qraved. This dataset is private so it cannot be used as a comparison model with Thesis which will build an AI model and then compare it with other models to strengthen the model validation results.

No.	Author	Subject	Description	Relevance	Difference
			significant performance improvements in Indonesian sentiment analysis models.		
4	(Asudani et al., 2023)	Impact of word embedding models on text analytics in deep learning environment: a review	This paper describes the word embedding technique represented by deep learning in various natural language processing (NLP) applications, such as text classification, sentiment analysis, named entity recognition, topic modeling, etc. This paper reviews the most well-known word representation methods and the most prominent deep learning models. This research describes the results of a comparative analysis of different techniques for carrying	This paper provides a reference that the long short term memory (LSTM) model can be used to improve the overall performance of text analysis tasks	This paper does not discuss Sentiment Analysis on the YouTube platform and the model used is only LSTM

No.	Author	Subject	Description	Relevance	Difference
			out text analysis tasks using various word embedding techniques. This research concludes that word embedding using Word2Vec with the long short term memory (LSTM) model can be used to improve the overall performance of text analysis tasks.		
5	(Mantoro et al., 2020)	Machine Learning Approach for Sentiment Analysis in Crime Information Retrieval	Sentiment Analysis uses a private dataset by scraping Twitter post data with eight keywords that represent the most viral topics. The Machine Learning algorithms used are Multinomial Naïve Bayes, Random Forest Classifier, Linear	This paper shows the Sentiment Analysis technique on a live dataset using the most viral topic keywords. This paper is a reference that the use of keywords related to crime can be used for Sentiment Analysis of Crime issues.	This paper does not discuss Sentiment Analysis on the YouTube platform

No.	Author	Subject	Description	Relevance	Difference
			SVM, and Nearest-neighborhood (kNN).		
6	(Isnain et al., 2020)	Bidirectional Long Short Term Memory Method and Word2vec Extraction Approach for Hate Speech Detection	This paper aims to detect hate speech or non-hate speech in Indonesian language tweets using the Bidirectional Long Short Term Memory method and the word2vec feature extraction method with the Continuous bag-of-word (CBOW) architecture with an accuracy of 94.66%, with each value precision 99.08%, recall 93.74% and F-measure 96.29%. Meanwhile, Bidirectional Long Short Term Memory with three layers has an accuracy of 96.93%. Add one	This paper uses the BiLSTM and Word2Vec models for hate speech classification and obtains very high accuracy results. So it can be concluded that the use of BiLSTM and Word2Vec increases accuracy significantly.	This paper does not discuss Sentiment Analysis on the YouTube platform.

No.	Author	Subject	Description	Relevance	Difference
			layer to BiLSTM increased 2.27%.		
7	(Muhammad et al., 2021)	Sentiment Analysis Using Word2vec And Long Short-Term Memory (LSTM) For Indonesian Hotel Reviews	In this paper, we show the implementation of Word2Vec and LSTM for sentiment analysis on hotel reviews. The dataset used is a private dataset with scraping Twitter post data and manual labeling. Word2Vec model parameters include architecture (Skip-gram and CBOW), evaluation techniques (Negative Sampling and Hierarchical Softmax), and vector dimensions (100, 200, and 300). In contrast, the LSTM model parameters include dropout values (0.2, 0.5, and	This paper uses LSTM and Word2Vec models on private Twitter datasets for Sentiment Analysis and obtains good accuracy results. So it can strengthen the idea that the use of LSTM and Word2Vec can increase accuracy in Sentiment Analysis on a dataset of YouTube comments.	This paper does not discuss Sentiment Analysis on the YouTube platform.

No.	Author	Subject	Description	Relevance	Difference
			0.7), learning rate values (0.0001 and 0.001), and pooling methods (max and average pooling). The average accuracy was 85.96%, with Skip-Gram used as the Word2Vec architecture, with Hierarchical Softmax as the evaluation method, and with the vector dimension value set to 300. This scheme was also supported by an LSTM model with the dropout value set to 0.2 , with the learning rate set to 0.001, and with the average pooling technique as the pooling technique.		
8	(Musleh et al., 2023)	Arabic Sentiment Analysis of YouTube	This paper examines sentiment analysis on Arabic YouTube	This paper strengthens the idea that sentiment	This paper uses an Arabic language dataset and uses

No.	Author	Subject	Description	Relevance	Difference
		Comments: NLP-Based Machine Learning Approaches for Content Evaluation	comments using SVM, Naïve Bayes, Decision Trees, Random Forest, KNN, and Logistic Regression. Furthermore, this paper also compares other models with other word embeddings, namely Fasttext.	analysis in languages other than English can be used.	SVM, Naïve Bayes, Decision Trees, Random Forest, KNN, and Logistic Regression models.
9	(Alhujaili & Yafooz, 2021)	Sentiment Analysis for Youtube Videos with User Comments: Review	In this paper, we conduct a review based on existing literature regarding sentiment analysis techniques on YouTube platform comments using Indonesian. This paper explains various techniques used to carry out sentiment analysis, namely SVM, KNN, Naïve Bayes,	This paper can be used as a reference in studying models that can be implemented into comments on the YouTube platform using Indonesian.	The paper discusses analysis based on literature studies.

No.	Author	Subject	Description	Relevance	Difference
			Logistic Regression, Decision Trees, and Deep Learning		
10	(Irawaty et al., 2020)	Vectorizer Comparison for Sentiment Analysis on Social Media Youtube: A Case Study	This paper explains sentiment analysis on YouTube comments using the TFID model with SVM and KNN, and compared with Hash Vectorize with SVM and KNN. The best results obtained were the TFIDF model using SVM.	This paper strengthens the idea that sentiment analysis in languages other than English can be used in YouTube comments.	This paper uses a private dataset using SVM and KNN models with TFIDF.
11	(Mantoro et al., 2021)	Sentiment Analysis of the Papuan Movement on Twitter Using Naïve Bayes Algorithm	Twitter social media is used to express public views on the Papua issue. This paper focuses on sentiment analysis to compare three related keywords, namely "Free Papua",	This paper can be used as a reference for the use of Sentiment Analysis to support the Government's considerations in assessing public opinion on nationally	This paper does not discuss Sentiment Analysis on the YouTube platform.

No.	Author	Subject	Description	Relevance	Difference
			"Indonesian part of Papua", and "Papua Special Autonomy". Sentiment analysis of tweets on Twitter using the Multinomial Naïve Bayes algorithm.	sensitive issues such as Papua.	
12	(Anwar et al., 2022)	Identifying Social Media Conversation Topics Regarding Electric Vehicles in Indonesia Using Latent Dirichlet Allocation	This paper explains identifying social media conversation topics related to electric vehicles in Indonesia using the Latent Dirichlet Allocation (LDA) method..	This paper provides ideas for building models to identify topics on social media.	This paper does not identify topics related to Pancagatra.
13	(Mutiah et al., 2022)	Topic Modeling on Covid-19 Vaccination in Indonesia Using LDA Model	This paper explains identifying social media conversation topics related to the Covid-19 Vaccine in Indonesia using the Latent Dirichlet Allocation (LDA) method.	This paper provides ideas for building models to identify topics on social media.	This paper does not identify topics related to Pancagatra.

2.3. Research Framework

A framework is an important component in scientific research to assist in formulating an initial understanding of the research problem. The framework was built based on a literature review and the results of previous research. The main purpose of the thinking framework is to provide an understanding of the relationship between the variables studied and provide a basis for formulating research objectives. The framework begins by explaining the symptoms or problems that are the focus of the research. This is a brief description of what will be researched and why it is important. In quantitative research, the framework describes the relationship between the variables to be studied, such as independent variables (variables that influence) and dependent variables (variables that are influenced).

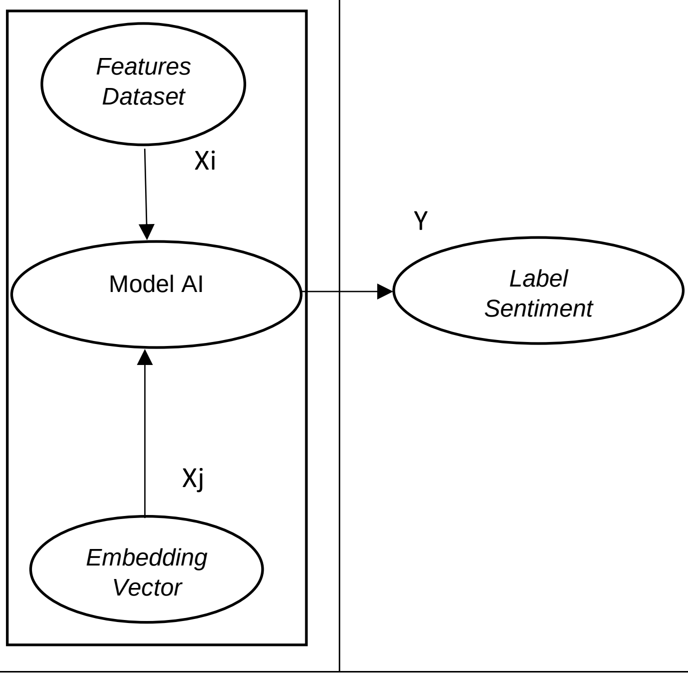
Variable Independent	Variable Dependent	Measurement
		Accuracy: Measuring the correctness of classifying data. F1 Scores: A metric that combines precision and recall into one single score

Chart 5. Research Framework

Independent variables in the form of Dataset Features in sentiment analysis research are factors or features that include various information that can influence the sentiment of the data to be analyzed. For example, in sentiment analysis of text, these independent variables may include key words, phrases, or other features extracted from the text. Furthermore, to improve understanding of the context and meaning of words in the text, these independent variables can include word representation vectors (word embeddings) such as Word2Vec. Word embeddings help AI models understand the relationships between words in text in a more contextual way. All independent variables are analyzed using the AI model to produce predictions or sentiment labels for the dependent variable in the form of sentiment labels.