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Climate Change Sentiment Analysis using LSTM Methods

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Abstract

This research aims to observe the sentiment of Indonesian people towards climate change using the Long Short-Term Memory (LSTM) methods. The data samples used in this study are primary data that have been collecting by using the Twitter Application Programming Interface (API) that provides by a platform known as RapidAPI. This data sample is text data with 2425 total samples obtained during the time period from 01 January 2020 to 25 August 2024. The sentiment is classified as positive, negative, and neutral. The performance of the LSTM model is evaluate using accuracy, precision, recall, F1-score, and confusion matrix and then compare with other models such as Ensemble Model, Naive Bayes, and Linear SVC. By conducting Exploratory Data Analysis (EDA), it is reveals that the distribution of public sentiment towards climate change in Indonesia from the collected data is mostly positive. However, there are not many individuals that are still ignorant and skeptical about the issue, resulting in a negative sentiment that can be fatal to the environment and its surroundings. When comparing the Ensemble Model, Naive Bayes, and Linear SVC, the LSTM model successfully identifies the perception patterns between sentences according to their sentiments. This research also highlights the technical challenges in processing and analyzing dynamic and diverse data so that the results obtained are better, especially in terms of data quality before further processing.

Keywords: *Climate Change, Data Science, Machine Learning, LSTM, Sentiment Analysis*

1. Introduction

Climate change is a significant global problem characterized by long-term temperature and weather patterns that change erratically from year to year. Originally caused by natural variations in the solar cycle, human activities such as the burning of fossil fuels, coal, oil and natural gas have exacerbated the problem. Despite being a popular topic of debate, climate change is often considered a tertiary issue, causing an increase in temperature and harmful pollutants, leading to unhealthy air quality in various regions. Despite its longevity, climate change remains an important concern for scientists and environmental activists [1] [2]. Climate change is a long-term phenomenon triggered by greenhouse gas-induced global warming from human activities. Research shows that factors such as social structure, social psychology, as well as macro factors such as prosperity and political-economic structure influence public opinion on climate change [3] [4].

Previous research conducted by [5] using the IndoBERT model for Twitter sentiment analysis related to climate change with data of 1533 Indonesian tweets collected through Twint. The data was manually labeled and processed with text cleaning, capitalization, removal of meaningless words, and stemming. The best model achieved an F1-score of 95.6% with a learning rate of 2e-5 and batch size of 16, although there were discrepancies in some test scenarios. Another study by [6] comparing random forest and naive bayes classifier (NBC) methods in sentiment analysis related to climate change used 1600 Indonesian tweets collected through Twitter API. The data was collected with the keywords “climate change,” “climate crisis,” and “global warming” during the period January-June 2022, with the division of positive and negative sentiments, as well as pre-processing using word weighting through TF-IDF. The results show that the NBC method is superior with 76.25% accuracy, 78% F1-score, and 80% recall, while random forest only achieves 70.6% accuracy, 69% F1-score, and 63% recall.

Indonesia has set and has a strong commitment to achieve Net Zero Emission (NZE) by 2060 or sooner through the implementation of an inclusive and sustainable green economy transformation in accordance with the UN Sustainable Development Goals

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(SDG). The main idea of this research is to present information and apply different methods from the two previous studies. Therefore, by referring to the aspects to be built through SDG number 13 [7], this research is in accordance with these objectives.

Even though Twitter is one of the main platforms used in this study to collect sentiment datasets, there are limitations such as not covering all opinions from various public groups proportionally. Therefore, the results of this study should be seen as a representation of the sentiments of active social media users based on the large volume of data, relevance, and speed of information related to climate change issues [8]. Integration with other data sources, such as surveys or other social media platforms can add diversity and value to the data collected so as to further generalize the results.

2. Research Methods

The design of the research scheme or flow will be divided into five main stages which can be seen as in Figure 1.

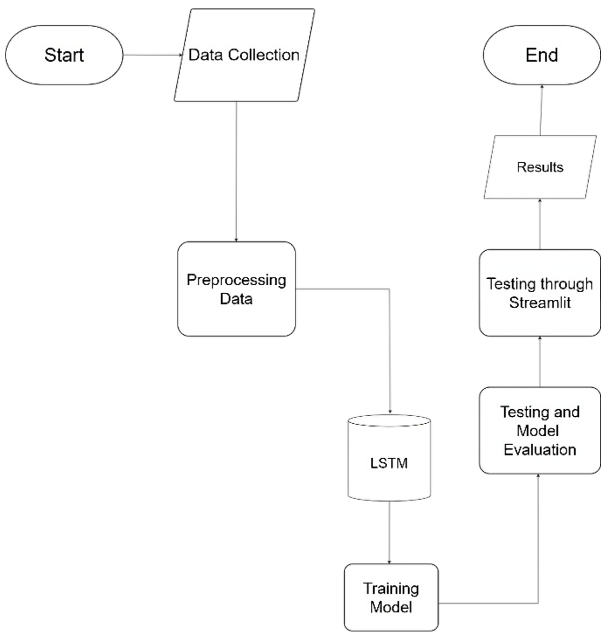

Figure 1. Research Flowchart

2.1. *Sentiment Analysis*

Sentiment analysis is a natural language processing (NLP) technique for assessing text messages and determine their emotional tone, whether positive, negative, or neutral. This topic is now a popular focus of research in various scientific and commercial fields, with the aim to track public opinion towards a product or topic [9]. In the context of climate change, positive sentiment usually supports the belief that climate change is cause by human activity, while negative sentiment is skeptical about it, and neutral sentiment is not clearly in favour or against it.

2.2. *Data Collection and Sentiment Labelling*

This research uses Twitter data collected through RapidAPI as a Twitter API provider during the period January 2020 to August 2024. The total samples collected reached 2425 tweets with a monthly time interval. The data was searching in Indonesian language using several main keywords such as ‘perubahan iklim’, ‘krisis iklim’, and ‘pemanasan global’ as well as other relevant keywords to obtain the comprehensive data.

When analyzing sentiment, the data was classified into three main categories: positive sentiment, negative sentiment, and neutral sentiment. Positive sentiment indicates support and optimism towards efforts to mitigate climate change and successful environmental management. Negative sentiment represents both skepticism and unbelief about climate change, whereas neutral sentiment presents the factual information without any particular opinion or emotional expression [10] [11]. Also to verify the sentiment labels and adjust the standards, it is done manually together with the other two authors with the most votes being the final result of labelling a sentiment.

2.3. *Long Short-Term Memory*

Long Short-Term Memory (LSTM) is a deep learning method that belongs to a type of recurrent neural network (RNN). LSTM is designed to overcome the *vanishing gradient* problem in conventional RNNs, making it capable of capturing patterns and relationships between words in sequential data, even on long sequences. This method is very effective in sentiment analysis, especially for short texts on social media such as Twitter (now X), as it is able to preserve the context and meaning of words [12] [13].

LSTM is designed to retain important context from previous sequences through the mechanism of cellular memory (cell state). By using cell state as the main pathway for information flow, LSTM effectively preserves and updates current data from previous steps in the sequence, ensuring the model can understand the sequence in the data. It accepts input in the form of numeric vectors that have been pre-processed, for example through vectorization, tokenisation and padding. Based on three main gates - forget gate, input gate, and output gate - the LSTM carefully manages the information that needs to be kept or forgotten from the data, allowing for better context understanding in time or text sequence analysis..

1. Forgot Gate:

$$f_t = \sigma\left(W_f * x_t + U_f * h_{t-1} + b_f\right) \quad (1)$$

where:

a. W_f, U_f, and b_f: Weight matrix and bias for the forget gate.

b. h_{t-1}: Hidden state from the previous time step.

c. x_t: Input at the current time step.

d. σ: Sigmoid activation function that output values between 0 and 1.

2. Input Gate:

$$i_t = \sigma(W_i * x_t + U_i * h_{t-1} + b_i) \quad (2)$$

where:

a. W_i, U_f, and b_i: Weight matrix and bias for the input gate.

b. h_{t-1}: Hidden state from the previous time step.

c. x_t: Input at the current time step.

d. σ: Sigmoid activation function that output values between 0 and 1.

3. Output Gate:

$$o_t = \sigma(W_o * x_t + U_o * h_{t-1} + b_o) \quad (3)$$

where:

a. W_o, U_o, and b_o: Weight matrix and bias for the output gate.

b. h_{t-1}: Hidden state from the previous time step.

c. x_t: Input at the current time step.

d. σ: Sigmoid activation function that output values between 0 and 1.

4. Cell State:

$$C_t = f_t * C_{t-1} + i_t * C_t' \quad (4)$$

where:

a. $f_t * C_{t-1}$: The part of the previous cell state Ct-1 that is retained by the forget gate. If ft is close to 1, the information will be forwarded. If it is close to 0, the information will be forgotten

b. $i_t * C_t'$: Part of the updated information that will be added to the cell state with C_t' as the new candidate value for the cell state.

LSTM is able to capture the relationship between words by considering the sequence of data, so it understands the context in which each word is used. Within the used architecture, the final layer with an activation function such as softmax returns a sentiment probability (positive, negative, or neutral) [14]. This makes LSTM a superior choice for sentiment analysis. An example of LSTM is shown in Figure 2.

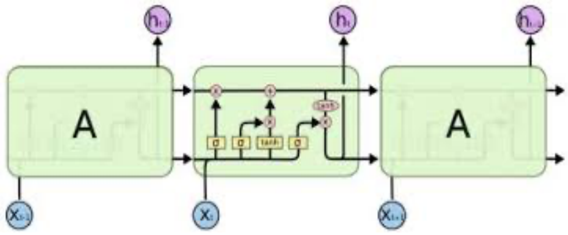

Figure 2. An LSTM Architecture [15]

In this research, the hyperparameter tuning process is carried out with the Grid Search method with the optimal parameter combination used is 256 and 128 number of units for both LSTM layers, 10 units of the first dense layer and 3 units of the second dense layer as the sentiment class output with a learning rate of 1e-5 and 150 epochs. The optimizer used is Adam while the loss function is sparse categorical crossentropy.

2.4. *Other Models for Comparison*

Besides LSTM, there are several other algorithms that will be used for comparison such as naive bayes, linear SVC, and Ensemble Model such as bagging classifier with AdaBoost as base estimator. It is necessary to see how LSTM performs against these models. Notes the time duration, pre-processing techniques (text cleaning, stopwords removal, stemming, etc), and hyperparameter tuning applied to all algorithms used. Imbalances between sentiments are removed by reducing duplicates and also limiting the number or length of sentiment sentences to maximize model performance.

3. Results and Discussion

3.1. *N-gram Analysis*

Visualization of top bigrams (Figure 3) and top trigrams (Figure 4) shows that climate change issues mainly focus on impact and crisis. Bigrams such as ‘climate crisis’ and ‘global warming’ and trigrams such as ‘climate crisis impact’ dominate, indicating a major focus on climate change impacts. In addition, phrases such as ‘emisi karbon’, ‘cuaca ekstrem’ and ‘food crisis’ reflect a deep understanding of technical causes. Interestingly, phrases such as ‘overcoming the crisis,’ ‘renewable energy,’ and ‘preventing global warming’ also appear, indicating a concern for solutions albeit with less frequency than the discussion of impacts. However, some words from this analysis were not included as search keywords.

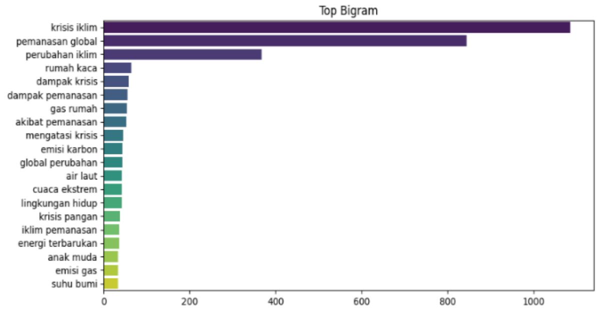

Figure 3. Top Bigram

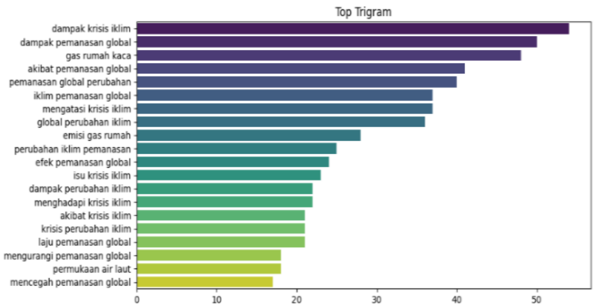

Figure 4. Top Trigram

3.2. *Trend Sentiment and LSTM Evaluation*

According to Figure 5 as well as the number of data samples collected, sentiment about climate change shows significant fluctuations with a negative peak in early 2023 due to major natural disasters such as floods in Kalimantan and a positive peak in the end of 2024 caused by government initiatives related to the use of renewable energy. Discussions tend to increase each year, with positive and neutral sentiments dominating over negative, especially in the 2023-2024 period. Analysis of top words, word clouds, N-grams and temporal trends provide complementary perspectives, highlighting the importance of communicating the urgency of the problem as well as concrete solutions based on evidence and local wisdom. Figure 6 and Table 1 show the confusion matrix and classification report of the LSTM Model

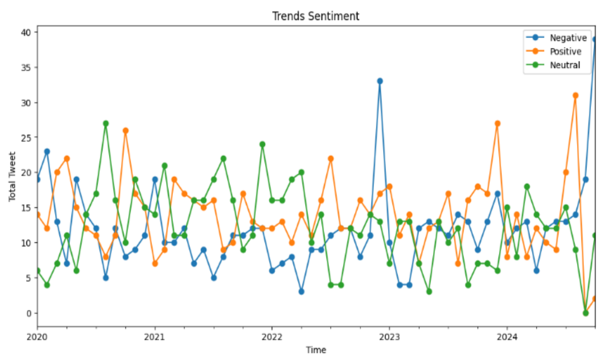

Figure 5. Trend Sentiment

Table 1. Classification Report

Sentiment	Precision	Recall	F1-score
0 (Negative)	0.56	0.54	0.55
1 (Positive)	0.64	0.81	0.71
2 (Neural)	0.60	0.44	0.50
Accuracy		0.60	

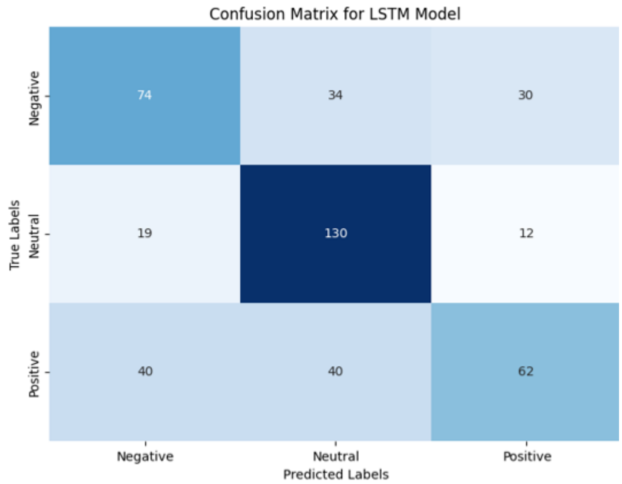

Figure 6. Confusion Matrix

The LSTM model achieve training accuracy around 0.6366 with a loss value of 0.8570. However, the testing accuracy only reaches 0.6031 with the number of units of the first layer of LSTM is 256, the second layer of LSTM is 128, the first dense layer is 10, and the second dense layer is 3 units according to the number of sentiment classes (positive, negative, and neutral). The number of epochs along with the model training time is 150 with a training time of about 88.37 seconds. Table 2 shows the comparison between the LSTM model and the naive bayes, linear SVC, and ensemble models.

Table 2. Models Comparison

Models	Accuracy	Training Time (s)	Precision	Recall	F1-score
LSTM	0.60	88.37	0.60	0.59	0.59
Ensemble Model	0.42	212.6	0.42	0.42	0.42
Linear SVC	0.35	0.36	0.35	0.35	0.35
Naive Bayes	0.34	0.48	0.34	0.34	0.33

From Table 2, it can be seen that the best result is from the LSTM model. Table 3 shows the comparison between models in predicting an unlabelled text input, for example ‘Perubahan Iklim adalah masalah global yang memerlukan tindakan segera dari semua negara.’ through a dashboard created using Streamlit. The result is that LSTM predicts the input sentence as a negative sentiment, while the other three models predict it as a positive sentiment.

Table 3. Model Prediction through Streamlit

Models	Prediction
LSTM	Negative
Ensemble Model	Positive
Linear SVC	Positive
Naive Bayes	Positive

Table 4 presents the experimental results with different data proportions along with training duration, accuracy, loss, and validation testing. The LSTM model can predict and perform quite well in learning patterns of sentiment with the proportion of training data amount of 1983 (90%) data samples and the total number of test data 221 (10%) resulting in an accuracy of about 0.5689 with a loss of 0.8726, testing accuracy reaches 0.5746, and the total training duration is about 89.46 seconds.

Table 4. Comparison of Experiment with Variation of Training and Testing Data of LSTM Model

Total Train Data	Total Test Data	Training Time (s)	Accuracy	Loss	Testing Accuracy
1983 (90%)	221 (10%)	89.46	0.56	0.87	0.57
1653 (75%)	551 (25%)	89.39	0.56	0.90	0.56
1542 (70%)	662 (30%)	83.82	0.53	0.94	0.55
1322 (60%)	882 (40%)	82.78	0.52	0.99	0.53

In the evaluation through confusion matrix, it can be seen that the model tends to be more accurate in predicting the 'Positive' class (with 130 predictions out of 161 data), compared to the 'Negative' or 'Neutral' class. It is also important to note that the model has enough errors in distinguishing between the 'Negative' or 'Neutral' sentiment classes with a significant number of incorrect predictions between all sentiment classes. This is why the model is better at recognizing the 'Positive' class but not the other sentiment classes. Balancing the amount of data between classes or improvements in the vector weighting process for the representation of words into their numerical form (e.g., through fine-tuning the embedding layer or adjusting the TF-IDF features) can help the model to be more accurate in distinguishing each sentiment class.

The evaluation results through the classification report on the precision, recall, and f1-score achieved by the model for the 'Positive' class (class 1), the model performed quite well, with a recall of 0.81 which means that the model managed to recognize many 'Positive' sentiment classes correctly. However, for the sentiment classes 'Negative' (class 0) and 'Neutral' (class 2), the precision and recall are relatively lower. This confirms more or less the same results as the confusion matrix obtained and that the model still has difficulty in identifying these sentiment classes well. The average macro and weighted values for precision, recall, and f1-score are around 0.59-0.60 which means that the performance of the model on all classes is not quite optimal. A possible improvement for this is to try to make further adjustments in data pre-processing and check whether the application of the pre-processing function is optimal or not. If it is not, then improvements can be made either directly in the pre-processing function or it is more advisable to manually check and ensure that the data is of good quality.

4. Conclusion

This research successfully analyses sentiment about climate change using the LSTM method and provides insights about the distribution of sentiment through EDA. From the datasets collection, negative and neutral sentiments dominate the discussion on the impacts of climate change, whereas positive sentiments highlight more proactive solutions. Bigram and trigram visualizations show that the public highlights both impacts and solutions, with phrases such as 'climate crisis' and 'renewable energy' being the main topics.

Sentiment trends show an increase in discussion intensity and significant fluctuations in the 2023-2024 period, reflecting the public's sensitivity to the issue. The stemming technique produced better validation accuracy than lemmatization, although it took longer, and experiments with hyperparameters have shown that there are opportunities for further improvement. The LSTM model has an accuracy of 60%, higher than linear SVC, naive bayes, and ensemble model, but still struggles to distinguish between negative and neutral sentiments according to the evaluation results of the confusion matrix. It has made a meaningful contribution to the understanding of climate change discourse even though there are still technical challenges that need to be refined.

Some suggestions that have not been done in this research can be applied for future research are improving data quality to ensure clean and consistent data through manual pre-processing that is more optimized if it turns out that the pre-processing function is not efficient. Experiments with similar models such as GRU or combinations with bidirectional models can also help improve performance, especially to overcome the difficulty of distinguishing similar sentiments. Exploration with word vector weighting methods apart from TF-IDF and the use of trained models such as IndoBERT can help the model to better understand the patterns and context of words in Indonesian. These steps are expected to improve the overall performance of the model, provide more optimal results, and contribute to similar research in the future.

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