Sentiment analysis of public response to measurable fishing capture policy using LDA and LSTM methods

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ABSTRACT

Illegal, unreported, and unregulated (IUU) fishing poses a significant threat by depleting fish stocks, damaging marine ecosystems, jeopardizing economic livelihoods, and undermining long-term environmental sustainability. To address this, the government has implemented a public policy of measured fishing within the blue economy framework. Given the involvement of numerous stakeholders, it is crucial for the government to gauge public sentiment through tweets on social media platforms to evaluate and refine the policy's implementation for greater effectiveness. While the long short-term memory (LSTM) method for sentiment analysis is adept at handling text sequences and context, it struggles with capturing contextual semantic correlations. Conversely, the latent Dirichlet allocation (LDA) method excels in identifying these correlations and uncovering dominant topics. This study shows that integrating LDA for topic modeling with LSTM for sentiment analysis enhances overall performance, providing more accurate and comprehensive insights into public responses and identifying key topics discussed in social media tweets.

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1. INTRODUCTION

Background: illegal, unreported, and unregulated (IUU) fishing depletes fish stocks and endangers livelihoods. To counter this, Indonesia's Ministry of Marine Affairs and Fisheries has implemented a policy based on blue economy principles. This policy aims to protect marine life through strong regulations and enforcement [1]. The blue economy promotes sustainable ocean resource use to boost economic growth, enhance livelihoods, create jobs, and protect marine ecosystems [2]. It prioritizes justice and equity, especially climate justice, to ensure fair distribution of benefits and sustainable impact management in planning and governance [3]. Policymakers must understand public sentiment for policy success [4]. Analyzing social media posts provides policymakers with global public reactions, aiding in better communication and policy decisions [5]. For example, state legislators in the U.S. use Twitter to debate policies and share their priorities [6]. Research shows that Twitter is increasingly used by citizens and groups to impact government decisions and policies [7].

Understanding public opinion in tweets depends on natural language processing (NLP) techniques, particularly sentiment analysis [8]. Machine learning algorithms such as naive Bayes, support vector machine (SVM), recurrent neural networks (RNNs), convolutional neural networks (CNNs), and long short-term memories (LSTMs) are effective for sentiment analysis, and their combination can improve accuracy [9].

Combining lexicosemantic features with deep learning boosts sentiment analysis effectiveness [8]. LSTM and bidirectional-long short term memory (Bi-LSTM) models outperform traditional RNNs in analyzing Twitter sentiments [10]. Using LSTM for sentiment analysis and latent Dirichlet allocation (LDA) for topic modeling improves the accuracy of tweet interpretation. LSTM is effective with sequential data, while LDA identifies important topics, resulting in better analysis and policy adjustments.

Related works: LSTM networks are effective in sentiment analysis due to their ability to capture and retain long-term dependencies [9], [11], [12]. Models such as LSTM-spiking neural P (LSTM-SNP) and BiLSTM-SNP models improve aspect-level sentiment analysis with attention mechanisms and bidirectional structures, outperforming baseline models [13], [14]. LSTM's gate mechanisms, especially the forgetting gate, tackle vanishing gradients in RNNs, enhancing accuracy in long-text sentiment analysis. Despite alternatives like naive Bayes, SVM, RNNs, and CNNs, LSTM is often favored based on data.

However, LSTM can struggle with capturing contextual semantic correlations in sentiment analysis [11] and managing the dominance of short-term over long-term gradients, which limits learning long-distance information [14]. Other challenges involve assessing errors before deployment and identifying new ones after deployment [15], the "black-box" nature of deep learning models due to high-dimensional features and unpredictable weights [16], and the challenge of making high-quality training sets with accurate labels due to complex and subjective sentiment annotations [17]. Improving interpretability, gradient management, error detection, and labeling strategies is key to enhancing LSTM-based sentiment analysis models.

LDA is commonly used to capture semantic correlations in document modeling and ontology learning [18]. LDA-based methods generate context-driven word representations and identify topics effectively [19]. However, traditional LDA models struggle with concept extraction and adapting to evolving corpora [20]. Extensions like LEOnto+ use LDA for dimension reduction and establish semantic links between topics and words via probability distributions [21]. These advancements improve LDA's capture of semantic correlations and enrich text with ontologies [22]. This research focuses on; i) integrating LDA-based topic modeling with LSTM and Twitter data for sentiment analysis and ii) analyzing how adding LDA-identified topics affects the accuracy of LSTM sentiment classification.

2. METHOD

2.1. Dataset

The dataset used in this study was obtained through a tweet-data search on social media platform X (Twitter) using the keywords "*penangkapan ikan terukur*" and "*ekonomi biru*." The dataset taken is the result of X (Twitter) user tweets between January 1, 2022 and June 30, 2023. The dataset used in this study was obtained through a tweet-data search on social media platform X (Twitter) using the keywords '*penangkapan ikan terukur*' and '*ekonomi biru*.' The lexicon-based data-labeling process aims to label documents based on word analysis using a lexicon dictionary, which can be enhanced by utilizing libraries like natural language toolkit (NLTK) [23] and Sastrawi [24] for better text processing. Figure 1 displays the tweet data distribution, revealing notable monthly variations. This distribution highlights fluctuations in discussion activity over time.

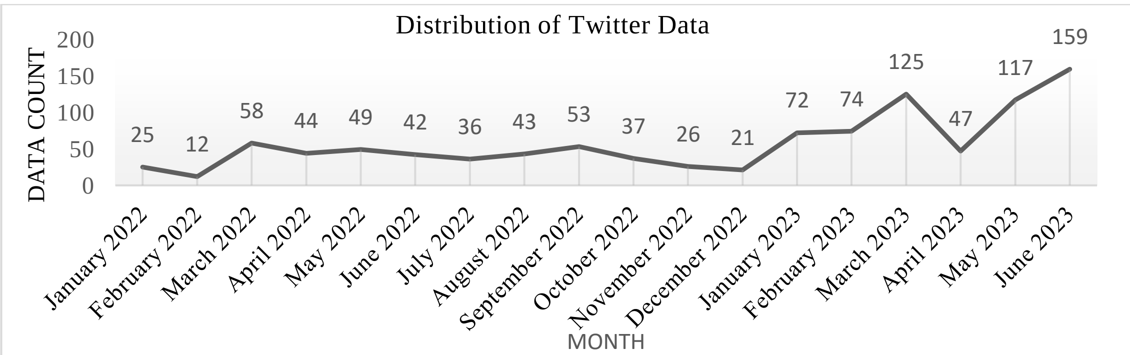


Figure 1. The distribution of tweet data

2.2. Experiment design

This study employs the system process flow shown in Figure 2 to analyze sentiment using a set of tweet documents. This procedure integrates lexicon-based labeling, word embedding, LDA-based topic modeling, and sentiment analysis with LSTM.

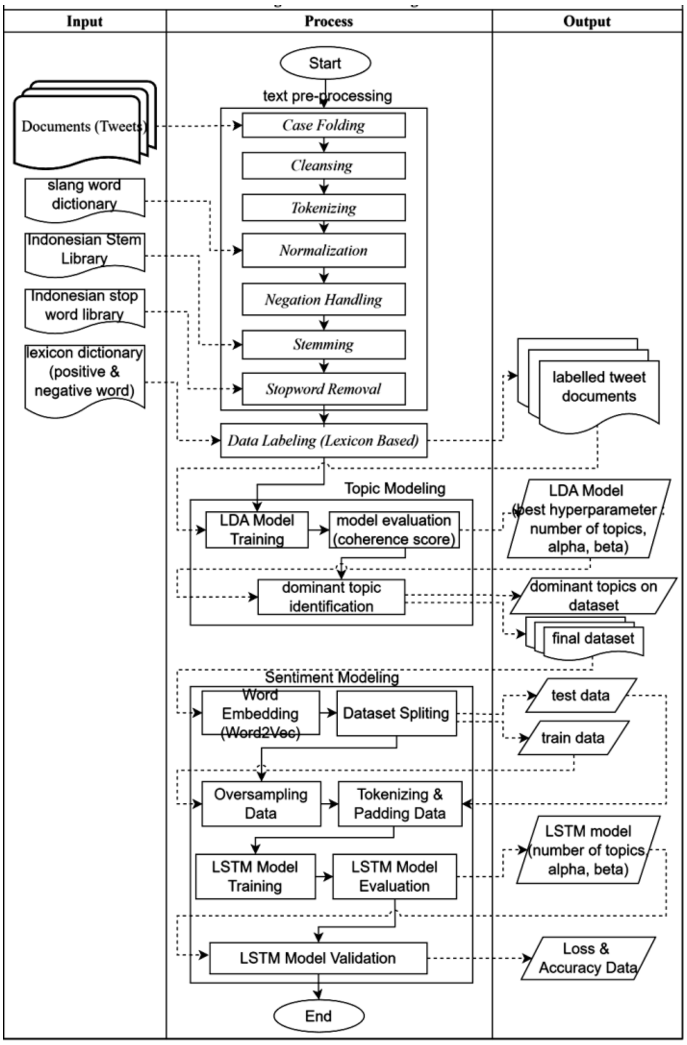


Figure 2. System process design of framework

2.3. Document labeling

The lexicon-based data-labeling process aims to label documents based on word analysis using a lexicon dictionary. The sentiment score is calculated for each document using a lexicon dictionary. The dictionary is in the form of a positive dictionary, which is a text file that contains a list of words that are considered positive. This process also uses a negative dictionary that contains a list of words considered negative.

2.3.1. Topic modeling using latent Dirichlet allocation

The LDA method is used to analyze textual data by encoding documents as word-frequency vectors. This method can also identify underlying themes or topics in a collection of documents, based on a probabilistic model [25]. Additionally, tools and libraries such as the Sastrawi library for stemming Indonesian text [24], the NLTK for various NLP tasks [23], and the NLTK project [26] provide essential resources for implementing LDA effectively.

Thus, this model explains the relationships between words and themes, providing insights into hidden structures and patterns in the data. In (1) calculates the probability of a word w appearing in a topic k.

$$P(w|k) = \frac{(n_{kw}+\beta)}{(\sum(n_k)+V*\beta)} \tag{1}$$

Where $P(w|k)$ is used to express the probability that a word will occur in topic k. The number n_{kw} indicates how often the word w appeared in the topic k. β is a multinomial parameter for each word in each document. n_k is the total number of words for topic k displayed and V is the total number of words in the entire document.

Meanwhile, LDA modeling calculates the distribution of topics (z) in documents (d) using (2):

$$P(z|d) = \frac{(n_{dz}+\alpha)}{(\sum n_d + K*\alpha)} \quad (2)$$

Where the probability that topic z will appear in document d is given by $P(z|d)$. The number n_{dz} indicates how often topic z is mentioned in document d, and α is the Dirichlet parameter for each document. The total number of words in document d as a whole is n_d. Where K denotes the predetermined number of topics.

Topic modeling involves training the LDA model and validating the resulting model. In this study, the LDA model training process applies a grid search method to obtain the best LDA parameters (α, β, K). Search space of parameter values α=[0.01, 0.31, 0.61, 0.91]; β=[0.01, 0.31, 0.61, 0.91]; K=[2, 3, 4, 5, 6]; This hyperparameter tuning process uses coherence counts to evaluate topic quality [27]. The model was trained with optimal parameters to generate topics and their distributions. Each document's dominant topic was identified by sorting topics by their distribution values.

2.3.2. Sentiment modeling using long short-term memory

Sentiment modeling starts with preprocessing LDA output, including word embedding (using Word2Vec), data splitting, over sampling, and tokenizing with padding [28]. This method generates word embeddings to capture semantic context. The dataset is split into 80% training and 20% test data, with Random Over Sampler used to address imbalance. Tweet text is tokenized into numerical representations, unnecessary characters are filtered out, and padding standardizes document length to a maximum of 20.

The next step involves training and validating the LSTM model, which includes four layers as outlined in Table 1. The model uses SoftMax activation and density measures to categorize sentiments into positive, neutral, or negative, employing Adam optimization and evaluating with categorical cross-entropy and accuracy. Hyperparameter tuning was performed using the hyperopt method to find the optimal LSTM parameters from the search space, including learning rates of [0.0001 to 0.01], LSTM units of [128, 256, 512], epochs of [25, 50], and batch sizes of [16, 32]. The impact of LDA topic modeling on the LSTM model was measured by comparing its predictions to a baseline LSTM model that lacked these features, using the best hyperparameters.

Table 1. LSTM model

Layer (type)	Output shape	Param #
input_1 (InputLayer)	[(None, 20)]	0
embedding (Embedding)	(None, 20, 300)	546300
lstm (LSTM)	(None, 128)	219648
sentiment (Dense)	(None, 3)	387
Total params: 766335 (2.92 MB)		
Trainable params: 220035 (859.51 KB)		
Non-trainable params: 546300 (2.08 MB)		

2.4. Metrics

2.4.1. Coherence score

Coherence measures the degree to which words in a topic correlate with each other and how semantically meaningful the topic is. For topics $T = \{T_1, T_2, \dots, T_K\}$ by the number of topics K, dan $W_k = \{w_{k1}, w_{k2}, \dots, w_{kW}\}$ are unique words that often appear for each topic (T_k). Coherence of word pairs (w_1, w_2):

$$C(w_1, w_2) = \log \frac{P(w_1, w_2)}{P(w_1) \cdot P(w_2)} \quad (3)$$

So, the calculation of topic coherence $(C(T_k))$ is the average coherence of all word pairs in a topic $(\mathrm{T_k})$,

$$C(T_k) = \frac{1}{|W_k|(|W_k|-1)} \sum_{i=1}^{|W_k|} \sum_{j=i+1}^{|W_k|} C(w_{ki}, w_{kj}) \quad (4)$$

The coherence of the LDA model $C(T)$ is the average coherence of all topics and can be expressed as (5):

$$C(T) = \frac{1}{K} \sum_{k=1}^{K} C(T_k) \quad (5)$$

2.4.2. Confusion matrix

A confusion matrix assesses classification by comparing predicted and actual values, including true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Table 2 displays the confusion matrix for sentiment classes (positive, neutral, and negative).

Table 2. Confusion matrix for sentiment class (positive, neutral, negative)

	Predicted negative	Predicted neutral	Predicted positive
Actual negative	(TP_{Neg})	$(FN_{\text{Neg\_Neutral}})$	$(FN_{\text{Neg\_Pos}})$
Actual neutral	$(FP_{\text{Neutral\_Neg}})$	(TP_{Neutral})	$(FN_{\text{Neutral\_Pos}})$
Actual positive	$(FP_{\text{Pos\_Neg}})$	$(FP_{\text{Pos\_Neutral}})$	(TP_{Pos})

2.4.3. Classification report

The classification report gives a thorough evaluation of a model's performance for each class, including precision (accuracy of positive predictions), recall (ability to find all relevant instances), and F1 score (a metric combining precision and recall). It also details the support for each class, which is the count of actual instances in the dataset. This information, presented in Table 3, helps in assessing the model's effectiveness and identifying areas for improvement.

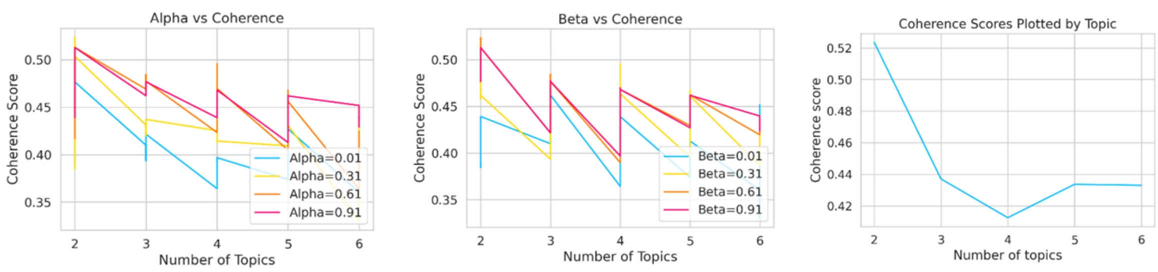
Table 3. Classification report metrics

Description	Formula
Accuracy indicates how often the model can correctly classify a tweet as positive, neutral, or negative compared with all predictions made.	$Accuracy = \frac{TP_{\text{Pos}} + TN_{\text{Neutral}} + TN_{\text{Neg}}}{Total\ Number\ of\ Samples}$ (6)
Precision is the proportion of correct positive predictions compared with all positive predictions. For each class.	$Precision_{kelas} = \frac{TP_{class}}{TP_{class} + FP_{class}}$ (7)
Recall is the proportion of correct positive predictions compared to all samples that are actually positive.	$Recall_{\text{class}} = \frac{TP_{\text{class}}}{TP_{\text{class}} + FN_{\text{class}}}$ (8)
The F1 score is the harmonic mean of precision and recall, offering a balanced measure of both metrics. It ensures the model maintains high precision (few FP) and high recall (few FN).	$\text{F1}_{\text{class}} = 2 \times \frac{\text{Presisi}_{\text{class}} \times \text{Recall}_{\text{class}}}{\text{Presisi}_{\text{class}} + \text{Recall}_{\text{class}}}$ (9)
The support metric in the context of classification model evaluation refers to the actual number of occurrences for each class in the tested dataset. Oversampling results in the number of samples in each class being the same as well as the value of this metric.	

3. RESULTS AND DISCUSSION

3.1. Experiment result

From the experiment, (α, β, K)=(0.31, 0.61, 2) is the combination of LDA topic modeling hyperparameters with the highest coherence score for each parameter as in Figure 3. Figure 3(a) shows that higher alpha values (0.91) improve coherence. Figure 3(b) reveals that beta 0.91 also yields the best coherence. Figure 3(c) indicates coherence scores decrease from 2 to 4 topics, then stabilize.



(a) (b) (c)

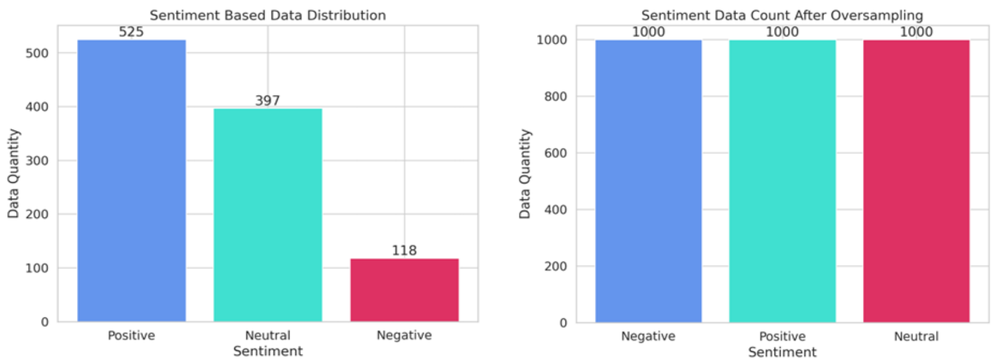
Figure 3. LDA hyperparameter tuning results; (a) alpha vs coherence score, (b) beta vs coherence score, and (c) number of topics vs coherence score

Figure 4 reveals that the main terms are "*kuota*" and "*ekonomi biru*." Figure 4(a) topic 0's word cloud emphasizes Indonesia's maritime policy, highlighting "*kuota*," "*nelayan*," and sustainable fishing programs. Figure 4(b) topic 1 focuses on economic initiatives, featuring "*kkp*," "*bangga*," and sustainable development in fisheries. The lexicon-based labeling creates imbalanced classes, as shown in Figure 5(a), which is addressed by oversampling to produce 1,000 synthetic samples per class for LSTM sentiment modeling, as shown in Figure 5(b).

The LSTM model with LDA topics showed low loss, as shown in Figure 6(a), and high accuracy on training data, as shown in Figure 6(b), outperforming the baseline model despite some overfitting. The optimal hyperparameters were {'batch_size': 16, 'epochs': 50, 'lr': 0.0067, 'lstm_units': 128}. Table 4 shows that the LDA-enhanced model improved precision, recall, and F1 score for all sentiment classes compared to the baseline. Although the baseline had slightly higher recall for the neutral class, the LDA model performed better overall, indicating enhanced sentiment classification accuracy.

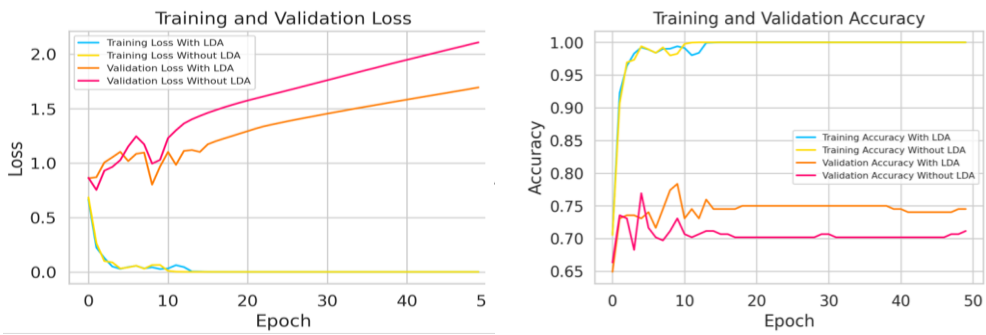
(a) (b)

Figure 4. Word cloud of; (a) topic 0 and (b) topic 1



(a) (b)

Figure 5. Distribution of the number of document samples for each sentiment label class (positive, neutral and negative); (a) before oversampling and (b) after oversampling



(a) (b)

Figure 6. Training and validation results of LSTM sentiment models with and without LDA dominant topic features in; (a) loss and (b) accuracy

Table 4. Sentiment model evaluation results

Model		Precision	Recall	F1 score	Support
LSTM without LDA	Negative	0.3750	0.2727	0.3158	22
	Neutral	0.7304	**0.8750**	0.7962	96
	Positive	0.7532	0.6444	0.6946	90
	Accuracy			0.7115	208
	macro avg	0.6196	0.5974	0.6022	208
	weighted avg	0.7027	0.7115	0.7014	208
LSTM with LDA	Negative	0.4000	0.3636	0.3810	22
	Neutral	0.7615	**0.8646**	0.8098	96
	Positive	0.8101	0.7111	0.7574	90
	Accuracy			0.7452	208
	macro avg	0.6572	0.6464	0.6494	208
	weighted avg	0.7443	0.7452	0.7417	208

3.2. Statistical analysis

Because LSTM's heuristic nature can cause fluctuating sentiment model results, statistical analysis through hypothesis testing is necessary. Hypothesis testing using multivariate analysis of variance (MANOVA) [29] in Table 5, showed that adding LDA topic features significantly improved LSTM performance ($p=0.037<0.05$) with macro and weighted averages of precision, recall, and F1 score evaluated.

Table 5. Hypothesis test results using MANOVA

Effect		Value	F	Hypothesis df	Error df	Sig	Partial eta squared	Noncent parameter	Oberserved power
Intercept	Pillai's trace	.998	6867.781[b]	3.000	36.000	.000	.998	20603.344	1.000
	Wilks' lambda	.002	6867.781[b]	3.000	36.000	.000	.998	20603.344	1.000
	Hotelling's trace	572.315	6867.781[b]	3.000	36.000	.000	.998	20603.344	1.000
	Roy's largest Root	572.315	6867.781[b]	3.000	36.000	.000	.998	20603.344	1.000
Condition	Pillai's trace	.207	3.133[b]	3.000	36.000	.037	.207	9.398	.680
	Wilks' lambda	.793	3.133[b]	3.000	36.000	.037	.207	9.398	.680
	Hotelling's trace	.261	3.133[b]	3.000	36.000	.037	.207	9.398	.680
	Roy's largest Root	.261	3.133[b]	3.000	36.000	.037	.207	9.398	.680

4. CONCLUSION

This research produced a framework for applying topic modeling with LDA to sentiment modeling using LSTM. The design is a cascading process system that utilizes LDA modeling to produce dominant topics from a collection of tweet documents on social media as a response to measurable public fishing policies created by the government. The evaluation of the use of these dominant topics as new features for sentiment modeling using LSTM resulted in a significant increase in the performance of the resulting model. This new feature can provide contextual semantic correlation information, which is useful for LSTM models. Applying topic modeling using LDA to sentiment modeling with LSTM has the advantage of carrying out sentiment analysis more accurately and determining what topics are dominantly discussed in public response tweets on social media. Handling overfitting that occurs in experiments and generalizing the model in future research can be a space for development that can be carried out to further improve model performance based on the results of this research.

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