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Dynamics of Indonesian Public Opinion on the Rohingya Crisis in Time Perspective Using Traditional Machine Learning and Deep Learning

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Abstract

The Rohingya are an ethnic minority who currently still face persecution and discrimination in Myanmar, so they have to flee to neighboring countries, such as Indonesia. However, the polemic regarding the issue of the existence of Rohingya refugees in Indonesia still shows that there are differences of opinion between groups who support and oppose it. For this reason, this research aims to determine the dynamics of Indonesian public opinion regarding the Rohingya from 2015-2023 via Twitter, as well as find out the topics that are often discussed each year using LDA. This research compares classification methods using traditional machine learning algorithms (NB, SVM, LR, and DT) and deep learning algorithms (LSTM, GRU, LSTM-GRU, and GRU-LSTM). The research results show that the traditional machine learning algorithm, LR, has the highest accuracy. There has been a change in sentiment from initially being dominated by positive sentiment to negative sentiment which is more dominant in the last five years. The topics that are often discussed for positive sentiment are the support of the Indonesian people for the Rohingya in providing assistance and shelter, while the negative topics are related to concerns about the social, economic, and security impacts that may be caused by the presence of Rohingya refugees.

A. Introduction

Rohingya are an ethnic minority group originating from the Rakhine region in Myanmar. Some historians acknowledge the existence of this ethnic group, but the debate surrounding their citizenship status still raises conflicts today. The Myanmar government refuses to recognize the Rohingya as citizens because they are not considered to be an ethnic group that existed in Myanmar before the country's independence in 1948. Since the 1950s, several acts of violence and discrimination have been accepted by the Rohingya [1] to force them to seek refuge in neighboring countries such as Bangladesh, Malaysia, Thailand, and other Southeast Asian countries, including Indonesia. According to UNHCR data in March 2024, 7,272 Rohingya refugees have arrived in Indonesia since 2006 [2].

In Indonesia itself, until now polemics related to the issue of Rohingya refugees in Indonesia still show differences of opinion between groups that support and oppose. Some parties support the presence of Rohingya refugees in Indonesia as a form of humanitarian response and international solidarity. However, some community groups or government parties may be concerned about potential security risks associated with the presence of Rohingya refugees in Indonesia such as radicalism or crimes involving refugees. Moreover, Indonesia did not ratify the 1951 Refugee Convention so Indonesia was not obliged to accept refugees from the Rohingya.

The existence of these pros and cons changes over time. For this reason, further research needs to be done on the dynamics of Indonesian public opinion towards the Rohingya crisis. Rohingya refugees first arrived in Indonesia in 2009. However, polemics related to Rohingya refugees in Indonesia emerged in 2015 when many boats from Rohingya continued to arrive in Indonesia via Aceh. In 2015, some fishermen and residents of Aceh ignored the Indonesian Armed Forces (TNI) ban on not providing aid to Rohingya adrift at sea. As a result, hundreds of Rohingya and Bangladeshi refugees managed to arrive on the Aceh mainland [3]. However, in 2023 the opposite happened, Acehnese people refused the arrival of Rohingya refugees. For this reason, this study will use a time perspective approach to understand the dynamics or changes in the sentiment of Indonesian citizens starting from 2015 to 2023.

Twitter is one of the microblogging social media to share people's experiences, thoughts, opinions, and feelings in the form of writing [4]. Twitter is one of the most popular social media in Indonesia [5]. Sentiment analysis is one of the techniques capable of classifying tweets from Twitter into positive, negative, or neutral opinions [6]. Sentiment analysis is widely used to analyze the sentiments or feelings contained in people's opinions related to certain topics. Sentiment analysis can be done with three approaches: machine learning-based approaches, lexicon, and hybrid techniques [7]. Machine learning involves using algorithms and machine learning techniques to identify sentiments in text. Machine learning that is often used in sentiment analysis is traditional machine learning and deep learning. Deep learning involves using deep neural network architecture to extract complex features from text data [8].

Sentiment analysis research related to Rohingya has been conducted by Das et al.[9], this study aims to detect daily reports related to hate speech from Bangladeshis against Rohingya refugees using Naïve Bayes' traditional machine learning approach (NB). The same thing was also done by Rochmawati & Wibawa [10]. This research also uses NB classification. This research was conducted to find out world opinion through Twitter related to Rohingya. The results of the study stated that positive and negative opinions were almost balanced.

Meanwhile, many current studies use Deep Learning, such as research by Aljedaani et al.[7] where models such as CNN (Convolutional Neural Network), LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit), and CNN-LSTM are used for comparison with the latest machine learning models, Logistic Regression is also used (LR), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Extra Trees Classifier (ETC), and Gradient Boosting Classifier (GBC). LSTM and LSTM-GRU achieved the highest accuracy of 0.97 and other models had more accuracy of 0.8. Other research was also conducted by Aslam et al.[11] to analyze sentiment and emotion detection using cryptocurrency-related tweets which are widely used to predict cryptocurrency market prices. The results of the proposed LSTM-GRU Ensemble show an accuracy of 0.99.

Even though deep learning is a popular algorithm today, deep learning does not always have higher accuracy than traditional machine learning. In research conducted by Maity & Sarkar[12] the kernel SVM, SVM, and LTSM methods were compared. As a result, composite kernel SVM achieved an average accuracy of 83%, SVM 79%, and LTSM only 77%. Likewise, research conducted by Wang et al.[13], the SVM and CNN algorithms were compared and the result was that the SVM accuracy was 0.86 while the CNN accuracy was 0.83. For this reason, a comparison between traditional machine learning and deep learning will be carried out.

Latent Dirichlet Allocation (LDA) is unsupervised learning. LDA can help in identifying the main topics in each document. Research conducted by Saura et al. [14] identified 10 topics related to the main opportunities and challenges for remote work using the LDA method. In research conducted by Cai et al.[15] also carried out topic modeling using LDA equipped with time series visualization to visualize sentiment based on time.

Based on previous research, this study aims to compare the performance between the use of traditional machine learning algorithms (NB, SVM, DT, LR) and deep learning (LSTM, GRU, LSTM-GRU, GRU-LSTM). These algorithms were chosen because they have been proven to have a high level of accuracy [7] [9] [11] [12] [13]. In addition, to identify changes in sentiment, a time series visualization of sentiment based on year will be carried out. To find out the causes of the dynamics of public opinion towards the Rohingya, topic modeling analysis will also be carried out using LDA. It is hoped that this research can prevent social tensions from occurring in Indonesia due to the Rohingya issue. It is hoped that the results of this analysis can be a reference for the Indonesian government and society in responding to the Rohingya issue and can also contribute to the development of theories and methods in the study of public opinion.

B. Research Method

The flow of research methods carried out can be seen in Figure 1.

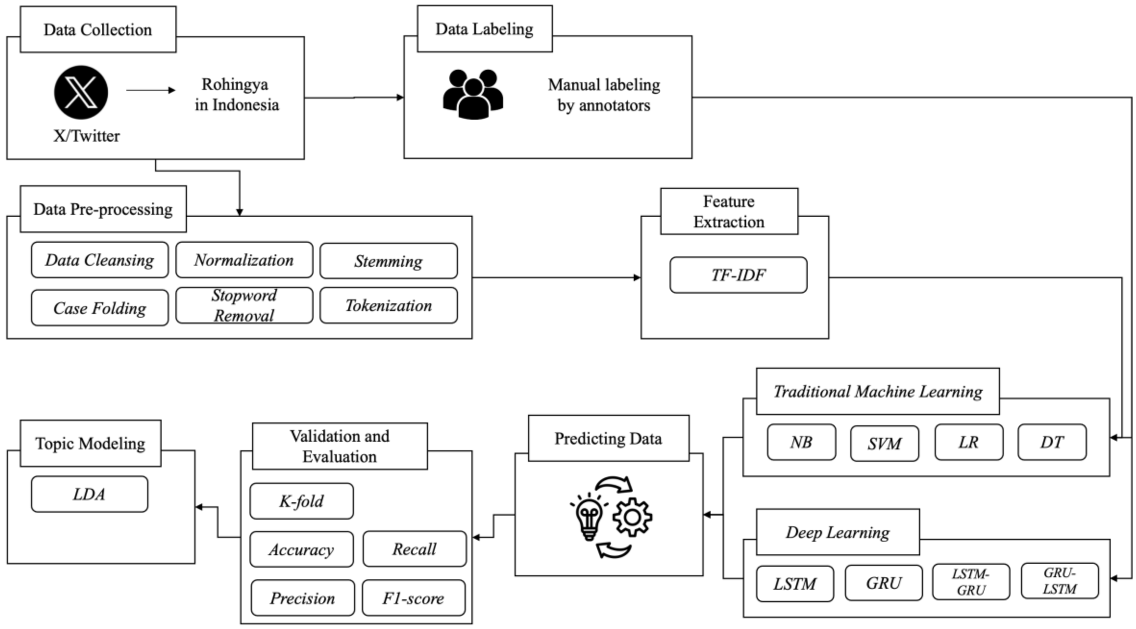

Figure 1. Flow of Research Methods

1) Data Collection

Data is obtained from the social media platform Twitter using *Crawling*. Data collection was carried out between January 2015 and December 2023 with the keywords "Rohingya" and in Indonesian. The data obtained after filtering the data, namely removing duplicates and filtering back the content in Indonesian, was 106,261 tweets.

2) Data Labeling

At the data labeling stage, the annotation process is carried out manually by three annotators who are given the same annotation guidance. Previously duplicate data was removed. Opinions from Twitter users are classified into three classes: positive, negative, and neutral sentiments. The annotation is carried out in two stages. In the first stage, the two annotators annotate independently so that the annotator cannot know the results of the other party's annotation until the annotation time ends. The second stage is done with the third annotator to label only tweets with different labels between the first and second annotators. As sample data to obtain the best classification model, as many as 400 tweets are taken annually, so a total of 3,600 tweets data are used as sample data. The measurement of the degree of agreement is done by Cohen's Kappa method between two annotators who annotate independently. Measurements are taken to ensure that both labeling results are sufficiently consistent. Cohen's Kappa value is 0.811 or above 0.8, indicating that consistency between the two labeling results is high.

3) Data Pre-processing

At this stage, it is carried out to eliminate unnecessary information or noise on Twitter data that has been collected at the data collection stage. Table 1 shows the difference before and after data pre-processing. Here are the steps performed in data pre-processing:

a) Data Cleansing: removes unnecessary things such as, removes links or URLs, emojis, mentions (@), hashtags (#), punctuation, and extra spaces contained in tweets.

b) Case Folding: changes the text in a tweet to lowercase.

c) Normalization: converting words into standard words based on self-developed word dictionaries.

d) Stopword Removal: removes low-information words or unimportant words like hyphens contained in tweets.

e) Stemming: turning words in tweets into root words

f) Tokenization: breaking text into tokens consisting of words.

Table 1. Examples of Tweets Before and After Data Pre-Processing

No	Before Data Pre-Processing	After Data Pre-Processing
1	*@diaryellakim @Nana_naa07 @Greschinov Mbak terlalu jauh khayalannya 😱. Orang Rohingya udah ada yg 10 tahun di sini, tepatnya di Sidoarjo. Mereka gak bisa kerja (karena bukan WNI). Mereka sering bantu kegiatan warga, kek bersih2 masjid. Pengungsi yg udah puluhan tahun di sini juga gak cuma Rohingya, ada Afganistan jg*	*mbak terlalu jauh khayal orang rohingya tahun sini tepat sidoarjo tidak kerja bukan wni sering bantu giat warga bersih masjid ungsi sudah puluh tahun sini tidak cuma rohingya ada afganistan jg*
2	*Yang jauh di seberang lautan di urusin bahkan di galangin dana (palestina). Sedangkan yg di depan mata di tidak mau di urus bahkan di bongkar tenda penampungannya (pengungsi rohingya). #Memalukan_sekali #warga+62*	*jauh seberang laut urusin bahkan galangin dana palestina yang depan mata tidak mau urus bahkan bongkar tenda tampung ungsi rohingya*

4) Feature Extraction

For feature extraction use Term Frequency-Inverse Document Frequency (TF-IDF) for traditional machine learning. TF-IDF is a technique for extracting and inferring expected contextual usage relationships from words in conversational passages. This technique is obtained by counting the frequency of words in the corpus and then converted into numerical representations before being processed by learning models [16].

5) Designing Sentiment Classification Models

A comparison of traditional machine learning and deep learning algorithms will be done to get the best model to classify the overall sentiment of the collected data.

Traditional machine learning also known as conventional machine learning, refers to the classical approach in the field of machine learning where a single model or algorithm is used to perform predictions or classifications based on a given training data [17]. Examples of Traditional machine learning algorithms such as NB, SVM, LR, and DT.

a) Naïve Bayes (NB): a multiclass classification model proposed by British scientist Thomas Bayes. This classification technique makes use of probability and statistical methods to anticipate the likelihood of future events based on experience, known as Bayes' Theorem [4].

b) Support Vector Machine (SVM): one of the supervised machine learning techniques that can be used for both classification and regression problems. SVM looks for hyperplanes that can separate data points into groups [18].

c) Logistic Regression (LR): a classification model that can provide probabilities and classify new data based on continuous or discrete datasets. LR can classify observations using a variety of data types and can easily determine the variables most effectively used for classification [7].

d) Decision Tree (DT)): a tree-based model. It uses nodes and leaves by sorting them by root and adopting a representation of the sum of products. This tree-based model is used for regression and classification problems [7].

Deep learning involves using deep neural network architecture to extract complex features from text data [8]. An example of a Deep Learning algorithm is the Recurrent Neural Network (RNN) which has advanced development, namely LSTM and GRU.

a) Long Short-Term Memory (LSTM): designed to deal with long-term dependency problems in sequential data. The LSTM model has a memory unit that allows it to store information over time, thus enabling long-term understanding of context in sequential data. This allows LSTM to be effective in tasks such as text classification, sentiment analysis, and time sequence prediction [8].

b) Gated Recurrent Unit (GRU): a type of neural network architecture similar to LSTM, but with a simpler structure. The GRU unit has gates that control the flow of information in and out of the unit, allowing it to store and update information in short-term memory in an efficient manner [8].

c) LSTM-GRU: a combination of LSTM and GRU used sequentially. The first input is given to the LSTM layer, which produces an output that is then given as input to the GRU layer. LSTM is responsible for parsing information and searching for longer-distance dependencies, while GRU processes the output from LSTM and can handle sequences efficiently. The LSTM-GRU architecture can be seen in Figure 2.

d) GRU-LSTM: a combination of GRU and LSTM used sequentially. The first input is given to the GRU layer, which produces an output that is then given as input to the LSTM layer. The GRU is responsible for deciphering the initial information and capturing sequence dependencies, while the LSTM processes the output from the GRU to maintain and manage the long-term information. The GRU-LSTM architecture can be seen in Figure 2.

A series of tests are carried out to validate and evaluate the model that has been built. Validation and evaluation are performed using k-fold cross-validation and confusion matrix which produces accuracy, precision, recall, and F1-Score output.

From the results of this evaluation, the best model is selected based on the documentation of the performance comparison evaluation results of each model that has been built. Once the entire dataset has been labeled with the selected classification model, sentiment analysis will be visualized with the Sentiment Time Series. In this visualization, we will see the dynamics of positive, negative, and neutral sentiment from Twitter data for 2015 – 2023 related to Rohigya by Indonesians. This Time Series will be presented using a time range per year.

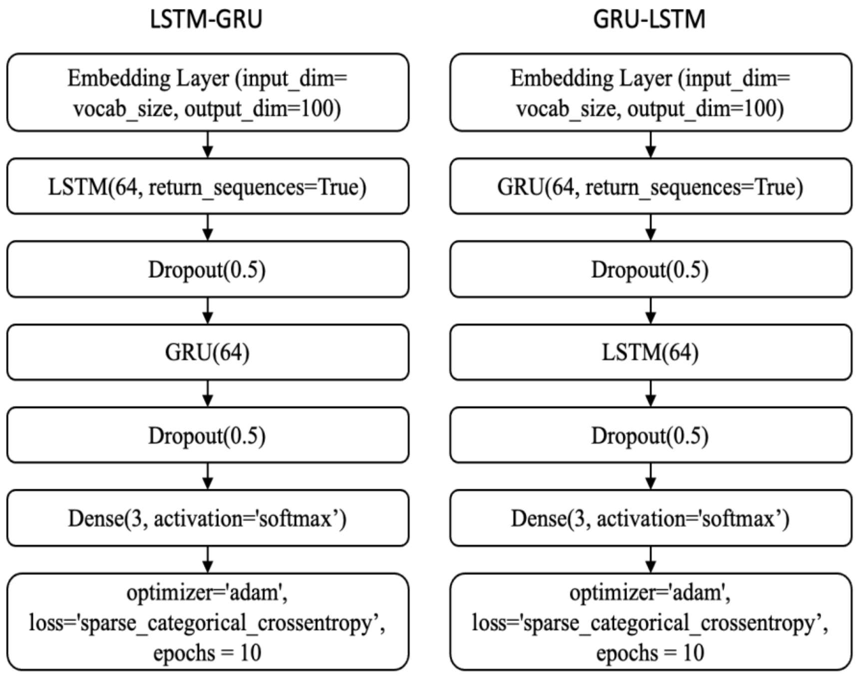

Figure 2. LSTM-GRU and GRU-LSTM architectures

6) Topic Modeling

At this stage, topic modeling is carried out to identify positive and negative topics using the Latent Dirichlet Allocation (LDA) method. LDA is unsupervised learning. LDA is a mathematical way to uncover hidden meanings in text. LDA can help identify key topics in any document. With a little human help, these topics can be labeled based on their main meaning. Datasets that have been classified into negative and positive sentiments become inputs in the topic modeling process[19]. Modeling this topic will show the factors of positive and negative sentiment each year from 2015-2023.

C. Result and Discussion

The annotator's labeling process on 3,600 sample data resulted in positive labels: 813, neutral: 1,438, and negative: 1,349. The sample data is used as training data and testing data to train and test machine learning models. Table 2 shows the macro average result of accuracy, precision, recall, and F1-score of k-fold cross-validation with a k-fold of 5 for the algorithm Traditional Machine Learning namely NB, SVM, LR, and DT as well as algorithms Deep Learning namely LSTM, GRU, LSTM-GRU, and GRU-LSTM. Table 2 indicates that on Traditional Machine Learning the highest average accuracy value was obtained with an LR classification of 0.620. Likewise, for the highest average score for F1 score, the LR classification is 0.622. While on Deep Learning LSTM scores have the highest average accuracy and F1-score, which are both 0.572.

Table 2. Classification Result

No	**Classification Type**	***Classification Algorithms***	***Macro Avg Accuracy***	***Macro Avg F1-score***

1	Traditional Machine Learning	NB	0.607	0.601
		SVM	0.608	0.606
		LR	**0.620**	**0.622**
		DT	0.517	0.510
2	Deep Learning	LSTM	0.572	0.572
		GRU	0.562	0.561
		LSTM-GRU	0.559	0.554
		GRU-LSTM	0.552	0.572

The confusion matrix for traditional machine learning algorithms (NB, SVM, LR, and DT) and deep learning algorithms (LSTM, GRU, LSTM-GRU, and GRU-LSTM) can be seen in Figure 3 and Figure 4.

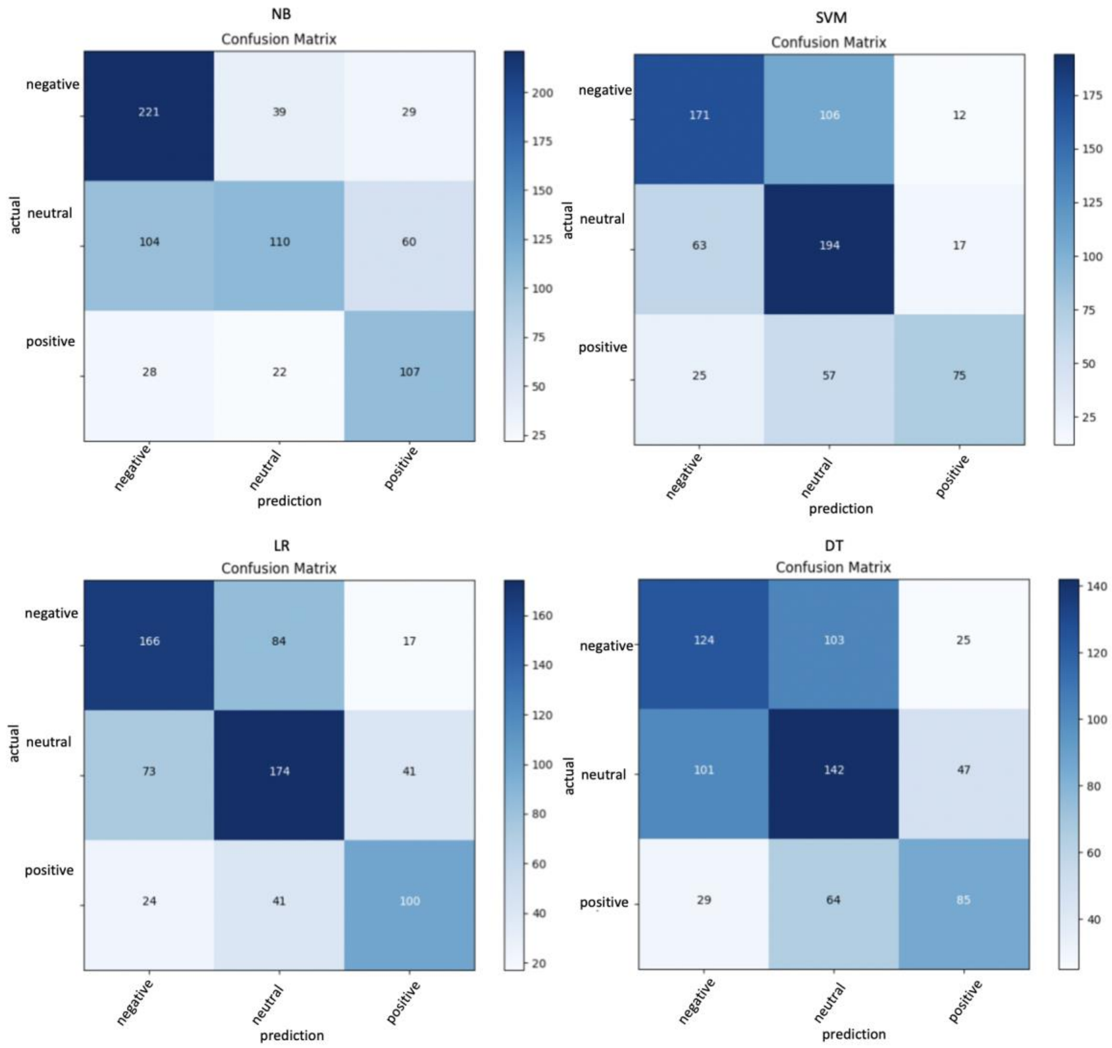

Figure 3. The confusion matrix for traditional machine learning algorithms (NB, SVM, LR, and DT)

In Figure 3, it can be seen that the LR confusion matrix produces the most balanced distribution compared to the other three classifications. In the NB classification, the highest prediction error was for tweets labeled neutral which could only predict correctly 40.14% (110 of 274 tweets), while for labeled negative it could predict correctly 76.47% (221 of 289 tweets), and for positive labels 68

.15% (107 of 149 tweets). The highest prediction errors in actual neutral and negative predictions were 37.95% (104 of 274 tweets). In the SVM clarification, the highest prediction error was in the positive label tweets which only predicted correctly 47.7% (75 of 157). The negative label can predict 59.16% (171 of 289 tweets) and the neutral label has the highest correct prediction, namely 70.8% (194 of 274 tweets). The highest prediction errors were actual negative and neutral predictions at 36.67% (106 out of 289 tweets) and neutral-negative at 36.3% (57 out of 157 tweets). In LR classification, it has balanced correct predictions between negative labels 62.17% (166 of 267 tweets), neutral labels 60.41% (174 of 288 tweets), and positive labels 60.61% (100 of 165 tweets). The highest prediction errors were actual negative and neutral predictions at 31.46% (84 out of 267 tweets) and neutral-negative at 25.34% (73 out of 288 tweets). Finally, in the DT classification, the correct predictions for the three labels are also balanced but have quite low values. Correct predictions for negative labels were 49.21% (124 of 252 tweets), 48.96% of neutral labels (142 of 290 tweets), and 47.75% of positive labels (85 of 178 tweets). There were three highest prediction errors, namely negative-neutral at 40.87% (103 out of 252 tweets), positive-neutral at 35.95% (64 out of 178 tweets), and neutral-negative (101 out of 290 tweets). The overall analysis results of the traditional machine learning algorithm's confusion matrix on this data experienced difficulty in predicting sentiment labeled neutral and negative.

Figure 4 shows the results of the confusion matrix as follows. In LSTM classification, false and correct predictions for each sentiment label are almost equal. The negative label had a correct prediction of 59.41% (161 of 271 tweets), the neutral label had a correct prediction of 52.26% (150 of 287 tweets) and the positive label had a correct prediction of 61.11% (99 of 162 tweets).). The high prediction errors were in actual negative and neutral predictions (negative-neutral) at 29.89% (81 of 271 tweets), neutral-negative at 26.13% (75 of 287 tweets), neutral-positive at 21, 6% (62 of 287 tweets), and positive-neutral 21.6% (35 of 162 tweets). In the GRU classification, the predictions are correctly balanced. For the negative label, it can predict correctly 61.48% (166 of 270 tweets), the neutral label has a correct prediction of 56.79% (163 of 287 tweets) and the positive label has a correct prediction of 52.76% (86 of 163 tweets).). The high prediction errors were in actual negative and neutral predictions (negative-neutral) at 30% (80 out of 270 tweets), neutral-negative at 29.26% (84 out of 287 tweets), and positive-neutral at 29.44% (48 of 163 tweets). In the LSTM-GRU classification, the correct predictions are almost equal. For the negative label, it can predict correctly 52.96% (143 of 270 tweets), the neutral label has a correct prediction of 62.71% (180 of 287 tweets) and the positive label has a correct prediction of 52.76% (86 of 163 tweets).). The high prediction errors were in actual negative and neutral predictions (negative-neutral) at 37.4% (101 out of 270 tweets), neutral-negative at 22.64% (65 out of 287 tweets), and positive-neutral at 27. 61% (45 of 163 tweets). In the GRU-LSTM classification, the predictions are correctly balanced. For negative labels, the correct predictions were 57.03% (154 of 270 tweets), neutral labels had correct predictions of 57.83% (166 of 287 tweets) and positive labels had correct predictions of 58.28% (95 of 163 tweets).). The high prediction errors were in actual negative and neutral predictions (negative-neutral) at 33.33% (90 out of 270 tweets), neutral-negative at 28.22% (81 out of 287 tweets), and positive-neutral at 26. 99% (45 of 163 tweets).

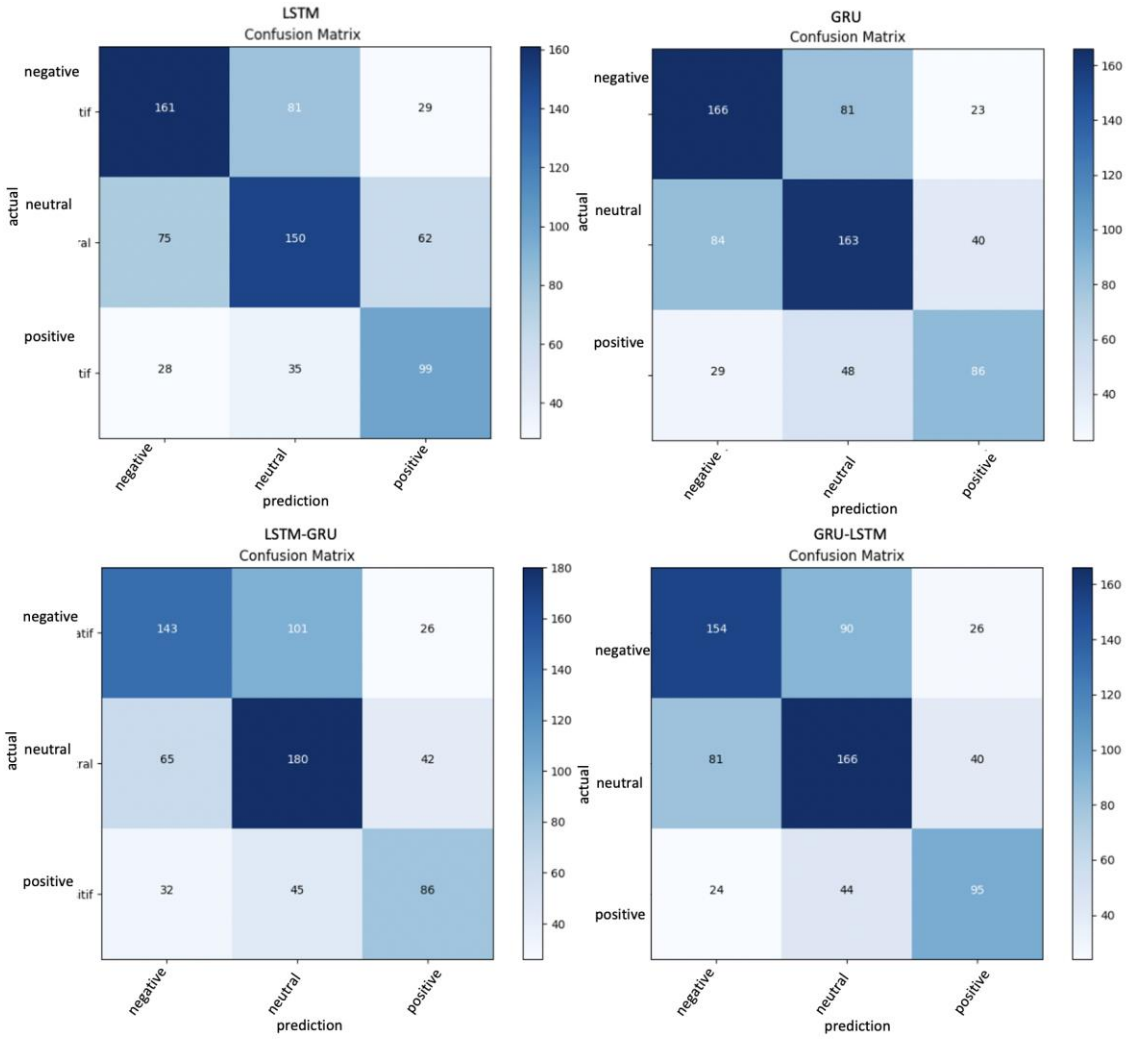

Figure 4. The confusion matrix for deep learning algorithms (LSTM, GRU, LSTM-GRU, and GRU-LSTM)

Based on the results of the confusion matrix. It can be concluded that the LR classification has the highest correct prediction and the lowest prediction error. These findings are consistent with the accuracy results shown in Table 2, so the LR model is chosen as the best model. Table 3 is an example of model prediction results using LR classification. The overall labeling of the data was carried out and resulted in a negative sentiment of as much as 43,872, then a slight difference with a neutral sentiment of as much as 40,535, and finally a positive sentiment of as much as 21,869. The overall sentiment results can be seen in Figure 5.

Table 3. Example of Prediction Results using LR classification

Actual	**Prediction with LR Classification**		
	Negative	**Neutral**	**Positive**
Negative	*@Nikkontol Sentimen warga Aceh udah mulai ngikutin warga*	*@AnnMaymann Tolong kembalikan Rohingya ke*	*Bubarkan UNHCR usir rohingya imigran ilegal*

	Malaysia yg udah kesal dgn ulah pengungsi Rohingya Mereka mending dipindahin ke Jakarta Jawa Barat dan Banten aja deh biar kita semua merasakan dampak dari para pengungsi tsb	*negaranya. Kami rakyat Indonesia tidak mau menampung mereka*	*human trafficking jangan kasih tempat di Indonesia*
Neutral	*Etnis Rohingya Tanpa Kewarganegaraan Jadi Tantangan Bagi Pemerintah Baru Myanmar*	*Permasalahan status pengungsi Rohingya asal Myanmar saat ini masih menjadi tanda tanya*	*Politisi PKS Ini Minta Kaukus Parlemen untuk Rohingya Perlu Segera Dibentuk*
Positive	*Kenapa kita tidak demo utk org2 Rohingya? Bukankah mrk saudara Muslim yg sdg dibunuh dan disiksa? #DoauntukAhok #DoauntukRohingya*	*Mahasiswa FK Unimal Ajarkan Rohingya Hidup Sehat #BeritaAceh*	*Alhamdulillah. ..ðŸ˜�ðŸ˜�@maspiyung an: Suasana Gembira Buka Puasa Pertama Pengungsi Rohingya di Aceh*

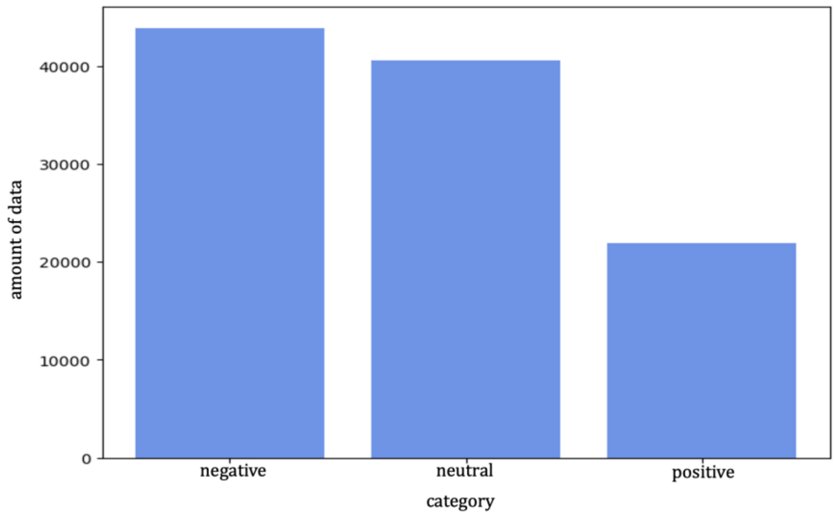

Figure 5. Overall Sentiment with LR Classification

Changes in sentiment are made annually using data that has been labeled with LR classification. To find out the dynamics of Indonesian public opinion related to Rohingya from 2015 – 2023 can be seen in Figure 6. The picture shows that there are sentiment dynamics that change from year to year. In 2015 - 2016 positive sentiment was higher than negative and neutral sentiment, then in 2017 - 2020, neutral and negative sentiment were almost the same, while positive sentiment decreased, then in 2021 - 2023, negative sentiment dominated. The factor of changing sentiment can be seen after discussions related to topic modeling.

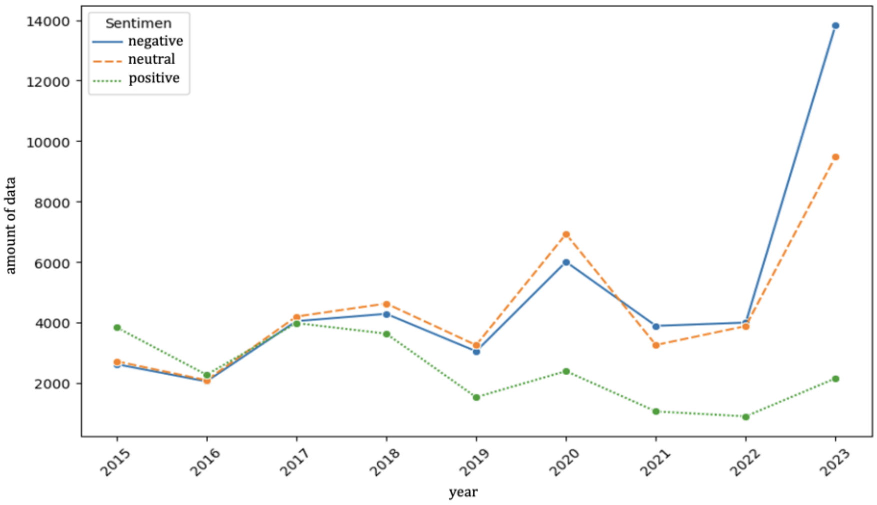

Figure 6. The Time Series Sentiment

Topic modeling is divided per year with each separate into positive and negative topics based on the results of sentiment analysis that has been carried out previously. The topic modeling results are summarized in Table 4.

Table 4. Summary of The Topics

Year	Positive Topics	Negative Topics
2015	• There is solidarity and support shown by the people of Aceh towards Rohingya refugees • There are aid and acceptance efforts provided by the people of Aceh to Rohingya refugees • Acceptance of Rohingya refugees and provision of shelter	• There is an issue of provocateurs defrauding Rohingya refugees in Aceh which has been declared unproven by the police. • Some refugees use marijuana. • There is the issue of smuggling and trafficking of Rohingya refugees. • Disappointing the Myanmar government because it is considered to have failed in handling the Rohingya humanitarian crisis.
2016	• Support from the community in providing sacrifices, alms, and prayers • Support for human rights protection. • Indonesia's efforts to open its doors to Rohingya refugees and provide necessary assistance.	• There is disappointment with Rohingya refugees who commit crimes • There is disappointment with the individuals who stole aid from the Rohingya • The Myanmar government is disappointed • There is negative sentiment regarding the issue of narcotics sentences where the sentences for Rohingya refugees are lighter than for Indonesian citizens
2017	• There is solidarity and support from the community for Rohingya refugees • There are continuous efforts from the Indonesian people to assist Rohingya refugees	• The use of sharp weapons in refugee camps. • There is negative sentiment due to bad news regarding the Rohingya. • There is negative sentiment due to the potential for bad results with the Rohingya case in Myanmar.
2018	• There is solidarity and support from the community for Rohingya refugees • There are continuous efforts from the Indonesian people to assist Rohingya refugees	• There is a stigma that Rohingya have bad behavior • There are cases of rape committed by Rohingya refugees • There is negative sentiment toward the Myanmar government

	• There is support to help the education of Rohingya children.	
2019	• There is solidarity and support from the community for Rohingya refugees • There are continuous efforts from the Indonesian people to assist Rohingya refugees • There is support to help the education of Rohingya children.	• There are cases of murder committed by Rohingya refugees in Bangladesh, which has affected the sentiments of Indonesian citizens. • There is negative sentiment towards the Myanmar government. • There is sentiment regarding the costs incurred by destination countries for Rohingya refugees. • There is a negative sentiment from some Indonesian people regarding the people's support for the Rohingya while in their own country, there are those who are oppressed
2020	• There is solidarity and support shown by the people of Aceh towards Rohingya refugees • Support from the community in providing aid and prayers • There are efforts to urge Myanmar to resolve the problems faced by the Rohingya.	• There is negative sentiment towards Rohingya due to bad behavior in refugee camps • There are feelings of anxiety, disturbance, or discomfort with the presence of Rohingya refugees in Indonesia • There are concerns about the social, economic, and security impacts that may be caused by the presence of Rohingya refugees
2021	There is solidarity and support shown by the Indonesian people, especially the people of Aceh, towards Rohingya refugees	• There is negative sentiment because they feel that the Rohingya are not native to Myanmar and therefore deserve to be expelled. • There was an earlier Rohingya Muslim opinion against the Myanmar military • There are feelings of disappointment and anger over the cruel treatment of the Rohingya community • There is negative sentiment towards Rohingya due to bad behavior in refugee camps
2022	• There is solidarity and support from the community for Rohingya refugees • There are efforts to provide protection	• Some refugees have fled • Aceh cannot continue to handle the influx of Rohingya refugees for a long time, • There is an opinion that Rohingya militants are massacring Hindus to convert them to Islam • There is a sentiment that the Rohingya are just a burden • There are feelings of anxiety, disturbance, or discomfort with the presence of Rohingya refugees in Indonesia • There are concerns about the social, economic, and security impacts that may be caused by the presence of Rohingya refugees
2023	There is solidarity and support from the community for Rohingya refugees	• There are feelings of anxiety, disturbance, or discomfort with the presence of Rohingya refugees in Indonesia • There are concerns about the social, economic, and security impacts that may be caused by the presence of Rohingya refugees

The results of sentiment dynamics seen in Figure 6 and topics in Table 4 can be correlated as follows:

In 2015 - 2016 positive sentiment was higher. This is due to the high level of support in the form of prayers, alms assistance, and the provision of shelter for Rohingya refugees. Feelings of compassion for the persecuted and slaughtered Rohingya in their home country increased public sympathy. Indonesians, especially Acehnese people who are co-religionists with Rohingya who are Muslims, showed strong solidarity.

In 2017 - 2019 negative sentiment was slightly higher than positive sentiment. This is due to cases of crime, rape, and drug use committed by Rohingya refugees. The existence of bad news, such as refugees fleeing, also adds to the negative sentiment of the Indonesian people.

In 2020 – 2023 there was a significant increase in negative sentiment towards the Rohingya, while positive sentiment decreased. Factors that cause this to happen are undesirable behavior in refugee camps, such as indiscipline, unwillingness to contribute to keeping shelters clean, and voters accepting assistance. In addition, the spread of bad opinions, including perceptions of militancy among the Rohingya who first carried out the attacks and the perception that they were only a burden to the state, further muddied the atmosphere. This issue raises concerns about the social, economic, and security impacts that may arise from the presence of Rohingya refugees, while within the country, there are still many communities that need similar assistance and attention.

Research Implications

This research has theoretical and practical implications.

1) Theoretical Implications

In this study, the accuracy of traditional machine learning can be higher than deep learning. This can be due to the small size of the training data and the complexity of the problem is quite simple. This makes deep learning models less likely to overfit limited data, whereas traditional machine learning models such as LR can generalize better to small datasets with simpler patterns.

Time series sentiment and topics with LDA can help know the factors of sentiment change.

2) Practical Implications

Regarding the dynamics or changes in sentiment that occur concerning the Rohingya, especially the increase in negative sentiment in recent years, actions from the government as policymakers and active participation of the Indonesian people are needed to prevent social tensions from arising. Some of the reasons for the rejection of the Rohingya, in general, can be seen in the topics of negative sentiment. For this reason, researchers try to provide examples of practical uses that can be done based on the findings of the results of this study.

The findings topic negative sentiment about disappointment with Rohingya refugees who commit crimes. The government must strictly enforce the law against Rohingya refugees who engage in criminal acts, indiscriminately. Rohingya refugees may experience high trauma and emotional distress as a result of their experiences, so the government and humanitarian agencies can provide psychosocial assistance and mental health services to help them cope with the problem and prevent criminal acts from occurring. There needs to be an awareness campaign in the community, so that people can better understand the situation and challenges faced by Rohingya refugees and that not all Rohingya refugees are involved in criminal acts.

The findings of the topic of negative sentiment about the stigma that Rohingya have bad behavior. Psychosocial and mental health assistance programs are also expected to be able to overcome this problem. In addition, there is a need for educational programs, especially those related to manners and customs that exist in Indonesia, so that Rohingya refugees better understand how they should behave and interact in the country. These programs can help refugees adapt to local cultures and minimize potential cultural conflicts. The public can actively participate in this educational program.

The findings topic negative sentiment related to the costs incurred by the state for Rohingya refugees. The government needs to publicly communicate the source of funds spent on the Rohingya, such as not only from the Indonesian government itself but also UNHCR, Non-Governmental Organizations (NGOs), humanitarian agencies, local communities, and others. UNHCR must also actively participate in delivering and financing Rohingya refugees. The government can emphasize that the Indonesian people are the country's top priority in terms of assisting. Indonesia is helping the Rohingya on humanitarian grounds.

The findings topic negative sentiment about concerns about the social, economic, and security impacts that the presence of Rohingya refugees may have. Governments can work with neighboring countries and international institutions to deal with this crisis and mitigate its impact. Involving communities, especially local communities, in decision-making related to Rohingya refugees is also important. Public participation can help create harmony and gain wider support from the community, thereby reducing turmoil or tension in society.

The above examples are potential uses that can be considered from the perspective of the researcher. Researchers provide these examples based on understanding and research, but not necessarily these examples can be applied effectively. It could be that these examples do not match the actual field conditions. However, the researchers hope to provide an idea of how the results of this study can be utilized.

D. Conclusion

This research provides a comprehensive overview of how Indonesians' views on the Rohingya crisis have evolved, as well as identifying key issues of public concern. The results of this research can be used as a basis for the development of more effective and targeted policies in dealing with the Rohingya refugee crisis and increasing public understanding of the dynamics of sentiment towards this issue. As for traditional machine learning algorithms, Logistic Regression (LR) is the best model with an accuracy of 62%. Negative sentiment increased significantly from 2015-2023 due to concerns about the social, economic, and security impacts that may arise from the presence of Rohingya refugees.

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