Classification of User Expressions on Social Media Using LSTM and GRU Models

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Abstract— **Social media serves as a platform for sharing information. Through social media, users can interact with others and express their feelings and emotions. Therefore, emotion analysis plays a crucial role in understanding users' conditions regarding various issues and social events. This study aims to compare the performance of emotion classification models in analyzing and identifying users' emotions on social media. The research process includes data preprocessing, training, and model performance evaluation. The dataset used is derived from Twitter social media and is available on Kaggle. It consists of two main columns: text and label, with the latter categorized into six groups. The dataset undergoes several preprocessing techniques to ensure it is ready for model training. The model training process implements the architectures of LSTM and GRU to analyze the emotions contained within the text. The evaluation results show that the model achieves an accuracy of 93% for LSTM and 94% for GRU, indicating that the GRU model slightly outperforms the LSTM in classifying emotions in textual data. This research is expected to contribute to emotion analysis systems based on deep learning.**

Keywords— Emotion analysis; social media; sentiment classification; LSTM; GRU.

I. INTRODUCTION

The advancement of technology today has significantly benefited various aspects of human life. One of the technologies currently evolving is social media, which facilitates communication and information sharing over the internet. Social media generates vast and diverse data daily from the interactions of millions of users on these platforms [1]. Through these interactions, users' emotional expressions can be observed. This makes emotion expression on social media a compelling aspect, as emotions can be identified through textual content. Therefore, this research develops a classification model to understand emotions in social media content, providing insights into users' conditions across various aspects of life, such as public opinion, brand sentiment, trend shifts, product marketing, and more [2].

One of the challenges in analyzing emotions on social media is the complexity of the data. Emotions are often not expressed explicitly and are influenced by various factors such as culture, communication styles, and others. This makes emotion classification a difficult task, requiring effective algorithms to recognize patterns in social media text. Previous studies have demonstrated that machine learning algorithms can be utilized to classify emotions in social media text [3][4][5]. One study conducted in 2019 focused on sentiment analysis of Twitter social media regarding fast-food restaurants. This study compared several machine learning methods for sentiment analysis, with the best results achieved using the bagging method [6]. Subsequently, in 2022, a study aimed to identify emotions in tweets on Twitter, categorizing them into six groups to analyze user behavior and public attitudes toward various global events. This research utilized the SVM method [7]. Finally, in 2024, a study developed a classification model to identify emotions expressed by Twitter users in their tweets, employing the BiLSTM method [8]. These existing studies serve as references for further research using two methods: Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), both of which fall under the category of artificial neural networks [9]. LSTM is used because of its ability to handle the vanishing gradient problem in long sequence data. Meanwhile, GRU is used due to its simpler and more efficient structure, with fewer parameters compared to LSTM. Both methods are capable of analyzing long-term dependencies in sequential data, making them suitable for emotion-related text analysis.

Therefore, this study provides a new contribution regarding the effectiveness of RNN models in emotion classification on social media. Scientifically, it offers insights into the emotion analysis process in the digital realm, capable of identifying patterns in social media interactions. The findings of this research can be useful for developing emotion analysis applications that can be implemented in fields such as marketing, social studies, and public policymaking. Understanding the emotional conditions of social media users can be utilized to devise data-driven strategies for decision-making.

This study aims to develop models using LSTM and GRU algorithms to classify emotions in social media text [10]. The data used to create these models was obtained from Kaggle, a publicly available dataset collected from the Twitter social media platform [11]. The dataset preprocessing, including various techniques to ensure all data contains essential information for building the models. Next, the models are trained using the architectures and parameters of both algorithms LSTM and GRU. The performance of the models is evaluated to assess their effectiveness. Evaluation techniques include metrics such as accuracy, precision, recall, and F1-score to determine the models' ability to classify emotions. The evaluation results of both models are then

p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2370, Copyright ©2025
Submitted : January 6, 2025, Revised : January 14, 2025, Accepted : January 24, 2025, Published : January 31, 2025

compared to identify the most suitable algorithm for emotion classification on social media.

Overall, the results of this study are expected to contribute to understanding the emotional condition of users on social media. Additionally, by understanding the emotions expressed in social media interactions, this can be used as input for decision-making and improve the understanding of user communication dynamics. Furthermore, it can also offer potential for promoting products with more targeted marketing strategies through the application of emotion analysis and social studies conducted on social media.

II. Research Methodology

A. System Overview

Figure 1 illustrates the workflow followed in this study to develop an emotion classification model for social media users using the LSTM and GRU methods. The workflow begins with data collection from the Twitter social media platform, including text from users' tweets. After the data is collected, preprocessing is performed to prepare it for model development. The preprocessing steps include techniques such as tokenization (splitting the text into words), cleaning (removing punctuation, special characters, and irrelevant symbols), padding (standardizing text length), and lowercasing (converting all text to lowercase). These processes aim to ensure that the dataset is in the proper format and contains relevant information ready for model training.

Next, the preprocessed text data is converted into numerical vectors so that it can be understood by the model. After that, the dataset is split into two parts: the training dataset and the testing dataset. The training dataset is used to train the model using the LSTM and GRU methods [12][13]. Once the model is trained, evaluation is performed to measure how well the model predicts emotions. The evaluation process uses several metrics, including accuracy, precision, recall, and F1-score. Finally, the evaluation results of both models (LSTM and GRU) are compared to determine which model yields the best results in terms of accuracy and prediction performance.

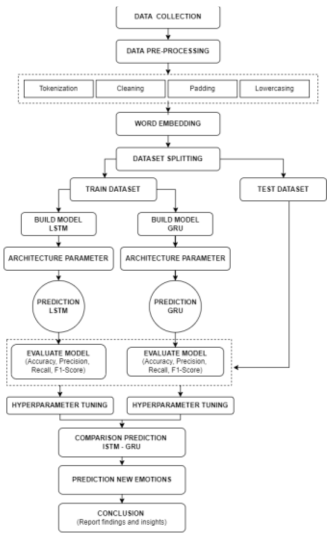


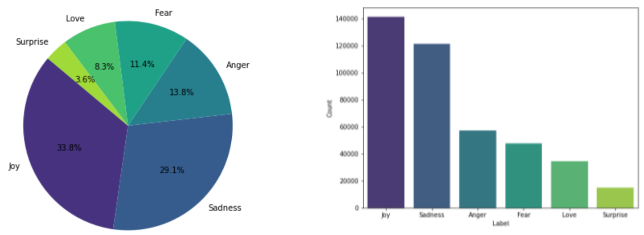
Fig. 1. System Overview

B. Dataset Description

The data used in this study was not directly measured by the researcher. It was obtained from the Kaggle platform, accessible to anyone via the website at www.kaggle.com. This dataset contains text from Twitter messages, labeled with six emotion categories: sadness, happiness, love, anger, fear, and surprise. The dataset consists of two columns: text and label. The text column contains the message data in string format, while the label column contains the emotion labels, which have been converted into numerical values ranging from 0 to 5, as shown in Table 1. Figure 2.a illustrates the distribution of data for each label, and the total number of data rows used is 416,809, with the number of data points for each label shown in Figure 2.b [14].

TABLE I. Category Label Code

Label Code	Category
0	Sadness
1	Joy
2	Love
3	Anger
4	Fear
5	Surprise



(a) (b)

Fig. 2. Dataset visualization: (a) distribution of categories, (b) count of each category

C. Data Preprocessing

In this section, the data preprocessing steps performed in this study are explained. The initial process begins with splitting the dataset into two parts: 90% for training data and 10% for testing data, using the *train-test split* method. This division ensures that the majority of the data is used for training to effectively train the model. After that, the visualization of the most dominant words across all emotion categories is shown in Figure 3, which helps in understanding the data distribution and provides an initial insight into the emotional patterns emerging in each category [15].

Next, the tokenization process is performed to break the text into word units, making it easier to analyze words separately. This process also converts the text into numerical format by assigning an index to each word. Following that, padding is applied to the data so that all word sequences have uniform length, ensuring the compatibility of the data with the LSTM and GRU models used in this study [16][17].

p-ISSN 2301-7988, e-ISSN 2581-0588
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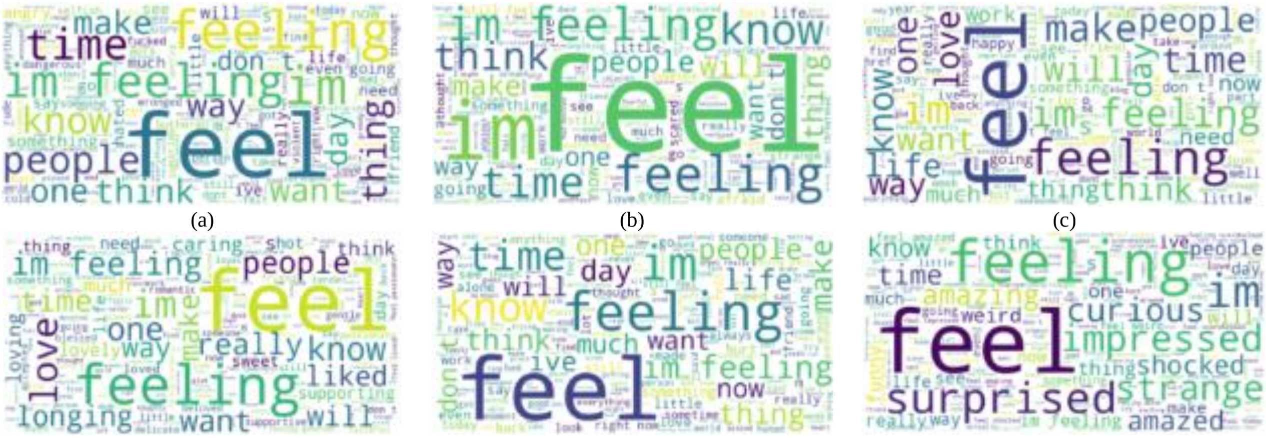
Submitted : January 6, 2025, Revised : January 14, 2025, Accepted : January 24, 2025, Published : January 31, 2025



(a) (b) (c) (d) (e) (f)

Fig. 3. Word cloud visualization from all categorie:(a) anger, (b) fear, (c) joy, (d) love, (e) sadness, (f) surprise

D. Long Short-Term Memory (LSTM)

The LSTM (Long Short-Term Memory) method is a type of Recurrent Neural Network (RNN) designed to address the vanishing gradient problem commonly encountered in traditional RNNs. In this study, LSTM is used to learn sequential data patterns, such as text. The LSTM process uses three main gates: the input gate, forget gate, and output gate. The input gate identifies important information from the words in the text sequence, which is stored in memory. The forget gate then discards irrelevant information that does not affect the classification process. Finally, the output gate integrates the information to establish relationships between words in the text sequence [18][19].

In its process, LSTM has two types of memory: cell state (long-term memory) and hidden state (short-term memory), which enable the network to learn long-term relationships between data in a time sequence [20]. The architecture of the LSTM model used in this study is explained in Table 2. The LSTM model starts with an Embedding Layer with a dimension of 128. It is followed by three LSTM layers: the first LSTM layer with 15 units, the second with 10 units, and the third with 5 units. After that, a Dropout layer with a ratio of 0.5 is used to reduce overfitting. Finally, the model ends with a Dense layer using 6 units and a Softmax activation function.

TABLE II. LSTM MODEL ARCHITECTURE

Layer	Properties
Embedding	input_dim=5,000, output_dim=128, input_length=max_length
1st LSTM	units=15, return_sequences=True
2nd LSTM	units=10, return_sequences=True
3rd LSTM	units=5, return_sequences=False
Dropout	rate=0.5
Dense	units=6, activation=Softmax

E. Gate Recurrent Unit (GRU)

The GRU method is a part or variation of LSTM that has a simpler architecture with only two types of gates: the reset gate and the update gate. The reset gate controls how much past information needs to be forgotten. Meanwhile, the update gate controls how much new information should be added and also determines how much old memory should be retained [21][22].

The GRU method is lighter compared to LSTM because GRU combines the cell state and hidden state into a single vector, making the computation process more efficient. Although the GRU architecture is simpler, it is still possible for GRU to provide better performance in emotion analysis and classification tasks. Table 3 explains the architecture used to build the GRU model with the same number of layers and units as the LSTM model. The number of units in each LSTM and GRU layer was selected based on experiments to achieve a balance between model complexity and performance. Gradual reduction of units improved generalization. A dropout rate of 0.5 was applied to prevent overfitting, while a Dense layer with 6 units and Softmax activation was used to classify data into 6 emotion categories.

TABLE III. GRU MODEL ARCHITECTURE

Layer	Properties
Embedding	input_dim=5,000, output_dim=128, input_length=max_length
1st GRU	units=15
2nd GRU	units=10
3rd GRU	units=5
Dropout	rate=0.5
Dense	units=6, activation=Softmax

F. Model Evaluation

The technique used for evaluation is the confusion matrix, which is a table containing four combinations of values between predicted and actual outcomes. These four combinations are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Through these combinations, we can calculate accuracy, precision, recall, and F-measure. The calculations for these values can be explained as shown in Table 4 [23][24][25].

TABLE IV. [22]EVALUATION MATRIX

Matrix	Equation
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$

p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2370, Copyright ©2025
Submitted : January 6, 2025, Revised : January 14, 2025, Accepted : January 24, 2025, Published : January 31, 2025

F1-Score	$F_\beta = \dfrac{1}{\beta \times \frac{1}{precision} + (1-\beta) \times \frac{1}{recall}}$

III. Result and Discussion

In this section, the results and testing of the model are explained based on the architecture designed using the LSTM and GRU methods. Tables 5 and 6 show the confusion matrix values for the LSTM and GRU models in classifying emotions. The categories Joy and Sadness have the highest accuracy values in both models, with correct predictions of 13,774 and 11,503 for LSTM and then 14,081 and 11,822 for GRU, respectively. Using these confusion matrix values, the model's performance in predicting each emotion category is calculated using accuracy, precision, recall, and F1-score.

Table 7 shows a comparison of the performance calculation results for accuracy between the LSTM and GRU models. The accuracy for the LSTM model is 93%, while the GRU model achieves 94%, which is slightly higher than that of LSTM. These results indicate that both models perform very well in emotion classification. Although the difference in results is minimal, GRU demonstrates a slight advantage in processing text data compared to LSTM.

Next, the performance results for precision, recall, and F1-score of the models are shown in Table 8, Table 9, and Table 10. It can be observed that the GRU model outperforms the LSTM model in several emotion categories. The precision value of GRU for the Love and Surprise categories reaches 100%, and the recall value for the Love category also reaches 100%. These results indicate that the GRU model has an advantage over LSTM in processing text data for emotion classification.

TABLE V. Confusion Matrix – LSTM Model

	Anger	Fear	Joy	Love	Sadness	Surprise
Anger	**5,276**	206	26	0	156	0
Fear	138	**4,614**	15	0	39	43
Joy	10	15	**13,774**	280	25	38
Love	1	1	884	**2,609**	0	0
Sadness	263	208	22	3	**11,503**	13
Surprise	0	422	119	0	12	**963**

TABLE VI. Confusion Matrix – GRU Model

	Anger	Fear	Joy	Love	Sadness	Surprise
Anger	**5,260**	139	25	0	243	0
Fear	172	**4,473**	7	0	197	0
Joy	24	12	**14,081**	5	16	4
Love	1	1	978	**2,515**	0	0
Sadness	112	64	13	1	**11,822**	0
Surprise	0	425	126	0	14	951

TABLE VII. Model accuracy performance

Method	Accuracy (%)
LSTM	93
GRU	94

TABLE VIII. Model precision performance

Label	LSTM (%) Precision	GRU (%) Precision
Anger	93	94
Fear	84	87
Joy	93	92
Love	90	100
Sadness	98	96
Surprise	91	100

TABLE IX. Model recall Performance

Label	LSTM (%) Recall	GRU (%) Recall
Anger	93	93
Fear	95	92
Joy	97	100
Love	75	72
Sadness	96	98
Surprise	64	63

TABLE X. Model F1-score Performance

Label	LSTM (%) F1-Score	GRU (%) F1-Score
Anger	93	94
Fear	89	90
Joy	95	96
Love	82	84
Sadness	97	97
Surprise	75	77

Figures 4 and 5 show the visualization of metrics for the LSTM and GRU models, including training accuracy and training loss. The training accuracy of the models (Figures 4.a and 5.a) shows an improvement as the number of epochs increases, indicating that the models are learning from the data used for training. Meanwhile, the training loss of the models (Figures 4.b and 5.b) shows a reduction in the model's error in performing the classification. Overall, these metrics demonstrate good performance of the LSTM and GRU models in emotion classification.

To obtain more comprehensive results, a comparison is made by testing several other machine learning methods. Table 11 presents a comparison of model performance based on evaluation metrics such as accuracy, recall, precision, and F1-score. Based on the results of the tests, it can be concluded that the GRU method achieved the highest accuracy compared to other methods in classifying emotions on social media.

TABLE XI. Comparison of Model Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
GRU	94	94	94	94
LSTM	93	93	93	93
BiLSTM	93	94	93	93
XGBoost	87	88	87	87
Random Forest	86	86	86	86
DT	84	84	84	84
Naive Bayes	83	85	83	82
AdaBoost	58	60	58	59
KNN	49	75	50	52

p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2370, Copyright ©2025
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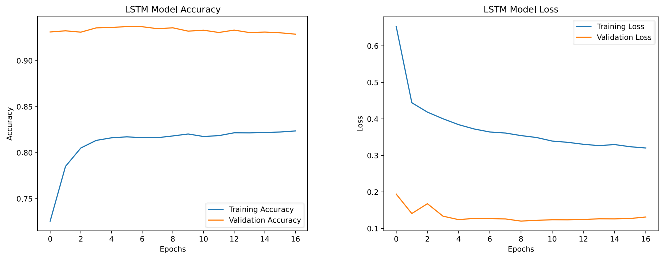
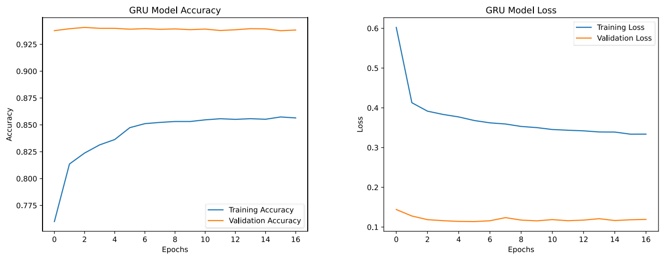


(a) (b)

Fig. 4. Visualization of metrics for LSTM: (a) training accuracy, (b) training loss



(a) (b)

Fig. 5. Visualization of metrics for GRU: (a) training accuracy, (b) training loss

ACKNOWLEDGMENT

I would like to express my sincere gratitude to ITB STIKOM Bali for their support throughout this research. I also wish to thank all of my colleagues for their continuous encouragement and assistance, which has been invaluable in the completion of this study.

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p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2370, Copyright ©2025
Submitted : January 6, 2025, Revised : January 14, 2025, Accepted : January 24, 2025, Published : January 31, 2025