Computer Engineering and Applications Vol. 14, No. 1, February 2025

Emotion Classification in Indonesian Text Using IndoBERT

Aditya Saiful Rizky[1*], Erwin Yudi Hidayat[2]

Department of Informatics Engineering, Faculty of Computer Science, Dian Nuswantoro University
**adityasrzky@gmail.com*

ABSTRACT

Mental health issues have become a challenge that affects many individuals around the world. A 2018 WHO report noted an increase in deaths by suicide, with a frequency of one case every 40 seconds. The Ipsos Global 2023 survey showed that 44% of respondents in 31 countries are concerned about mental health, while 30% identified stress as a major issue. In Indonesia, the mental health situation is also a serious concern. The 2022 I-NAMHS survey found that 34.9% of adolescents face mental health problems, but only 2.6% of them utilize counseling services. Emotion detection in text is challenging due to the absence of facial expressions or voice modulation. This study aims to classify emotions in Indonesian text using the IndoBERT model. The dataset used consists of 5079 tweets with five emotion labels: Angry, Fear, Joy, Love, and Sad. Parameter variations include the composition of training, validation, and test data split (80:10:10, 75:15:15, and 60:20:20), as well as the combination of learning rate (1e-2 to 1e-7) and batch size (8, 16, and 32). The model was trained for 25 epochs with the application of early stop and patience for 5 epochs. The experimental results showed that the composition of data split 80:10:10, learning rate 1e-6, and batch size 8 resulted in optimal classification. Although some experiments showed indications of overfitting, this research has important implications in the early detection of emotions and can help in mental health treatment efforts.

Keywords: Accuracy, Batch Size, IndoBERT, Emotion Classification, Learning Rate, Split Data

1. INTRODUCTION

Mental health issues are a global challenge that affects millions of individuals in various parts of the world. A report from the World Health Organization (WHO) in 2018 noted an increase in suicide deaths, with a frequency of one case every 40 seconds, and contributing 1.4% to total global mortality [1]. Then, the Ipsos Global 2023 survey showed that 44% of 23,274 respondents across 31 countries were most concerned about mental health, while 30% identified stress as a major health issue [2]. In Indonesia, the mental health situation is also a serious concern. Based on the Indonesia - National Adolescent Mental Health Survey (I-NAMHS) in 2022, 34.9% of adolescents, or around 15.5 million individuals, faced mental health problems in the past year. In the same period, 5.5% of adolescents or

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

around 2.45 million individuals experienced mental disorders. However, only 2.6% of them sought and utilized support or counseling services [3].

Lack of awareness and understanding of mental health often triggers stigma and inappropriate treatment of affected individuals [4]. In addition, access to mental health services is a significant challenge in Indonesia. A factor influencing the uneven distribution of mental health professionals is that the majority are centered in big cities. Currently, there are only about 2,808 clinical psychologists for a population of about 270 million people in Indonesia, or one clinical psychologist for 96,100 people. This is far below the World Health Organization (WHO) recommendation of one clinical psychologist for every 30,000 people [5]. Therefore, mental health issues should be a major concern for all parties.

Emotional intelligence has a significant influence on individual mental health. In understanding mental health, attention to emotional aspects is important because emotions are the basis of emotional intelligence [6]. Understanding emotions well and appropriately will have a positive impact on the physical and mental health of individuals [7]. With the development of technology, individuals easily express themselves on social media, including having opinions. Opinions often arise in response to messages conveyed by communicators, triggering discussions and reactions. Emotional reactions can be verbal or non-verbal. Verbal emotions involve the use of spoken or written language, while non-verbal emotions are seen in facial expressions, hand gestures and more. Detecting emotions in text is challenging as there are no facial expressions or voice modulations. One approach to detecting emotions is through classification based on certain criteria [8].

In the field of Artificial Intelligence (AI), text classification is a task of Neural Language Processing (NLP) [9]. NLP enables understanding, interpretation and response to human language, and facilitates interaction between humans and computers. Its close integration with Machine Learning (ML) and AI enables the development of voice systems, language translation, sentiment analysis, and other applications. Currently, pre-trained languages have helped to increase progress in various fields of NLP. Many ML models have been developed, including conventional models such as Support Vector Machine (SVM), Naïve Bayes Classifier (NBC), as well as deep learning models based on neural networks. One of the latest developments is Transformer, including Bidirectional Encoder Representations from Transformers (BERT) [10].

BERT is an example of a pre-trained model with large data, so it has parameters suitable for tasks related to language understanding [11]. Within the BERT model, there are various variations such as DistilBERT, ALBERT, RoBERTa, and many more [12]. As one of the most widely used languages, Indonesian has great potential in research in the field of NLP. The use of the IndoBERT model as a pre-trained language model for Indonesian can help optimize existing language resources [13]. IndoBERT is a transformer-based model that adapts the BERT architecture, specially trained as a masked language model using Hugging Face with a BERT-base (uncased) configuration [14].

Previous research has examined the classification of emotions in text. One study [8] using the IndoBERT-Unceased model showed an accuracy of 89.1%, while the IndoBERT model had an accuracy of 76%. Although there is a significant difference, both have good performance. Another study [15] used the IndoBERT model to detect sentences with symptoms of depression, resulting in an accuracy of 51%. Research focusing on IndoBERT gave the best results, achieving 94% accuracy [9]. Tests in other studies show the accuracy, F1-score, recall, and

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

precision values obtained in the training set (89%, 89%, 89%, and 90%), as well as the validation set (70%, 71%, 70%, and 72%) [16]. Research by [17] classified positive sentiment using IndoBERT (80%), IndoBERTweet (68%), and CNN-LSTM (53%) with a 2020 dataset from Twitter.

Based on the mentioned research, IndoBERT shows significant potential in classifying emotions in text [8][15][9][16][17]. This research aims to classify emotions in Indonesian text using the IndoBERT model. The data used includes five emotion labels namely Angry, Fear, Joy, Love, and Sad obtained from 5079 tweets. In addition, this study varies several parameters to produce optimal classification. The results of this study have important implications in the early detection of emotions and can be the first step in mental health treatment efforts.

2. MATERIAL AND METHODS

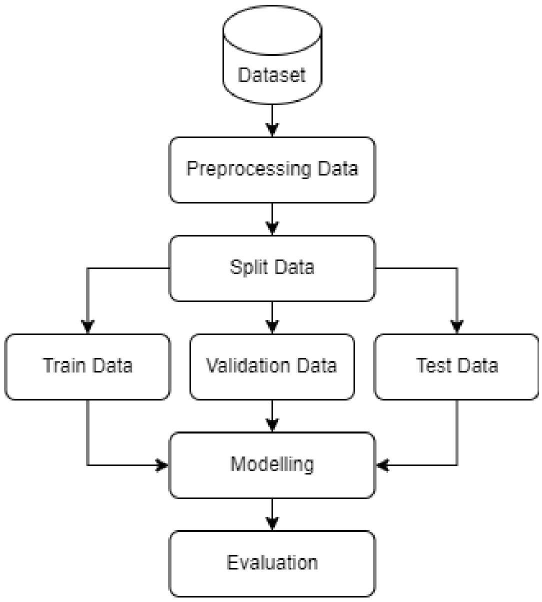


FIGURE 1. Research Methods

The research starts by searching for relevant datasets, as illustrated in Figure 2. The datasets then undergo a data pre-processing stage before being used to train the model. After pre-processing, the dataset is divided into three parts: training, validation, and test data. The model is trained using the training data, and its performance is evaluated with metrics such as graphical accuracy, graphical loss, and confusion matrix. This evaluation provides insight into the effectiveness of the model in classifying and predicting outcomes.

2.1 DATASET

This research uses a multi-labeled dataset of emotions in Indonesian from the Emotion Dataset from Indonesian Public Opinion. This dataset consists of 5079 tweets labeled with five emotions: Angry, Fear, Joy, Love, and Sad.

TABLE 1.
Emotion Label Dataset

Tweet	Label
pagi2 udah di buat emosi :)	Angry (Marah)
kok suaranya aneh dan bikin merinding ya	Fear (Takut)
semangat buat hari ini!	Joy (Senang
very kucing t__t lucu banget.. jadi jatuh hati	Love (Cinta)
iyhh, jadi sepi bngett huhuu	Sad (Sedih)

2.2 PREPROCESSING DATA

The next step involves data pre-processing. This process goes through several stages, including converting text to lowercase, removing irrelevant characters that may affect the results such as tags, URLs, numbers, punctuation marks and spaces. After that, perform data tokenization to break the text into small units or meaningful tokens. This stage has a very important role in preparing the data before proceeding to the further analysis stage. The result of data pre-processing that is null will also be removed.

2.3 SPLIT DATA

The next step in this research is to split the dataset into three parts: training, validation, and test data. Before being used for modeling, the dataset will be split into these three parts with the composition as illustrated in Table 2.

TABLE 2.
Data Split

Train Data (%)	Validation Data (%)	Test Data (%)
80	10	10
75	15	15
60	15	15

By ensuring the same class distribution in each dataset, this approach is used to evaluate the performance of the model.

2.4 MODELLING

This research uses the IndoBERT model which is a development of BERT (Bidirectional Encoder Representations from Transformers). This model is specifically designed for data processing and training in Bahasa Indonesia using the Transformer architecture. The Transformer architecture was originally designed with an encoder-decoder architecture for machine translators. However, in BERT only Encoder architecture is used. BERT utilizes the encoder architecture of the Transformer for contextual understanding in the language [18].

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

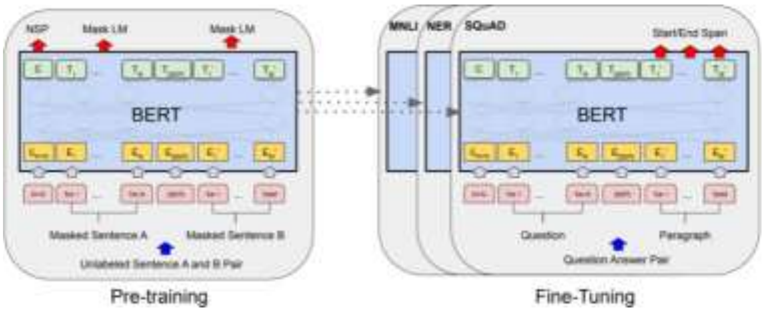


FIGURE 2. BERT Architecture

The architecture of the BERT model is a two-way, multi-layered Transformer. There are two main stages in BERT, the pre-training stage and the fine-tuning stage. In the pre-training stage, the BERT model is trained using unlabeled data with various language tasks. After that, in the fine-tuning stage, the BERT model is initialized with the parameters obtained during pre-training, and all parameters are adjusted using data with labels [14].

In determining how the model learns and adapts to the data, categorical crossentropy is used as a loss function to measure how well the model predicts category labels from the training data. This function is a common metric for multiclass classification tasks. Adam is the optimizer used in this research because it is efficient for training neural networks. The metric used to evaluate the model's performance is categorical accuracy, which measures the extent to which the model can correctly classify the data. With this setting, the model is ready to be trained with appropriate training data [19].

In the pre-train stage, the model is given contextual understanding through labeled data. For the IndoBERT model architecture, a large dataset was collected consisting of about four billion words and about 250 million sentences in Bahasa Indonesia. This dataset includes news texts from various sources, including local online, social media, Wikipedia, online articles, subtitles from video recordings, and a parallel dataset known as Indo4B. Indo4B includes formal word data, informal word data, and casual words in Indonesian [20].

During the training process, the model is trained using the training data with the implementation of callbacks to stop the training when the set criteria are met. By visualizing the loss and accuracy graphs of both data sets (training data and validation data), it can be seen how the model understands the patterns in the training data and to what extent it can generalize to data that it has not seen before (validation data). This analysis helps to understand the performance and progress of the model during the training process as well as identify if there is overfitting or underfitting [19].

2.5 EVALUATION

In this research, the evaluation is performed by comparing several parameters, including data split composition, learning rate, and batch size by using confusion matrix to calculate evaluation metrics such as accuracy, precision, recall, and F1-score. Confusion Matrix is based on the concepts of True Positive (TP), True

Negative (TN), False Positive (FP), and False Negative (FN). The results of the confusion matrix will be compared and explained to evaluate the performance of each parameter.

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

In equation (1), Accuracy describes the ratio of correct predictions to the total predictions made by the classifier on the test data.

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

Equation (2), is an example of the Precision equation or also known as the positive prediction value, representing the number of correct predictions among all positive predictions.

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

In equation (3), is Recall or often referred to as sensitivity, measuring the relative proportion of correctly classified positive examples out of all positive examples.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

Equation (4), is calculated based on Precision and Recall values. F1-Score provides a balance between Precision and Recall.

3. RESULTS AND DISCUSSION

3.1 DATASET

This research utilizes the Emotion Dataset form Indonesian Public Opinion [21] which contains tweets in Indonesian with five emotion labels: 760 tweets for Love emotion label, 1130 tweets for Angry emotion label, 1003 tweets for Sad emotion label, 1275 tweets for Happy emotion label, and 911 tweets for Fear emotion label. This dataset has a total of 5079 tweets.

3.2 PREPROCESSING DATA

The next step performs data pre-processing. This process includes converting the text to lowercase, removing irrelevant characters that could potentially affect the results such as tags, URLs, numbers, punctuation marks, and spaces, and performing tokenization.

TABLE 3.
Preprocessing Data

Step	Before	After
Preprocessing	pagi2 udah di buat emosi :)	pagi udah di buat emosi
Tokenization	pagi udah di buat emosi	['pagi', 'udah', 'di', 'buat', 'emosi']

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

3.3 SPLIT DATA

The next step, the dataset which has a total of 5079 tweets is divided into three parts, namely training data, validation data, and test data with the composition of data split and the amount of data split for each part as in table 4.

TABLE 4.
Data Split

Data Split			Train Data	Validation Data	Test Data
Train Data	Validation Data	Test Data			
80%	10%	10%	4063	508	508
75%	15%	15%	3555	762	762
60%	15%	15%	3047	1016	1016

3.4 MODELLING AND EVALUATION

TABLE 5.
Experiment with the Highest Accuracy Result

No	Data Split			Learning Rate	Batch Size	Accuracy			Average Confusion Matrix		
	Train	Val	Test			Train	Val	Test	Precision	Recall	F1-Score
1	80	10	10	1e-5	32	0.99	0.86	0.84	0.83	0.84	0.84
2	80	10	10	1e-6	8	0.91	0.85	0.83	0.82	0.83	0.83
3	80	10	10	1e-6	32	0.89	0.85	0.82	0.82	0.82	0.82

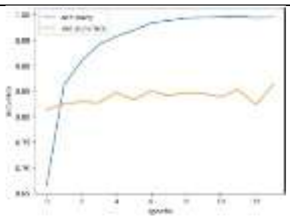
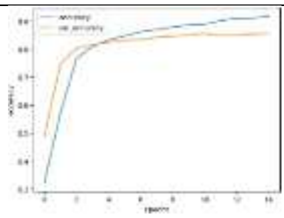
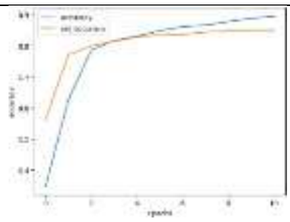
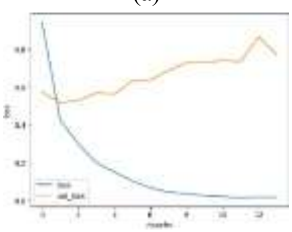
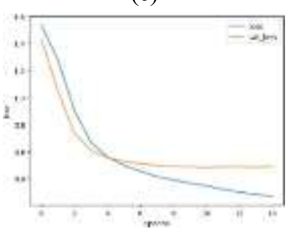
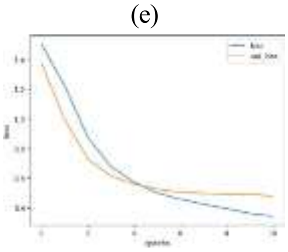
Graph	Data Split		
	No. 1	No. 2	No. 3
Accuracy	 (a)	 (c)	 (e)
Loss	 (b)	 (d)	 (f)

FIGURE 3. Graph (a) accuracy (b) loss

Emotion classification experiments were conducted using the IndoBERT model with a barlabel dataset derived from Tweets. This dataset was classified into five labels: 'Love', 'Angry', 'Sad', 'Happy', and 'Fear'. In training, there are several control variables including the dataset, IndoBERT model 'indobenchmark/indobert-base-p2', data split composition (80:10:10, 75:15:15, and 60:20:20), as well as learning rate combination (from 1e-2 to 1e-7), and batch size (8, 16, and 32). The model was trained for 25 epochs with the application of early stop and patience for 5 epochs.

In Table 5, presenting the three experiments that have the best accuracy results, it is found that the highest accuracy results are in experiment number 1 which uses a data split composition of 80:10:10, a learning rate of 1e-5, and a batch size of 32. On the other hand, experiment number 2 which uses the same data split composition but has a learning rate of 1e-6 and a batch size of 8 shows a good balance between accuracy and average confusion matrix values (precision, recall, and F1-score).

In Figures 3 (a) and (b), the training and validation data graphs show indications of overfitting. Although the model achieved high accuracy during training with a data split composition of 80:10:10, a learning rate of 1e-5, and a batch size of 32, its performance decreased at the validation stage. However, the good average confusion matrix value indicates the model's potential for optimal performance on data that has never been seen before.

Furthermore, in Figure 3 (c) and (d), the graphs with a data split composition of 80:10:10, a learning rate of 1e-6, and a batch size of 8 show adequate results. Although the training accuracy is lower than experiment number 1, the difference between training and validation or test accuracy is not significant, indicating better balance. This graph indicates that the model tends to be more general and may be more resistant to overfitting. The good average confusion matrix value also indicates the model's potential for optimal performance on data that has not been seen before.

Figure 3 (e) and (f) show that the graphs with a data split composition of 80:10:10, a learning rate of 1e-6, and a batch size of 32 produce more stable results compared to experiment 1. Although the training accuracy is lower, the difference between the training and validation or test accuracy remains reasonable. Similar average confusion matrix values indicate the model's potential for optimal performance on data that has not been seen before.

Overfitting occurs when there is a significant difference between the training graphs on the training data and the validation data. In Figure 3, graph (a) shows the improved performance on the training data, but the validation graph has no significant change. The results from experiment number 2 in Table 5 show that the difference between the training graph and the validation graph is relatively small. If the model is trained too specifically on the training data, it is likely to perform poorly on new data because the model only remembers the patterns in the training data, not general patterns that can be applied to data that has not been seen before.

In this experiment, there are several factors that cause difficulties in classifying the data by the model. Different sentences may produce different results when processed. Especially, sentences containing two or more emotions may produce different emotions at each stage. Conversely, in the pre-processing process involving punctuation removal, some sentences produce different outputs due to different semantic meanings.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

3.5 DISCUSSION

The experimental results conducted in this study with data split compositions of 80:10:10, 75:15:15, and 60:20:20 show that the data split composition of 80:10:10 shows the highest accuracy results in Table 5 among other data split compositions. This also implies that the data split composition affects the performance of the model. This finding is in line with several previous sources [22][23][24], which also highlighted the influence of data split composition on accuracy results.

In addition, other factors that affect the accuracy results in this study are learning rate and batch size. Experiments with a data split composition of 80:10:10, a learning rate of 1e-5, and a batch size of 32 achieved the highest accuracy. However, with the same data split composition, the use of learning rate 1e-6 and batch size 8 resulted in more stable accuracy overall. This finding is supported by previous research [25], which confirms that learning rate and batch size play an important role in accuracy results.

4. CONCLUSION

This study aims to classify emotions in Indonesian text using the IndoBERT model. The data used includes five emotion labels: Marah (Marah), Takut (Fear), Senang (Joy), Cinta (Love), and Sedih (Sad) obtained from 5079 tweets. In the experiment, this study explored control variables such as data split composition, learning rate, and batch size. The results show that the data split composition of 80:10:10, learning rate 1e-6, and batch size 8 produce more stable accuracy overall. Although some experiments show indications of overfitting, the results of this study have important meaning in early detection of emotions and can help in mental health treatment efforts.

REFERENCES

[1] F. Purnomosidi, S. Ernawati, D. Riskiana, and A. Indriyani, “Kesehatan Mental Pada Remaja,” Jurnal Pengabdian Kepada Masyarakat, vol. 2, no. 1, pp. 1–7, Feb. 2023, doi: 10.54066/abdimas.v2i1.257.

[2] Ipsos, “Ipsos Global Health Service Monitor - 2023,” Sep. 2023.

[3] Center for Reproductive Health, University of Queensland, and Johns Bloomberg Hopkins School of Public Health, “Indonesia – National Adolescent Mental Health Survey (I-NAMHS): Laporan Penelitian,” 2022.

[4] M. A. Putri, I. Bimantoko, N. Herton, and R. A. Listiyandini, “Gambaran Kesadaran, Akses Informasi, dan Pengalaman terkait Layanan Kesehatan Mental pada Masyarakat di Indonesia,” Journal Psikogenesis, vol. 11, no. 1, pp. 14–28, Dec. 2023, doi: 10.24854/jps.v11i1.1961.

[5] N. Lisnarini, J. R. Suminar, and Y. Setianti, “Keunggulan dan Hambatan Komunikasi dalam Layanan Kesehatan Mental pada Aplikasi Telemedicine Halodoc,” Psikobuletin:Buletin Ilmiah Psikologi, vol. 4, no. 3, p. 176, Sep. 2023, doi: 10.24014/pib.v4i3.25231.

[6] A. D. Rizkyanti and E. Mastuti, “Peran Kecerdasan Emosional terhadap Kesehatan Mental pada Emerging Adulthood,” Buletin Riset Psikologi dan

Kesehatan Mental (BRPKM), vol. 2, no. 1, pp. 128–136, Jan. 2022, doi: 10.20473/brpkm.v2i1.31822.

[7] S. Mutiara Puspita, “Kemampuan Mengelola Emosi Sebagai Dasar Kesehatan Mental Anak Usia Dini,” Jurnal Program Studi PGRA, vol. 5, no. 1, pp. 85–92, Jan. 2019, doi: doi.org/10.29062/seling.v5i1.434.

[8] A. T. B. Widianto and D. H. Fudholi, “Klasifikasi Emosi pada Teks dengan Menggunakan Metode Deep Learning,” Jurnal Ilmiah Indonesia, vol. 6, no. 1, 2021, doi: 10.36418/syntax-literate.v6i1.4758.

[9] S. Dharmawan, V. C. Mawardi, and N. J. Perdana, “Klasifikasi Ujaran Kebencian Menggunakan Metode FeedForward Neural Network (IndoBERT),” Jurnal Ilmu Komputer dan Sistem Informasi, vol. 11, no. 1, Jun. 2023, doi: 10.24912/jiksi.v11i1.24066.

[10] J. I. T. Krisna, A. Luthfiarta, L. D. Cahya, S. Winarno, and A. Nugraha, “Comparing Optimizer Strategies For Enhancing Emotion Classification In IndoBERT Models,” Advance Sustainable Science, Engineering and Technology, vol. 6, no. 2, p. 0240203, Mar. 2024, doi: 10.26877/asset.v6i2.18228.

[11] F. Ilham and W. Maharani, “Analyze Detection Depression In Social Media Twitter Using Bidirectional Encoder Representations from Transformers,” Journal of Information System Research (JOSH), vol. 3, no. 4, pp. 476–482, Jul. 2022, doi: 10.47065/josh.v3i4.1885.

[12] C. Özkurt, “Comparative Analysis of State-of-the-Art Q A Models: BERT, RoBERTa, DistilBERT, and ALBERT on SQuAD v2 Dataset,” ADBA Information Technology and Publishing Limited Company, Jul. 2024, doi: 10.69882/adba.chf.2024073.

[13] A. T. B. Widianto, “Klasifikasi Emosi Pada Teks Menggunakan Metode Deep Learning,” Jul. 2022. Accessed: Aug. 04, 2024. [Online]. Available: https://dspace.uii.ac.id/handle/123456789/40586

[14] F. Koto, A. Rahimi, J. H. Lau, and T. Baldwin, “IndoLEM and IndoBERT: A Benchmark Dataset and Pre-trained Language Model for Indonesian NLP,” in Proceedings of the 28th International Conference on Computational Linguistics, Stroudsburg, PA, USA: International Committee on Computational Linguistics, 2020, pp. 757–770. doi: 10.18653/v1/2020.coling-main.66.

[15] I. R. Hidayat and W. Maharani, “General Depression Detection Analysis Using IndoBERT Method,” International Journal on Information and Communication Technology (IJoICT), vol. 8, no. 1, pp. 41–51, Aug. 2022, doi: 10.21108/ijoict.v8i1.634.

[16] K. Hulliyah, F. Rayyan, and N. S. A. A. Bakar, “Development Of A Chatbot For The Online Application Telegram Chat With An Approach To The Emotion Classification Text Using The Indobert-Lite Method,” in 2022 4th International Conference on Cybernetics and Intelligent System (ICORIS), IEEE, Oct. 2022, pp. 1–4. doi: 10.1109/ICORIS56080.2022.10031483.

[17] S. Saadah, Kaenova Mahendra Auditama, Ananda Affan Fattahila, Fendi Irfan Amorokhman, Annisa Aditsania, and Aniq Atiqi Rohmawati, “Implementation of BERT, IndoBERT, and CNN-LSTM in Classifying Public Opinion about COVID-19 Vaccine in Indonesia,” Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), vol. 6, no. 4, pp. 648–655, Aug. 2022, doi: 10.29207/resti.v6i4.4215.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

[18] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in Proceedings of the 2019 Conference of the North, Stroudsburg, PA, USA: Association for Computational Linguistics, 2019, pp. 4171–4186. doi: 10.18653/v1/N19-1423.
[19] E. S. Budi, A. N. Chan, P. P. Alda, and M. A. F. Idris, "Optimasi Model Machine Learning untuk Klasifikasi dan Prediksi Citra Menggunakan Algoritma Convolutional Neural Network," Media Online, vol. 4, no. 5, p. 509, 2024, doi: doi.org/10.30865/resolusi.v4i5.1892.
[20] L. D. Cahya, A. Luthfiarta, J. I. T. Krisna, S. Winarno, and A. Nugraha, "Improving Multi-label Classification Performance on Imbalanced Datasets Through SMOTE Technique and Data Augmentation Using IndoBERT Model," Jurnal Nasional Teknologi dan Sistem Informasi, vol. 9, no. 3, pp. 290–298, Jan. 2024, doi: 10.25077/teknosi.v9i3.2023.290-298.
[21] Riccosan, K. E. Saputra, G. D. Pratama, and A. Chowanda, "Emotion dataset from Indonesian public opinion," Data Brief, vol. 43, p. 108465, Aug. 2022, doi: 10.1016/j.dib.2022.108465.
[22] R. Oktafiani, A. Hermawan, and D. Avianto, "Pengaruh Komposisi Split data Terhadap Performa Klasifikasi Penyakit Kanker Payudara Menggunakan Algoritma Machine Learning," Jurnal Sains dan Informatika, pp. 19–28, Jun. 2023, doi: 10.34128/jsi.v9i1.622.
[23] Baiq Nurul Azmi, Arief Hermawan, and Donny Avianto, "Analisis Pengaruh Komposisi Data Training dan Data Testing pada Penggunaan PCA dan Algoritma Decision Tree untuk Klasifikasi Penderita Penyakit Liver," JTIM : Jurnal Teknologi Informasi dan Multimedia, vol. 4, no. 4, pp. 281–290, Feb. 2023, doi: 10.35746/jtim.v4i4.298.
[24] S. Lasniari, J. Jasril, S. Sanjaya, F. Yanto, and M. Affandes, "Pengaruh Hyperparameter Convolutional Neural Network Arsitektur ResNet-50 Pada Klasifikasi Citra Daging Sapi dan Daging Babi," Jurnal Nasional Komputasi dan Teknologi Informasi (JNKTI), vol. 5, no. 3, pp. 474–481, Jun. 2022, doi: 10.32672/jnkti.v5i3.4424.
[25] N. Rochmawati, H. B. Hidayati, Y. Yamasari, H. P. A. Tjahyaningtijas, W. Yustanti, and A. Prihanto, "Analisa Learning Rate dan Batch Size pada Klasifikasi Covid Menggunakan Deep Learning dengan Optimizer Adam," Journal of Information Engineering and Educational Technology, vol. 5, no. 2, pp. 44–48, Dec. 2021, doi: 10.26740/jieet.v5n2.p44-48.