Comparison of Classification Methods on Twitter Sentiment Analysis of PDAM Tugu Tirta Kota Malang

Anisa Dewi Anggraeni[1], Muhammad Farhansyah[2], Muhammad Risky Pratama Hermawan[3], Galih Wasis Wicaksono[4], Christian Sri Kusuma Aditya[5]

[1,2,3,4,5]*Informatics, University of Muhammadiyah Malang, Indonesia*

[1]anisa049@gmail.com,[2]muhammad1farhansyah@gmail.com,[3]riskyhermawan90@gmail.com,
[4]galih.w.w@umm.ac.id,[5]christianskaditya@umm.ac.id

Abstract - The Regional Drinking Water Company (PDAM) Tugu Tirta is a public service company in Malang's drinking water distribution field. The company uses a customer complaint feature that is provided on the website. However, only a few people know about it and use it. From this problem, the researcher uses social media data, namely Twitter, to explore data sources and collect feedback tweets from the customer. However, analyzing the sentiment of the 1000 data used is elusive. The tweets contain unstructured text, so the researcher applies the labeling from the dataset, preprocesses the text, and then extracts the tweets by applying the classification methods by comparing Support Vector Machine (SVM), Naive Bayes (NB), Random Forest (RF), Logistic Regression (LR), Short-Term Long-Term Memory (LSTM), and Indonesian BERT to achieve highly accurate results. The tests with six methods show that Logistic Regression and Indonesian BERT are the best methods, with an accuracy of 85%. In this study, we obtained an effective algorithm to classify a comment as positive, negative, or neutral related to the Tugu Tirta Regional Drinking Water Company (PDAM).

Keywords: Sentiment analysis, comparison of methods, PDAM Tugu Tirta

I. INTRODUCTION

A public service is a form of service that has become the responsibility and is carried out by government agencies at the Central, Regional, and within BUMN (State Owned Enterprises) or BUMD (Regional Owned Enterprises) to meet the needs of the community. In line with the service provider agency management, the public service paradigm has developed, focusing on the customer-driven government to realize excellent and quality services. Feedback is needed from the community as service users so that the government as a service provider knows about public complaints about public services that have been implemented.

Tugu Tirta Regional Drinking Water Company (PDAM) is located at Jalan Canal Danau Sentani No. 100, Madyopuro, Kedungkandang District, Malang City [5] is a public service company in the field of drinking water distribution in Malang City. The company has a customer complaint feature that has been provided on its website, but only a few use it because only some customers are aware of this feature. Sometimes, the customer fills in irrelevant data so that data processing cannot be carried out.

Twitter is a social media where opinions are stored as a computational technique to extract, classify, understand, and evaluate statements in content [6]. The worldwide population who access social media Twitter reaches 436 million active users, and the number of tweets on Twitter continues to grow daily. This makes it suitable for performing sentiment analysis on customer feedback.

Previous research on sentiment analysis has been carried out by (Nalini Chintalapudi et al. 2021) with the title "Sentimental Analysis of COVID-19 Tweets Using Deep Learning Models". This research applies several models, namely Bidirectional Encoder Representations from Transformers (BERT), Logistic Regression (LR), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM). The results show that the BERT model gets the highest accuracy of 89%, LR 75%, SVM 74.75%, and LSTM 65% [1]. (Sigit Kurniawan et al.2019) With the title "Comparison of Classification Methods for Sentiment Analysis of Political Figures in Online News Media Comments," The study used Indonesian text preprocessing using the Gata Framework Text Mining, then extracted information by applying two methods. Namely, classification NB and SVM are optimized using Particle Swarm Optimization. The test results showed that the Particle Swarm Optimization-based Support Vector Machine obtains an accuracy of 78.40% and 0.850 for the area under the curve (AUC).

Meanwhile, NB only got 68.21% accuracy for AUC 0.672 [2]. (Veny Amilia Fitri et.al 2019) With the title "Sentiment Analysis of Social Media Twitter with Case of Anti LGBT Campaign in Indonesia using Naive Bayes, Decision Tree, and Random Forest Algorithm," the research implemented several stages, namely preprocessing data, data processing, classification, and evaluation. In this method, the results obtained are 86.43% accuracy for the NB method, and for the Decision Tree and Random Forest methods, the accuracy is 82.91% [3]. (Siwi Cahyaningtyas et.al 2021) This study has the title "Deep Learning for Aspect-Based Sentiment Analysis on Indonesian Hotel Reviews," Four stages are carried out: data collection, preprocessing, aspect classification, and sentiment classification. Eight deep learning methods are used for sentiment classification (RNN, LSTM, GRU, BiLSTM, Attention BiLSTM, CNN, CNN-LSTM, CNN-BiLSTM). The best LSTM model gives an accuracy of 0.926, and the CNN model gives an accuracy of 0.904 [27]. (Farrikh Alzami et.al 2020) With the title "Document Preprocessing with TF-IDF the Polarity Classification Performance of Unstructured Sentiment Analysis," the researcher uses several extraction features of Word Bags, TF-IDF, Word2Vector, and a combination of TF-ID and Word2Vector with machine learning models. The models used are Random Forest, SVM, K-Nearest Neighbors, and NB. Snowball is used as a stemming algorithm. The result suitable for getting the polarity classification is TF-IDF with the SVM model for unstructured sentiment analysis and getting a performance result of 87.3% [26].

The main objective of this research is to provide PDAM Tugu Tirta Malang City with more extensive customer sentiment and can provide customer needs in a better way. This study discusses several tweet pre-processing techniques by implementing six machine learning classification algorithms: SVM, NB, RF, LR, LSTM, and Indonesian BERT. The results of the six classification methods are then compared to find the method with the best accuracy results. This research is also expected to provide solutions to public tweets on Twitter and analysis of netizen sentiment classification on social media, especially on Twitter, and to support further research discussions on other research studies, such as service satisfaction in public services in other government agencies.

II. METHOD

To bring about the objectives of this study, the authors designed and implemented several analysis steps, as shown in Fig. 1.

A. Crawling Data and Labeling Data

The data set is text (user tweets) obtained from the social network Twitter by applying Python programming mining techniques. Crawling data is retrieving data from the server using the Twitter API (Application Programming Interface) from the user or tweet data. The data search uses the hashtag (#) keyword "Tugu Tirta." The data was taken from January 14, 2022, to March 10, 2022, and a total of 1000. After the data crawling process, the tweet data that has been obtained is converted into a data frame and stored in a CSV file format. The following is a representative crawling data shown in Fig. 2.

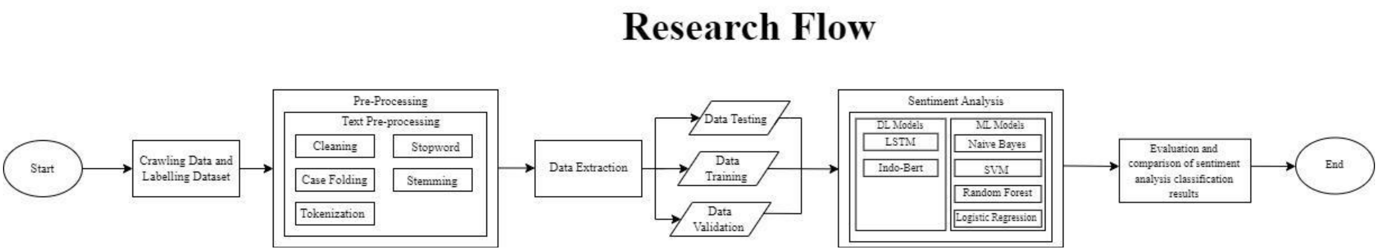

Fig. 1 Research flow

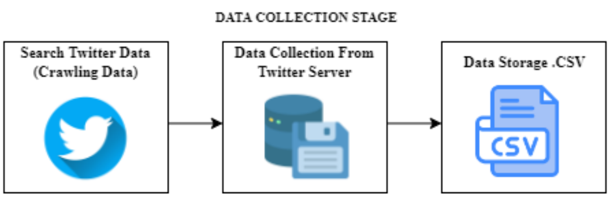

Fig. 2 Data collection stage

One thousand pieces of data that have been collected will be divided into training data, test data, and validation data. Then, sentiment labeling is determined manually by analyzing each tweet and categorizing it into three categories. An Indonesian language expert, Mrs. Arti Prihatini, S.Pd., M.Pd, a lecturer at the University of Muhammadiyah Malang, carried out sentiment class labeling and data validation. The number of positive sentiments obtained is 351 data, 222 neutral sentiments, and 427 negative sentiments. Table I shows data analysis indicators, and Table II shows an example of labeling the tweet data class. The data is then disseminated in class labeling, shown in Fig. 3.

B. Pre-processing

Pre-processing is the first step before the classification stage. This process helps the data to be processed easier for the next step. The settings done in preprocessing are data cleaning, case folding, tokenization, stopword, and stemming.

The cleaning process clears data sentences containing HyperText Markup Language (HTML) characters, hashtags (#), mentions, and punctuation. Fold case converts all letters to the same format, which is lowercase. Tokenisation is done to convert sentences into the words or phrases that compose them. The stop word removes words that don't have a specific meaning but appear frequently. Finally, the root word is made to change the word into its basic form by eliminating the affixes at the beginning or end of the word. Root generation is done using the Sastrawi library.

C. Data Extraction

The extraction feature used in this process is the Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF is a word weighting technique that determines the importance of a document that contains it. The weighting is adapted from the Information Retrieval approach.

TABLE I
DATA ANALYSIS INDICATOR

No	Sentiment	Indicator	Characteristics of Meaning	Impact
1	Negative	Negative sentiment words are more than the number of positive sentiment words.	Leak, Stupid	Destroying the company's image.
2	Positive	There are more positive sentimental words than negative sentiment words.	Hope, Cheers, and Thank You	Can increase traffic and customer satisfaction.
3	Neutral	There are no sentimental words that are positive or negative.	Please, Regarding the question, the Sentence is ambiguous	No impact on the company.

TABLE II
CLASS LABELING EXAMPLE

No	Tweet	Class
1	Alhamdulillah, it's flowing again thank you so much.	Positive
2	Estimate how long?	Neutral
3	As long as the water is dead using PDAM	Negative

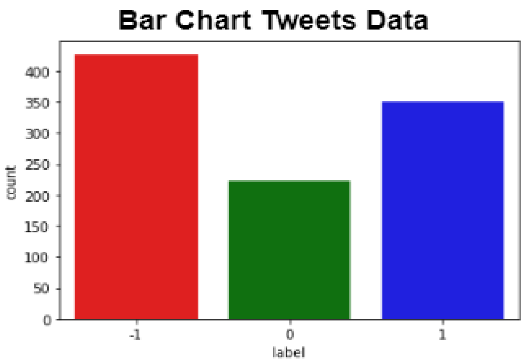

Fig. 3 Class labeling dissemination

Weighting is calculated on each word, and TF manifests that the higher the occurrence of a word in a document, the more important the word is to represent the document. And suppose the Inverse Document Frequency value indicates the event of a word having a high frequency in a particular document. In that case, the word becomes an important feature and can represent the document. On the other hand, if the word appears in all documents, then the word is standard and cannot describe the document and has an IDF value of 0.

D. Modeling

At this point, the data is divided into training, testing, and validation data. The information is divided into 80% training data, 10% test data, and 10% validation data. The classification methods used are Support Vector Machine (SVM), Naive Bayes, Random Forest (RF), Logistic Regression (LR), Long Short-Term Memory (LSTM), and Indonesian BERT to predict the variables. tweet about Tugu Tirta. Compare the accuracy results of each method to find the forms with the best accuracy.

E. Evaluation

The method to evaluate the algorithm used is the confusion matrix which will produce accuracy, precision, recall, and f1-score (Table III). The confusion matrix is used to measure the accuracy of the classification results, measurements in the form of a matrix table by calculating statistical measures, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) [10].

The confusion matrix model equation is obtained by calculating the following (1), (2), (3), and (4).

$$Accuracy = \frac{TP + TN}{(TP + TP + FP + FN)} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$F1\ Score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (4)$$

III. RESULT AND DISCUSSION

A. Data Pre-processing

After going through the cleaning, case folding, tokenization, stopword, and stemming stages, the data results are clean and ready for classification. An example of this process can be seen in Table IV.

B. TF-IDF

Based on the feature selection results performed on the word weights of the TF-IDF procedure, the terms are sorted from 1.0 with the highest weight to the lowest (Fig. 4). The times with high weight values are then assumed to be 5%, 10%, 15%, 20%, 25%, and 30% of the total data [28].

TABLE III
CONFUSION MATRIX

Class	Classified as Negative	Classified as Neutral	Classified as Positive
Negative	True Negative (TNe)	False Negative (FNt)	False Positive (FP)
Neutral	False Negative (FNe)	True Neutral (TNt)	False Positive (FP)
Positive	False Negative (FNe)	False Neutral (FNt)	True Positive (TP)

TABLE IV
DATA PRE-PROCESSING

Pre-processing	Before	After
Cleaning	@tugutirtamalang Ok, thanks for the response..hopefully it will be followed up soon and the water will flow again	Ok thank you for the response hopefully it will be followed up soon and the water will flow again
Case folding	Ok thank you for the response hopefully it will be followed up soon and the water will flow again	ok thank you for the response hopefully it will be followed up soon and the water will flow again
Tokenization	ok thank you for the response hopefully it will be followed up soon and the water will flow again	‘ok’ ‘thank’ ‘you’ ‘for’ ‘the’ ‘response’ ‘hopefully’ ‘it’ ‘will’ ‘be’ ‘followed’ ‘up’ ‘soon’ ‘and’ ‘the’ ‘water’ ‘will’ ‘flow’ ‘again’
Stopword	ok thank you for the response hopefully it will be followed up soon and the water will flow again	ok thank you for the response hopefully it will be followed up soon and the water will flow again
Stremming	ok thank you for the response hopefully it will be followed up soon and the water will flow again	thank you for the response immediately followed up with the flow again

```
(0, 1125)     1.0
(1, 916)      0.49224372509664294
(1, 563)      0.6908270962590042
(1, 404)      0.529579114181567
(5, 1378)     0.36843863737202587
(5, 1351)     0.39107451676370625
(5, 1198)     0.3399208019812127
(5, 836)      0.3399208019812127
(5, 730)      0.1804527891215551
(5, 688)      0.26252821916171815
(5, 344)      0.39107451676370625
(5, 224)      0.36843863737202587
(5, 18)       0.3000846671555939
(6, 674)      0.38118995055341387
(6, 630)      0.39856352026500674
(6, 546)      0.3100091342782144
(6, 533)      0.3677139629417783
(6, 484)      0.16604709270957216
(6, 231)      0.3148430384204474
(6, 186)      0.4230501914756935
(6, 29)       0.39856352026500674
(7, 1451)     0.5175307002225379
(7, 1182)     0.4663217414925518
(7, 916)      0.3474182215074695
(7, 664)      0.5175307002225379
```

Fig. 4 TF-IDF

After classification, the results from the SVM, NB, RF, LR, LSTM, and Indonesian BERT methods are shown from the confusion matrix in Fig. 5.

C. Support Vector Machine (SVM)

Fig. 5 shows that the total accuracy of predictions is 84%, obtained from the number of correct predictions being positive = 22, neutral = 15, and negative = 47. A total of 32 wrong forecasts due to the result not matching the actual class (positive, neutral, or negative). Wrong predictions occur due to training data not fully representing the test data, and the prediction results must match the actual data. This method uses a linear kernel, improving accuracy results because it is more suitable for data with large dimensions than other kernels.

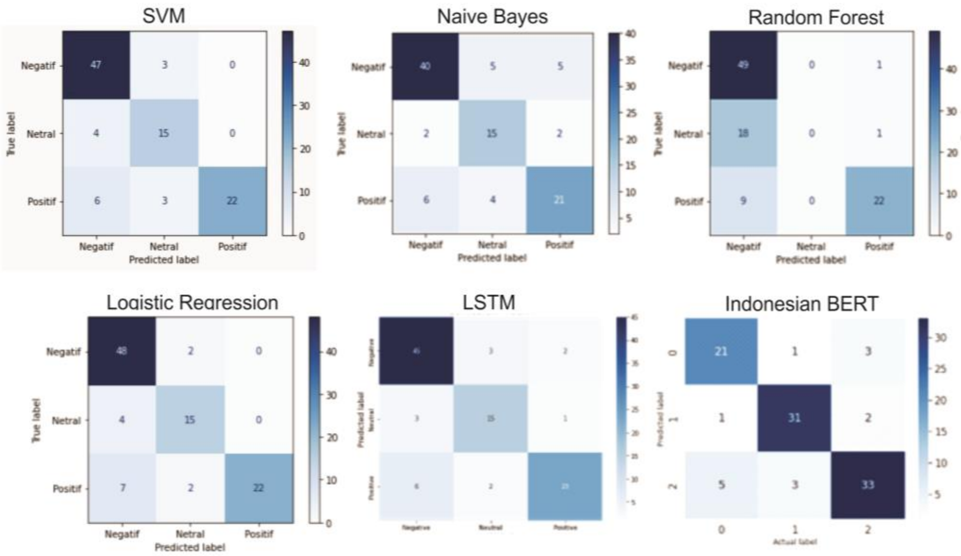

Fig. 5 Confusion matrix

D. Naive Bayes

Fig. 5 shows a total prediction accuracy of 76%, with 21 positive, 15 neutral, and 40 correct negative predictions. There are 24 wrong predictions from the actual class (positive, neutral) due to using SGD and a batch of 64. The test results from the classification report table show that 50 data are predicted to be negative, 19 are expected to be neutral, and 31 are predicted to be positive. This method has good accuracy but needs improvement due to naive Bayes accuracy and low speed when applied to a dataset whose number is not too large.

E. Random Forest (RF)

The Random Forest method uses a predetermined max depth of 0 and a random state of 0. The test results in Fig. 5 show that the prediction accuracy is 71%, with 22 positive, 0 neutral, and 49 negative correct predictions. There are 29 wrong predictions from the actual class (positive, neutral, or negative). Incorrect predictions are caused due to the training data not being fully represented by the test data, and the prediction results do not match the actual data. The accuracy results are promising but lower than the Naive Bayes method due to fewer trees, which affects the accuracy obtained.

F. Logistic Regression (LR)

The test results in Fig. 5 show that the total prediction accuracy is 85%, with 22 positive, 15 neutral, and 48 correct negative predictions. There are 15 wrong predictions from the actual class (positive, neutral, or negative). Training data not fully representing the test data, and the prediction results do not match the real data. The model gets an accuracy of 85%, which proves that it is very suitable for classifying large amounts of data.

G. Long Short-Term Memory (LSTM)

Before testing, the data is first processed through encoding and padding with a maximum word of 5000 and a max_len of 50. The data goes through the integration of size 32, and the learning rate is 0.1, one step per 20 epochs. The optimizer uses SGD and batches 64. The result in Fig. 5 shows 23 positive, 15 neutral, and 45 negative correct predictions. There are 17 wrong predictions from the actual class (positive, neutral, or negative) caused by training data that do not fully represent the test data and prediction results that do not match the actual data. By getting 83% accuracy, it proves that the resulting model still needs to be improved and can only represent a small amount of data. The accuracy obtained proves that LSTM has good accuracy for text data and can process relatively long data.

H. Indonesian BERT

After preprocessing, a clean tweet is generated from the original table. Before testing, the data is first processed through a padding and tokenizing process with a max_len of 64. Processed through this process and further tested at the learning rate. The set is 0.0002 every 20 epochs, the optimizer uses AdamW, and a batch of 32 uses the Indo 5benchmark/IndoBERT core. -base-p1. Test results in Fig. 5 show that the total prediction accuracy is 85%, with 31 positive, 21 neutral, and 33 negative correct predictions. Total prediction error of 15, the result of an error in a prediction from the actual class (positive, neutral, or negative). BERT has not 100% accuracy because errors during prediction are due to training data that only partially represent the test data, and the prediction results do not match the actual data. Getting an accuracy of 85% proves that the resulting model is very suitable for representing large amounts of data.

I. Comparison

At the evaluation stage, the system performance measurement uses accuracy, recall, and F1 scores, the results of which are used to ensure that the model that has been implemented can work efficiently. According to success rates mean values given in Table V and a comparison of the accuracy of the proposed model in Fig. 6.

TABLE V
SYSTEM PERFORMANCE MEASUREMENTt EVALUATION

Classification Model		**Negative**	**Neutral**	**Positive**	**Accuracy**
Support Vector Machine	Precision	0.82	0.71	1.00	
	Recall	0.94	0.79	0.71	84%
	F1-Score	0.88	0.75	0.83	
Naïve Bayes	Precision	0.83	0.62	0.75	
	Recall	0.80	0.79	0.68	76%
	F1-Score	0.82	0.70	0.71	
Random Forest	Precision	0.64	0.00	0.92	
	Recall	0.98	0.00	0.71	71%
	F1-Score	0.78	0.00	0.80	
Logistic Regression	Precision	0.81	0.79	1.00	
	Recall	0.96	0.79	0.71	85%
	F1-Score	0.88	0.79	0.83	
Long Short-Term Memory	Precision	0.86	0.78	0.92	
	Recall	0.84	0.74	0.71	83%
	F1-Score	0.85	0.76	0.80	
Indonesian BERT	Precision	0.87	0.78	0.89	
	Recall	0.78	0.84	0.91	85%
	F1-Score	0.89	0.81	0.90	
Average		0.85	0.64	0.82	

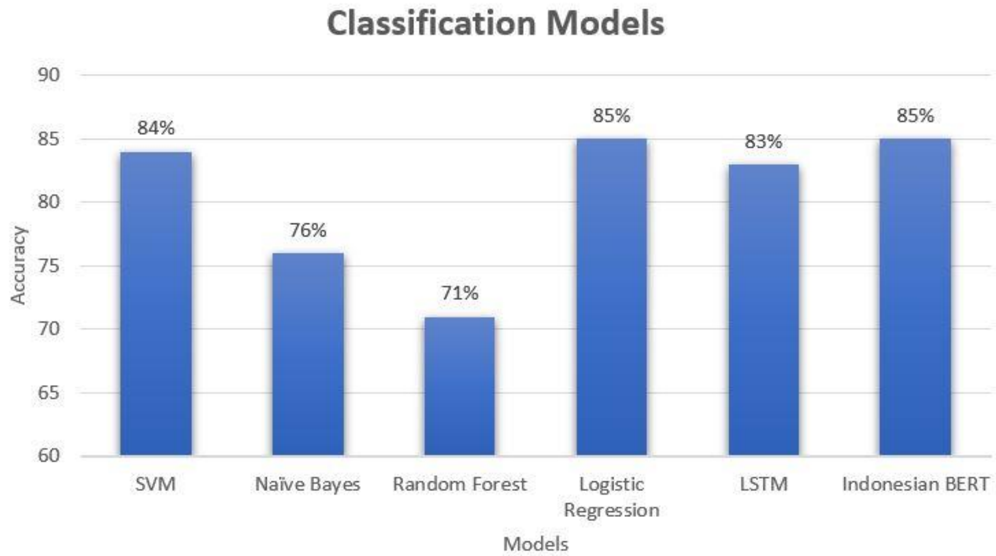

Fig. 6 Bar charts

Comparing the six methods, the Logistic Regression method and the Indonesian BERT method yielded the highest accuracy by obtaining the same accuracy of 85%. Therefore, we recommend demonstrating the application of this method to a text analysis study.

J. Twitter Sentiment Analysis

Shows the results of Fig. 7 tweets that have been analyzed through preprocessing, with the consequences of sentiment being 35.1% positive, 42.7% negative, and 22.2% neutral. Fig. 8 shows a word cloud that displays the words with the most frequency in the analyzed tweets.

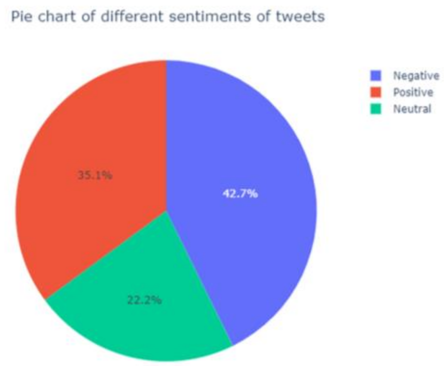

Fig. 7 Pie charts

Fig. 8 Word cloud

From the word cloud results, positive sentiment generally discusses admin services from PDAM Tugu Tirta Malang City Twitter, which responds to help customers with their complaints. Word Cloud's negative view shows that most customers complain about water that often dies, leaks, and takes long updates from the PDAM regarding problems experienced by customers.

IV. CONCLUSION

A study applying six models shows that using logistic regression and the Indonesian BERT classification model achieves an accuracy of 85%, better than other models. We offer that logistic regression and Indonesian BERT effectively handle text data classification because both methods are more lengthy and complex. The logistic regression classifier is unconstrained on the independent variables. It does not require them to be in the form of intervals so that it can achieve a good level of accuracy. In contrast, his BERT classification method for Indonesia is well suited for implementation in this sentiment analysis because the dataset used by the researchers uses the Indonesian language. Research results show that the state of the data drives excellent or bad model performance, the data's balance, and the model's accuracy. Also, applying the six classification methods yielded a percentage of positive values of 82%, neutral values of 64%, and negative values of 85%. Therefore, from the presentations received, Tugu Tirta Regional Drinking Water Company (PDAM) Public Service in Malang City has a lot of negative sentiments. It is, therefore, necessary to improve the associated work system by renewing the equipment and infrastructure of the tools used. Not only do we need to improve our customer service and speed of handling public complaints, but we also need to be better able to respond to community reports. Of course, please try to improve the quality of service for customers of PDAM City Tugu Tirta Malang. Tugu Tirta Regional Drinking Water Company (PDAM) Another study that analyzed public service sentiment in Malang applied receiver operating characteristic (ROC) curve visualization to calculate the AUC. We evaluated performance related to available classification problems comparison with measurement model 1. etc.

REFERENCES

[1] N. Chintalapudi, G. Battineni, and F. Amenta, ‘Sentimental analysis of COVID-19 tweets using deep learning models’, Infect Dis Rep, vol. 13, no. 2, Apr. 2021, doi: 10.3390/IDR13020032.

[2] S. Keputusan Dirjen Penguatan Riset dan Pengembangan Ristek Dikti et al., ‘Perbandingan Metode Klasifikasi Analisis Sentimen Tokoh Politik Pada Komentar Media Berita Online’, masa berlaku mulai, vol. 1, no. 3, pp. 176–183, 2017.

[3] V. A. Fitri, R. Andreswari, and M. A. Hasibuan, ‘Sentiment analysis of social media Twitter with case of Anti-LGBT campaign in Indonesia using Naïve Bayes, decision tree, and random forest algorithm’, in Procedia Computer Science, 2019, vol. 161, pp. 765–772. doi: 10.1016/j.procs.2019.11.181.

[4] S. K. Dirjen et al., ‘Analisis Sentimen E-Wallet Pada Google Play Menggunakan Algoritma Naive Bayes Berbasis Particle Swarm Optimization’, masa berlaku mulai, vol. 1, no. 3, pp. 377–382, 2017.

[5] ‘PERUMDA Air Minum Tugu Tirta’. https://perumdatugutirta.co.id/ (accessed Jan. 21, 2022).

[6] H. Chen and D. Zimbra, ‘AI and Opinion Mining’, 2010. [Online]. Available: www.computer.org/intelligent

[7] ‘• Most used social media 2021 | Statista’. https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/ (accessed Apr. 03, 2022).

[8] H. Hassani, C. Beneki, S. Unger, M. T. Mazinani, and M. R. Yeganegi, ‘Text mining in big data analytics’, Big Data and Cognitive Computing, vol. 4, no. 1, pp. 1–34, Mar. 2020, doi: 10.3390/bdcc4010001.

[9] U. M. Fernandes Dimlo, R. Harish Kumar, and C. Chandana, ‘WORD CLOUD GENERATION OF WEIGHTED WORDS FOR SENTITIMENT ANALYSIS’.

[10] Maria Navin J R and Pankaja R, ‘Performance Analysis of Text Classification Algorithms using Confusion Matrix’, International Journal of Engineering and Technical Research (IJETR), vol. 6, no. 4, 2016.

[11] N. N. Tri Puspaningsih and P. Riyasa, ‘ANALISIS FAKTOR-FAKTOR YANG MEMPENGARUHI KEPUASAN PELANGGAN TERHADAP PELAYANAN PDAM KOTA DENPASAR’, 2015.

[12] Z. Li, Y. Fan, B. Jiang, T. Lei, and W. Liu, ‘A survey on sentiment analysis and opinion mining for social multimedia’, Multimed Tools Appl, vol. 78, no. 6, pp. 6939–6967, Mar. 2019, doi: 10.1007/s11042-018-6445-z.

[13] A. Aziz, ‘Analisis Sentimen Identifikasi Opini Terhadap Produk, Layanan dan Kebijakan Perusahaan Menggunakan Algoritma TF-IDF dan SentiStrength’, Abdul Aziz, 2022.

[14] K. Yan, D. Arisandi, and) Tony, ‘Jurnal Ilmu Komputer dan Sistem Informasi ANALISIS SENTIMEN KOMENTAR NETIZEN TWITTER TERHADAP KESEHATAN MENTAL MASYARAKAT INDONESIA’.

[15] I. Alsmadi and G. K. Hoon, ‘Term weighting scheme for short-text classification: Twitter corpuses’, Neural

Comput Appl, vol. 31, no. 8, pp. 3819–3831, Aug. 2019, doi: 10.1007/s00521-017-3298-8.

[16] A. Kumar and T. M. Sebastian, ‘Sentiment Analysis on Twitter’, 2012.

[17] A. Witanti, B. Yogyakarta Jl Raya Wates-Jogjakarta, K. Sedayu, K. Bantul, and D. Istimewa Yogyakartalamat, ‘ANALISIS SENTIMEN MASYARAKAT TERHADAP VAKSINASI COVID-19 PADA MEDIA SOSIAL TWITTER MENGGUNAKAN ALGORITMA SUPPORT VECTOR MACHINE (SVM)’, Jurnal Sistem Informasi dan Informatika (Simika) P-ISSN, vol. 5, pp. 2622–6901, 2022.

[18] D. Gunawan, D. Riana, D. Ardiansyah, F. Akbar, and S. Alfarizi, ‘Komparasi Algoritma Support Vector Machine Dan Naïve Bayes Dengan Algoritma Genetika Pada Analisis Sentimen Calon Gubernur Jabar 2018-2023’, doi: 10.31294/jtk.v4i2.

[19] H. Saif, Y. He, and H. Alani, ‘Semantic sentiment analysis of twitter’, in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2012, vol. 7649 LNCS, no. PART 1, pp. 508–524. doi: 10.1007/978-3-642-35176-1_32.

[20] D. Duei Putri, G. Forda Nama, W. Eko Sulistiono Jurusan Teknik Elektro Universitas Lampung, B. Lampung Jl Sumantri Brojonegoro No, and B. Lampung, ‘Analisis Sentimen Kinerja Dewan Perwakilan Rakyat (DPR) Pada Twitter Menggunakan Metode Naive Bayes Classifier’, 2022.

[21] D. Rizki Aditya, E. Supriyati, and T. Listyorini, ‘ANALISIS SENTIMEN PENGGUNA TWITTER TERHADAP ROKOK ELEKTRIK (VAPE) DI INDONESIA MENGGUNAKAN METODE NAÏVE BAYES’.

[22] N. Sucahyo et al., ‘SWADHARMA (JRIS) ANALISIS SENTIMEN MASYARAKAT TERHADAP UU CIPTA KERJA PADA MEDIA SOSIAL TWITTER’.

[23] A. Kustanto, ‘DINAMIKA PERTUMBUHAN PENDUDUK DAN KUALITAS AIR DI INDONESIA’, JIEP, vol. 20, no. 1, 2020.

[24] D. N. Fitriana and Y. Sibaroni, ‘ARJUNA) Managed by Ministry of Research, Technology, and Higher Education’, Accredited by National Journal Accreditation, vol. 4, no. 2, pp. 846–853, 2020.

[25] O. F. Prihono and P. K. Sari, ‘Comparison Analysis Of Social Influence Marketing For Mobile Payment Using Support Vector Machine’, Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, pp. 367–374, Oct. 2019, doi: 10.22219/kinetik.v4i4.921.

[26] F. Alzami, E. D. Udayanti, D. P. Prabowo, and R. A. Megantara, ‘Document Preprocessing with TF-IDF to Improve the Polarity Classification Performance of Unstructured Sentiment Analysis’, Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, pp. 235–242, Aug. 2020, doi: 10.22219/kinetik.v5i3.1066.

[27] S. Cahyaningtyas, D. Hatta Fudholi, and A. Fathan Hidayatullah, ‘Deep Learning for Aspect-Based Sentiment Analysis on Indonesian Hotels Reviews’, Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, Aug. 2021, doi: 10.22219/kinetik.v6i3.1300.

[28] M. A. Suprayogi and R. A. Supono, “Klasifikasi Helpdesk Menggunakan Metode K-Nearest Neighbor dan TF-ABS,” Techno.Com, vol. 20, no. 4, pp. 508–517, 2021, doi: 10.33633/tc.v20i4.5094.