JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)

VOL. 9. NO. 1 AUGUST 2023
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v9i1.4201

SENTIMENT LABELING AND TEXT CLASSIFICATION MACHINE LEARNING FOR WHATSAPP GROUP

Susandri Susandri[1*]; Sarjon Defit[2]; Muhammad Tajuddin[3]

Faculty of Computer Science[1]
STMIK Amik Riau
https://sar.ac.id/
susandri@sar.ac.id[1*]

Faculty of Computer Science [2]
UPI YPTK Padang
https://upiyptk.ac.id/
sarjonde@yahoo.co.uk[2]

Faculty of Computer Science [3]
Bumigora University
https://universitasbumigora.ac.id/
tajuddin@universitasbumigora.ac.id[2]

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

Abstract*—The use of WhatsApp Group (WAG) for communication is increasing nowadays. WAG communication data can be analyzed from various perspectives. However, this data is imported in the form of unstructured text files. The aim of this research is to explore the potential use of the SentiwordNet lexicon for labeling the positive, negative, or neutral sentiment of WAG data from "Alumni94" and training and testing it with machine learning text classification models. The training and testing were conducted on six models, namely Random Forest, Decision Tree, Logistic Regression, K-Nearest Neighbors (KNN), Linear Support Vector Machine (SVM), and Artificial Neural Network. The labeling results indicate that neutral sentiment is the majority with 7588 samples, followed by 324 negative and 1617 positive samples. Among all the models, Random Forest showed better precision and recall, i.e., 83% and 64%. On the other hand, Decision Tree had slightly lower precision and recall, i.e., 80% and 66%, but exhibited a better f-measure of 71%. The accuracy evaluation results of the Random Forest and Decision Tree models showed significant performance compared to others, achieving an accuracy of 89% in classifying new messages. This research demonstrates the potential use of the SentiwordNet lexicon and machine learning in sentiment analysis of WAG data using the Random Forest and Decision Tree models*

Keywords*: Label Sentiment; Whatsapp Group; Text Classification; Machine Learning.*

Intisari—*Penggunaan WhatsApp Group (WAG) untuk komunikasi semakin meningkat saat ini. Data komunikasi WAG dapat dianalisis dari berbagai sudut pandang. Namun data tersebut diimpor dalam bentuk file text tidak terstruktur. Penelitian bertujuan mencari potensi penggunaan Leksikon SentiwordNet untuk pelabean sentimen positif, negatif, atau netral data WAG "Alumni94" dan melatih serta menguji dengan model klasifikasi teks Machine learning. Pelatihan dan pengujian dilakukan pada enam model yaitu Random Forest, Decision Tree, Logistic Regression, K-Nearest Neighbors (KNN), Linear support vector machine (SVM), dan Artificial Neural Network. Hasil pelabelan data menunjukan sentimen Netural lebih mayoritas dengan komposisi 7588, 324 Negatif, dan 1617 Positif. Dari semua model Random Forest memberikan presisi, recall yang lebih baik yaitu 83%, 64% Sedangkan Decision Tree lebih rendah sedikit pada presisi, recall yaitu 80%, 66% dengan ukuran-f yang lebih baik yaitu 71%. Hasil evaluasi akurasi model random forest dan decision tree menunjukkan kinerja yang signifikan dibanding yang lain dengan akurasi 89% untuk mengklasifikasi pesan baru. Penelitian ini menunjukkan potensi penggunaan Leksikon SentiwordNet dan pembelajaran mesin dalam analisis sentimen data WAG dengan model Random Forest dan Decision Tree*

Kata Kunci*: Label Sentimen; Whatshapp Group; Klasisfikasi Teks; Machine Learning.*

INTRODUCTION

Text classification (TC), also known as text categorization, is the process of assigning textual data to well-organized groups. The TC automatically analyzes texts and assigns them to predetermined categories. TC are crucial for processing and extracting information from unstructured data [1], [2]. Categorization of TC can be delineated into three distinct systems, namely rule-based systems, machine learning-based systems, and hybrid systems[3]. Rule-based systems utilize a predetermined set of rules to categorize texts into organized groups, while machine-learning-based systems employ past observations to classify them. Hybrid systems combine the basic classifiers trained using machine learning and rule-based systems.

Improvements in words and new text categories require more accurate text-classification methods [4]. Utilized a multi-label text classification method that combines dynamic semantic representation models and neural networks for word embedding and clustering algorithms in selecting semantic words. The experimental results show that this method outperforms others with the best accuracy at 10% and 20% variables. Machine learning (ML) has been developed and applied in this field, with newly developed word embedding methods or word representation using two powerful learning models, Recurrent Neural Networks and Convolutional Neural Networks [5], [6]. Research in the field of TC has been conducted to classify social media texts [7]. These studies have used different data, methods, and results. Communication model within WhatsApp can be classified and used as the basis of research [8] Important timeline information about who was involved, when the conversation took place, and at what time could be extracted [9] [10].

The data in the WhatsApp Group (WAG) can be highly variable and unstructured, making it difficult to analyze or categorize the information contained within them Data from the WAG in the form of text files are unstructured. Data contain information about encrypted messages and calls from WAG members to other members [11]. Data also includes dates, times, mobile numbers or names of WAG members, as well as messages consisting of words, sentences, links, emojis (emoticons), and <Media omitted>, which are traces of WAG members sending messages in the form of images or other multimedia [12]. As WAG messages increase and become unreadable and ignored by WAG members, data analysis can be performed on various aspects, including sentiment.

Sentiment analysis can be conducted at the document, sentence, phrase, and aspect levels using LSTM neural network and TensorFlow [13]. Two layers were created to train and test the data. This model was developed to identify the sentiment of transliterated Malayalam texts. The average accuracy of the model was 81.5%, and it can be further improved by adding more datasets. Sentiment analysis in WhatsApp groups can be performed to understand the members' feelings or sentiments towards a specific topic or issue. By conducting sentiment analysis, one can determine whether the sentiment is positive, negative, or neutral towards a particular topic or issue. The results of the analysis can aid in determining the appropriate way to communicate and respond within the group context, as well as understanding trends and behavioral patterns of the group members. However, sentiment clustering and labeling have not yet been applied to WhatsApp conversation data.

This study utilized Sentiword labeling on the "Alumni94" WhatsApp data, predominantly discussing reunions and alumni meetings, sharing experiences and careers after graduation, and the latest social life news. The labeling results were tested using a classification ML model.

Several studies have explored communication data on social media platforms, including WhatsApp. Different perspectives were applied in this study. Several separate asynchronous texts were conducted using pipes [14] Text classification was performed using different metrics with a minimum class distance. The results can calculate an error rate of 16.54%, which is caused by similar-length messages being marked as separate classes by the system [15]. conducted the development and testing of an incident-based keyword indexing and search tool on WhatsApp data. The survey results showed that 64% of respondents strongly agreed and agreed, and 72% agreed that keyword indexing was easy. They also positively agreed that users can easily search for keywords, and 40% were satisfied with the displayed relevant keyword analysis. Interaction of text, images, and videos in WhatsApp communication is increasing, with an abundance of emotional and sentimental expressions [16]. Adopting Text Classification Technique as a Supervised Machine Learning Method, analyzing and visualizing various views expressed by lecturers in a WhatsApp Group. The results show that out of over sixteen thousand total messages, only 8.7% were found to be relevant, while 43.3% were irrelevant.

Another study analyzed sentiment in long sentences on WhatsApp [17] classifying messages and writings based on emotions through sentiment analysis in WhatsApp chats. The same was also done by [7], [18]. With the increasing use and prevalence

Accredited Rank 2 (Sinta 2) based on the Decree of the Directorate General of Higher Education, Research and Technology. Ministry of Education, Culture, Research and Technology of the Republic of Indonesia No.225/E/KPT/2022, 07 December 2022. Published by LPPM Universitas Nusa Mandiri

VOL. 9. NO. 1 AUGUST 2023
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v9i1.4201

of emojis, emojis have become essential in sentiment analysis. Unstructured WhatsApp messages were structured using data mining techniques for sentiment analysis. The result showed a sentiment accuracy of 77.78% for relevant sentiment and 22.22% for irrelevant sentiment. Additionally, positive, neutral, and negative opinions have been classified using sentiment analysis and ML algorithms [8], [19], [20], and ML analysis has also been performed to classify messages related to bullying [21]. Finally, the efficiency of communication traffic and data in instant multimedia messaging applications was studied [22].

Training of machine learning models using a rule-based approach has involved the utilization of various parametric classifiers such as K-Nearest Neighbor (KNN), XGBoost, and Support Vector Machine (SVM). The classifiers were executed by applying TF-IDF and Bag of Words techniques for word weighting [23]. Result was an SVM accuracy model that achieved an f1 score of 79%, the lowest error rate of 0.23, and an accuracy of.

The objective of this research is to explore the potential use of the SentiwordNet lexicon for sentiment labeling and text classification using machine learning, utilizing unstructured data from WAG. Given the differences in data formats between WAG and other social media platforms, special treatment of the data used is required. Special treatment in this study includes preprocessing and feature extraction. Preprocessing involves data cleaning, tokenizing, data translation, and labeling data (positive, neutral, and negative) for the analysis models. Feature extraction involves sentiment classification using machine learning models.

MATERIALS AND METHODS

Development and testing stages were conducted using a data collection procedure on WAG. Labeling the data in the form of sentiment, preprocessing to transform the data into an appropriate format, feature extraction, and model evaluation shown in figure 1. Experimental evaluation was conducted by utilizing classification framework that included multiple models such as random forest, decision tree, logistic regression, KNN, linear SVM, and artificial neural network. In addition, all models were subjected to labeling, preprocessing, and feature extraction stages to ensure a thorough analysis. Final stage of this study involved comparing the performance evaluation results of the constructed models.

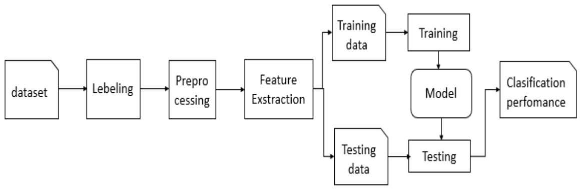

Figure 1. Development and Testing Phases

A. Dataset

Dataset used in this study was obtained from WAG. Selected WAG was the "Alumni94" WAG conversation data were obtained using an OPPO A15 smartphone, Android Version 10 operating system, octa-core processor, 3 Giga Byte RAM. Data were exported in the form of text files and sent directly to an email. WAG was created on 1/1/2019. The data used ranged from 20/1/2021 to 26/3/2022, with 132 members and a file size of 2563 KB.

B. Labeling

File data from WAG in the form of text are unstructured [24]. The data contain information about encrypted messages and calls from WAG members to other members and the time at which the WAG was created. This data consists of dates, times, mobile numbers or WAG member names, and messages that include words, sentences, links, emojis (emoticons), and <Media omitted>, which are traces of WAG members sending messages in the form of images or multimedia. Message data had no sentiment classification; therefore, emotional sentiment analysis was based on SentiWordNet emotional dictionary [25] [26] was used to determine the classification. Building models and analyzing emotional words and sentences were performed to label sentiment stages, as shown in figure 2.

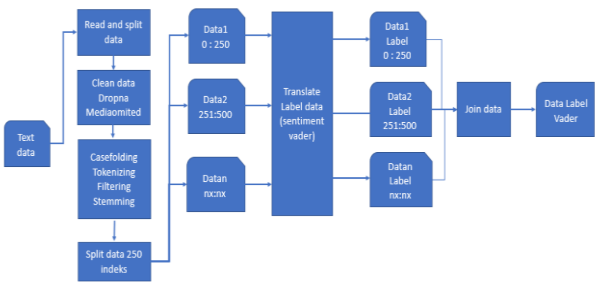

Figure 2. Data Labeling Procedure

Data reading and grouping were performed using regular expressions. Each line was read and divided by commas, and the first item was returned from the split function. The grouped data are parsed by giving specific tokens to detect date and time tokens and author tokens. More regular expression matching is required to detect message authors with patterns that store member names on a WAG. Extraction and combination of existing messages consist of text messages, emojis, and URL links sent by WAG members. Messages are classified on the basis of "message," "emoji," and "urlcount." Each line is then divided based on comma (,), hyphen (-), colon (:), and space ( ) separators so that necessary tokens can be extracted and stored in a data frame and displayed using the pandas library. Data that was read consists of 4479 rows and 6 columns, in the "Message" column. Data are cleaned in the "Message" column of empty messages, media upload traces (<Media omitted>), and emojis. Case folding was performed during the data cleaning process. The result was that 4479 rows of data after cleaning were reduced to 2811 rows, with 1668 rows deleted.

Data labeling grouped based on positive, neutral, and negative patterns, focusing on the message column. Labeling process begins by tokenizing words, filtering stop words using NLTK library, Sastrawi, and stemming. Tokenizing, filtering, and stemming processes depend on the amount of data to be processed. Result of this process reduced the amount of data to 2498 rows. Extraction was performed by adding a Message_English column, which translates data from the Message column into English using the Google Translator library. The process of adding the Message_English column, data were divided into 250 rows to facilitate language translation. The Message_English column was extracted by adding positive, negative, neutral, and compound columns, using the nltk.sentiment.vader SentimentIntensity Analyzer library. The compound column is extracted again to add a sentiment column with the condition that if the compound >= 0.05, the sentiment is ('Positive'), if the compound <= -0.05, the sentiment is ('Negative'), otherwise, the sentiment is ('Neutral'). Some of the labeling results were displayed in Table 1, and an overall result of the labeled data set is illustrated in Figure 3. Labeled data was saved in a alumni.csv file.

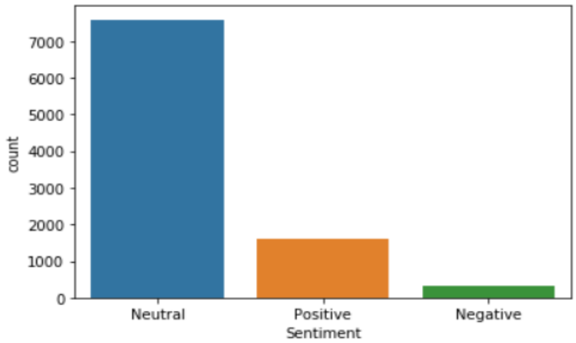

Figure 3. Sentiment Labeling Results

Table 1. Sentiment label data from WAG

no	Message_English	Sentiment
1	Alhamdulillah Success Smoothly we Work Forum	Positive
2	Name of Member of Social Activities List of Love Alumni 94 2020	Positive
3	Alhamdulillah 168 members of alumni 94 Registered majors	Neutral
4	Near the friend's house Maxim Simpang Kalumpang	Neutral
5	Allah SWT Lift the Body Disease Hengki Irawan Allah SWT Health Healing Allah SWT The Force of Birth of Allah SWT Lightens the burden of Allah SWT Gleads the Prayer of Allah SWT Amiin Yarabbal Alamin	Negative
6	Alhamdulillah Healthy Zul Aamiin Family	Positive
7	Alhamdulillah Healthy Wag God Aamiin Sustenance	Positive
8	Works is empty of buk budget	Negative
9	My friend son of forgate until burning sweet potatoes until the burnt black burned to eat	Positive
10	Steady chairman of eating wearing the chairman of the chairman of eating chairman	Neutral
11	Chairman No Package	Negative
12	Human cruel doesn't escape RT	Negative

C. Preprocessing

Preprocessing was performed the translated and labeled data. Cleaning process involves removing links and web addresses from messages sent by WAG members, replacing negation words with antonyms in text (negation), removing punctuation marks (punctuation), and returning words to their base form (lemmatization). Next step involved case folding, removing stop words, repeating words, and short words. Result of this preprocessing does not change the number of rows, but there is a change the uniqueness of words from 7131 to 7006. Data cleaning process reduced 125 words had no meaning, numerical symbols, or punctuation marks.

D. Feature Extraction

Feature extraction is performed to obtain the characteristics or features of a form, and the obtained values are analyzed and processed in the next stage. Feature extraction is performed by reducing dimensionality of the input data to groups that are easier to handle. Data cleaned in the preprocessing stage were subjected to an extraction process to determine sentiment using SentiWordnet library. Prior to this, Parts of Speech (POS) tagging performed mark words in text format for certain parts of the Message_ English column and assign certain tokens to each word by marking grammar. Furthermore, sentiment prediction from Message_english is extracted as pos, neg, and obj. The result of Predicted_Sentiment is different from the sentiment result data labeling process, neutral

VOL. 9. NO. 1 AUGUST 2023
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v9i1.4201

sentiment decreases and positive and negative sentiments increase, as shown in figure 4.

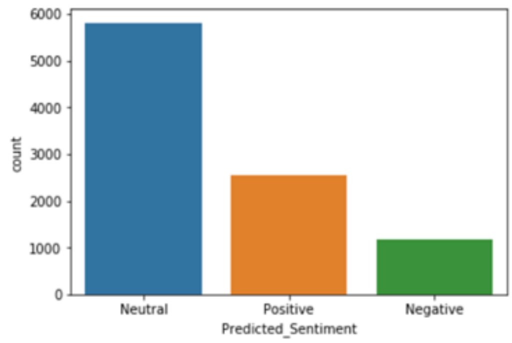

Figure 4. Predicted Sentiment Labeling Results

Results of extraction were evaluated using precision, recall, and f1-score metrics calculated using Sklearn, metrics classification_report library. Sentiment column in the dataset used as y_true, and the predicted _ sentiment column resulting from the extraction used as y_pred. The calculation results of this dataset show support of 324 negative, 7588 neutral, and 1617 positive with an accuracy of 0.72, average precision of 0.52, and recall of 0.64. Results are still low and have high potential for improvement. These results serve as the basis for further development before using the ML classification algorithm model.

RESULTS AND DISCUSSION

ML model was tested, and the result of extracting the Message_English column using SentiWordNet transformed into five columns. Machine learning testing stage is a continuation of the preprocessing stage with minor changes, taking X variable from extracted sentiment prediction results as shown in figure 5. Machine learning model testing used pos, neg, and obj columns as X values and sentiment column as Y variable.

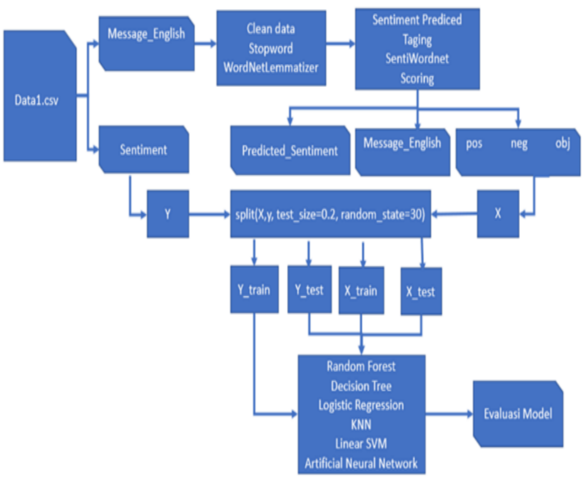

Figure 5. Model Testing Phase

Data divided into test and training sets using 80:20 ratio and distributed into X_train, X_test, Y_train, and Y_test variables with following composition: X_train= (7623,3), X_test= (1906,3), Y_train= 7623, and Y_test= 1906. Six machine-learning classification models tested, and their respective models and parameters are listed in Table 2.

Table 2. Model Architecture and Parameter Configuration

Model	Type
Random Forest	parameters include bootstrap, ccp_alpha, class_weight, criterion, max_depth, max_features, max_leaf_nodes, max_samples, min_impurity_decrease, min_impurity_split, min_samples_leaf, min_samples_split, min_weight_fraction_leaf, n_estimators, n_jobs, oob_score, random_state, verbose, and warm_start
Decision Tree	parameters include ccp_alpha, class_weight, criterion, max_depth, max_features, max_leaf_nodes, min_impurity_decrease, min_impurity_split, min_samples_leaf, min_samples_split, min_weight_fraction_leaf, presort, random_state, and splitter
Logistic Regression	LogisticRegression(C=1.0, class_weight=none, dual=False, fit_intercept=True, intercept_scaling=1, l1_ratio=none, max_iter=100, multi_class='auto', n_jobs=none, penalty='l2', random_state=none, solvent = 'lbfgs', tol = 0.0001, verbose = 0, warm_start = False)
K-Nearest Neighbors (KNN)	KNeighborsClassifier(algorithm= 'auto', leaf_size=30, metric= 'minkowski', metric_params= None, n_jobs= None, n_neighbors=5, p=2, weights= 'uniform')
Linear support vector machine (SVM)	LinearSVC(C=1.0, class_weight= None, dual= True, fit_intercept= True, intercept_scaling=1, loss= 'squared_hinge', max_iter =1000, multi_class ='ovr', penalty ='l2', random_state= None, tol=0.0001, verbose=0)
Artificial Neural Network	Model: "sequential" Layer(type) Output Shape Param =================================== flatten3 (Flatten) (None, 3) 0 dense9 (Dense) (None, 100) 400 dense10 (Dense) (None, 50) 5050 dense11 (Dense) (None, 3) 153 =================================== Total params: 5,603 Trainable params: 5,603 Non-trainable parameters: 0

This study evaluated performance of a proposed model using various machine learning algorithms, including random forest, decision tree, logistic regression, K-Nearest Neighbors, Linear Support Vector Machine, and Artificial Neural Network. Model's efficacy was assessed using a range of evaluation metrics. Results of the precision, recall, F1 score, and accuracy testing are presented in Table 3. The findings suggest a significant enhancement in comparison to the assessment outcomes of the extraction and machine learning model findings in the studies reviewed [27].

Table 3. Model Testing Results

Model	Accuracy	Precision	Recall	F1
Random Forest	0.89	0.83	0.64	0.69
Decision Tree	0.89	0.80	0.66	0.71
Logistic Regression	0.84	0.70	0.50	0.53
KNN	0.88	0.76	0.62	0.67
Linear SVM	0.84	0.70	0.46	0.48
Artificial Neural Network	0.87	0.55	0.50	0.51

Of all the models, Random Forest provided the best precision and recall (83% and 64 %, respectively). Meanwhile, the Decision Tree was slightly lower in terms of precision and recall, that is, 80% and 66%, respectively. Among the models used in this testing, a better F-measure was obtained for the Decision Tree (71 %). Models were evaluated based on their accuracy performance, and the comparison results are presented in figure 6. As the figure, it is evident that both random forest and decision tree models displayed remarkable performance compared to the other models, registering an accuracy rate of 89%. However, concerning precision, the Random Forest model outperformed the Decision Tree model by 0.03 points. Conversely, in terms of recall and F1 score, the Decision Tree model demonstrated higher values.

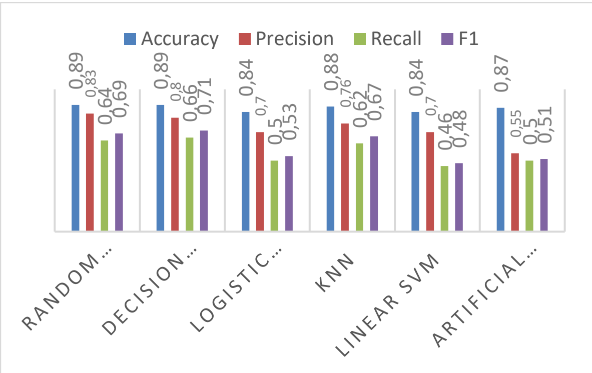

Figure 6. Performance Comparison of Accuracy, Precision, Recall, and F1 Score

CONCLUSION

The use of WhatsApp Group (WAG) for communication is increasingly prevalent nowadays. The communication data within WAG can be analyzed from various perspectives. However, this data is usually in the form of unstructured text files. This research utilizes the SentiwordNet lexicon as a tool to label the positive, negative, or neutral sentiment of the data from "Alumni94" WAG. Subsequently, the data is trained and tested using machine learning-based text classification models. Six models were employed in the training and testing process, namely Random Forest, Decision Tree, Logistic Regression, K-Nearest Neighbors (KNN), Linear Support Vector Machine (SVM), and Artificial Neural Network. The labeling results indicate that neutral sentiment is the majority with a total of 7588 samples, while negative and positive sentiments have 324 and 1617 samples respectively. Among all the models tested, Random Forest exhibited better precision and recall, i.e., 83% and 64%. On the other hand, Decision Tree had lower precision and recall, i.e., 80% and 66%, but showcased a higher f-measure of 71%. The accuracy evaluation results revealed that both Random Forest and Decision Tree models performed significantly better compared to other models, achieving an accuracy of 89% in classifying new messages. This research demonstrates the potential use of the SentiwordNet lexicon and machine learning in sentiment analysis of WAG data using the Random Forest and Decision Tree models. Future research could explore dedicated deep-learning classification models or hybrid classification models to advance this study.

REFERENCE

[1] M. P. Akhter *et al*, "Document-Level Text Classification Using Single-Layer Multisize Filters Convolutional Neural Network," *IEEE Access*, vol. 8, no. Ml, pp. 42689–42707, 2020, doi: 10.1109/ACCESS.2020.2976744.

[2] A. Wahdan *et al*, "A systematic review of text classification research based on deep learning models in Arabic language," *Int. J. Electr. Comput. Eng.*, vol. 10, no. 6, pp. 6629–6643, 2020, doi: 10.11591/IJECE.V10I6.PP6629-6643.

[3] W. Fang *et al*, "Automated text classification of near-misses from safety reports: An improved deep learning approach," *Adv. Eng. Informatics*, vol. 44, no. March 2019, p. 101060, 2020, doi: 10.1016/j.aei.2020.101060.

[4] T. Wang *et al*, "A multi-label text classification method via dynamic semantic representation model and deep neural network," *Appl. Intell.*, vol. 50, no. 8, pp. 2339–2351, 2020, doi: 10.1007/s10489-020-01680-w.

[5] H. Yang *et al*, *Deep Learning and Its Applications to Natural Language Processing*. 2019.

[6] R. Joshi *et al*, "Deep Learning for Hindi Text Classification: A Comparison," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and*

Accredited Rank 2 (Sinta 2) based on the Decree of the Directorate General of Higher Education, Research and Technology. Ministry of Education, Culture, Research and Technology of the Republic of Indonesia No.225/E/KPT/2022, 07 December 2022. Published by LPPM Universitas Nusa Mandiri

VOL. 9. NO. 1 AUGUST 2023
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v9i1.4201

Lecture Notes in Bioinformatics), 2020, pp. 94–101. doi: 10.1007/978-3-030-44689-5_9.

[7] A. Mohta *et al*, "Pre-processing and emoji classification of whatsapp chats for sentiment analysis," in *Proceedings of the 4th International Conference on IoT in Social, Mobile, Analytics and Cloud, ISMAC 2020*, 2020, pp. 514–519. doi: 10.1109/I-SMAC49090.2020.9243443.

[8] K. Masood *et al*, "Semantic Analysis to Identify Students' Feedback," *Comput. J.*, vol. 00, no. 00, 2020, doi: 10.1093/comjnl/bxaa130.

[9] H. Shidek *et al*, "WhatsApp Chat Visualizer: A Visualization of WhatsApp Messenger's Artifact Using the Timeline Method," *Int. J. Inf. Commun. Technol.*, vol. 6, no. 1, pp. 1–9, 2020, doi: 10.21108/ijoict.2020.61.489.

[10] S. Defit *et al*, "Timeline of Exploration on the Best Response Time in WhatsApp Group " Our Jokes at STMIK Amik "," *Matrik J. Manajemen, Tek. Inform. dan Rekayasa*, vol. 20, no. 2, p. 317~324, 2021, doi: 10.30812/matrik.v20i2.1149.

[11] N. Sharma *et al*, "Machine Learning and Deep Learning Applications-A Vision," *Glob. Transitions Proc.*, pp. 0–8, 2021, doi: 10.1016/j.gltp.2021.01.004.

[12] Ravishankara K *et al*, "Whatsapp Chat Analyzer," *Int. J. Eng. Res. Technol.*, vol. 9, no. 5, pp. 897–900, 2020, doi: 10.17577/ijertv9is050676.

[13] M. Thomas and C. A. Latha, "Sentimental analysis of transliterated text in Malayalam using recurrent neural networks," *J. Ambient Intell. Humaniz. Comput.*, vol. 11, no. 7, 2020, doi: 10.1007/s12652-020-02305-3.

[14] A. Sinha *et al*, "Text Segregation on Asynchronous Group Chat," in *Procedia Computer Science*, Elsevier B.V., 2020, pp. 1371–1380. doi: 10.1016/j.procs.2020.04.147.

[15] S. H. S. Nizam *et al*, "Keyword Indexing And Searching Tool (KIST): A Tool to Assist the Forensics Analysis of WhatsApp Chat," *Int. J. Inf. Commun. Technol.*, vol. 6, no. 1, pp. 23–30, 2020, doi: 10.21108/ijoict.2020.61.481.

[16] A. Ahmad and M. Abubakar, "Sentiment Analysis and Classification of Asuu Whatsapp Group Post using Data Mining," *J. Confl. Resolut. Soc. Issues*, vol. 1, no. 2, pp. 17–26, 2022.

[17] L. Dogruel and A. Schnauber-Stockmann, "What determines instant messaging communication? Examining the impact of person- and situation-level factors on IM responsiveness," *Mob. Media Commun.*, vol. 9, no. 2, pp. 210–228, 2020, doi: 10.1177/2050157920943926.

[18] D. B. G, J. A, and P. K. V, "Toxic Sentiment Identification Using R Programming," *Int. J. Eng. Technol. Manag. Sci.*, vol. 4, no. 5, pp. 76–81, 2020, doi: 10.46647/ijetms.2020.v04i05.014.

[19] A. Yadav *et al*, "Understanding the political inclination of WhatsApp chats," in *ACM International Conference Proceeding Series*, 2020, pp. 361–362. doi: 10.1145/3371158.3371227.

[20] L. Blasi *et al.*, "Reactions and countermeasures of medical oncologists towards the incoming COVID-19 pandemic: A whatsapp messenger-based report from the Italian college of chief medical oncologists," *Ecancermedicalscience*, vol. 14, pp. 1–11, 2020, doi: 10.3332/ECANCER.2020.1046.

[21] I. Saputra *et al*, "Comparison of the Performance of the k-Nearest Neighbor, Naïve Bayes Classifier and Support Vector Machine Algorithm With SMOTE for Classification of Bully Behavior on the WhatsApp Messenger Application," 2021, pp. 143–149. doi: 10.2991/assehr.k.201230.028.

[22] T. K. Eds *et al.*, "Beyond social chit chat? Analysing the social practice of a mobile messaging service on a higher education teacher development course," *Adv. Intell. Syst. Comput.*, vol. 3, no. 1, pp. 1–6, 2020, doi: 10.1177/1750481319868853.

[23] S. Kalakala, "A Rule Based Sentiment Analysis of Whatsapp Reviews in Telugu Language," 2021.

[24] H. Taha Assaggaf, "A Discursive and Pragmatic Analysis of WhatsApp Text-based Status Notifications," *Arab World English J.*, vol. 10, no. 4, pp. 101–111, 2019, doi: 10.24093/awej/vol10no4.8.

[25] Y. Zhou *et al*, "Text Sentiment Analysis Based on a New Hybrid Network Model," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–15, 2022.

[26] B. S. Rintyarna *et al*, "Evaluating the performance of sentence level features and domain sensitive features of product reviews on supervised sentiment analysis tasks," *J. Big Data*, vol. 6, no. 1, 2019, doi: 10.1186/s40537-019-0246-8.

[27] F. E. Ayo *et al*, "Machine learning techniques for hate speech classification of twitter data: State-of-The-Art, future challenges and research directions," *Comput. Sci. Rev.*, vol. 38, p. 100311, 2020, doi: 10.1016/j.cosrev.2020.100311.