JURNAL INFORMATIKA, Vol. 11 No. 2 October 2025, Page 68-74
ISSN (Print) 2355-6579 | ISSN (Online) 2528-2247
DOI: https://doi.org/10.31294/inf.v12i2.25323

Opinion Mining on Spotify Music App Reviews Using Bidirectional LSTM and BERT

Primandani Arsi[1*], Reza Arief Firmanda[2], Iphang Prayoga[3] , Pungkas Subarkah[4]

[1,2,3,4] Faculty of Computer Science, Universitas Amikom Purwokerto
Jl. Letjend Pol. Soemarto No.127, Watumas, Purwanegara, Kabupaten Banyumas, Indonesia

Correspondence e-mail: ukhti.prima@amikompurwokerto.com

Submission:	Revision:	Acceptance:	Available Online:
20-02-2025	03-05-2025	27-05-2025	01-10-2025

Abstract

The increasing number of user reviews on digital music platforms such as Spotify highlights the importance of sentiment analysis to better understand user perceptions. This study aims to develop a sentiment classification model for Spotify user reviews using a Bidirectional Long Short-Term Memory (BiLSTM) approach combined with BERT embeddings. The dataset consists of multilingual user reviews collected from the Google Play Store. Preprocessing steps include text cleaning, tokenization, and padding. BERT is utilized to generate contextual word embeddings, which are then processed by the BiLSTM model to classify sentiments as either positive or negative. The model's performance is evaluated using a confusion matrix with accuracy, precision, recall, and F1-score metrics. The results show that the BiLSTM-BERT model achieves an F1-score of 0.8852, a recall of 0.9396, a precision of 0.8375, and an accuracy of 0.8374. These findings demonstrate the model's effectiveness in handling multilingual sentiment analysis tasks, offering valuable insights for developers in enhancing user experience through data-driven decision-making.

Keywords: Opinion mining; App reviews; Bidirectional LSTM and BERT

1. Introduction

Spotify is a music streaming application that allows users to listen to music across various genres from different artists (Aldabbas et al. 2020). With over 188 million users in 2022 (businessofapps), Spotify dominates the music streaming market(Josi, Arindawati, and Nurkinan 2020). In today's digital era, sentiment analysis plays a crucial role in understanding user opinions, and applications like Spotify provide a rich dataset of reviews that can be analyzed to improve services and user experience(Locarso 2022) (Rahayu, Fauzi, and Rahmat 2022).

Several approaches have been employed in sentiment analysis, including machine learning-based methods and natural language processing (Wahyudi and Kusumawardana 2021) (Verma 2022). For instance, Karim (2020) used the Multichannel Convolutional-LSTM method to classify a dataset from Bengali news articles, Facebook pages, and tweets, achieving a top accuracy score of 78.36%(Karim et al. 2020). Similarly, Kahn (2022) applied the CNN-LSTM method for sentiment analysis on datasets in both English and Romanized Urdu, achieving a top accuracy score of 84.1% for the English dataset. While these methods yielded promising results, they did not fully account for contextual factors in their analysis(Khan et al. 2022).

However, there are limitations in these approaches, particularly in terms of context understanding. While LSTM models have a forget gate feature to retain the text they have previously received, they can only read text in one direction, which limits deeper understanding of word relationships in a sentence(Jahangir et al. 2021)(Imrana et al. 2021)(Yu et al. 2024)(Liu and Guo 2019). Additionally, GloVe, as a word embedding technique, does not consider the position of words in a sentence, which can lead to inaccurate results even when the word order changes. Furthermore, while BERT helps clarify word forms in sentences, some previous studies did not optimally implement BERT(Otter, Medina, and Kalita 2021)(Chinnalagu and Durairaj 2021)(David, Cui, and Rahimi 2020)

This study proposes the use of Bidirectional LSTM (BiLSTM) and BERT as an alternative to LSTM and GloVe/Word2Vec. BiLSTM can read text in both directions, allowing for a better understanding of word context and relationships in a sentence. Additionally, BERT, which uses a two-way transformer technique, enables richer contextual modeling and more accurate sentiment analysis.

The aim of this study is to explore the effectiveness of a BiLSTM model combined with BERT in sentiment analysis of user reviews for the Spotify application. With this approach, it is expected that a deeper and more accurate understanding of user opinions regarding the application can be achieved, contributing to the development of more advanced sentiment analysis methods in the future.

2. Research Methods

The experiments in this study were conducted on a Lenovo ThinkPad T14 equipped with an AMD Ryzen 7 7730U processor (8 cores / 16 threads, 2.0 / 4.5 GHz, 4MB L2 / 16MB L3 cache) and 16 GB RAM with 512 GB SSD storage. The flow of sentiment analysis research, which includes the implementation of Bidirectional LSTM and the BERT Tokenizer, is illustrated in Figure 1.

Figure 1 illustrates the stages of the research methodology conducted. These stages will be explained in the following statements. The dataset consists of reviews of Spotify and was obtained through web scraping. This dataset contains sentiment data in various languages (multilingual). In the 'rating' attribute, it was observed that the distribution is bimodal, with two distinct peaks that are far apart(Indrawati 2021). The dataset will be segmented based on the average rating score.

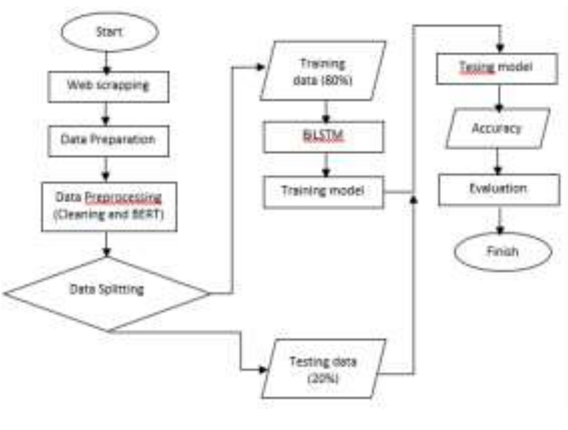

Figure 1. Research concept

There are two stages of data preprocessing, which include the data cleaning process and BERT Tokenization. During data cleaning, text attributes undergo processes such as case folding (Rachman, Goejantoro, and Amijaya 2020), punctuation removal, and stop word elimination (Heryanto and Pramudita 2020). Meanwhile, the BERT tokenizer breaks down the text within the documents into tokens(Firdaus and Firdaus 2021)(Anhar, Adji, and Akhmad Setiawan 2019)(Prihatno et al. 2021)(Varghese et al. 2019). The model used for implementing BiLSTM is based on a recurrent neural network architecture, specifically Recurrent Neural Network (RiNN).

The BiLSTM model training employs the following functions: Binary Cross Entropy loss, Adaptive Moment Estimation (Adam) Optimizer with a learning rate of 1e-4, and a total of 5 epochs(Ratna 2020)(Pandika Pinata, Sukarsa, and Dwi Rusjayanthi 2020)(Fhadli et al. 2022). The metrics used for model evaluation include the Confusion Matrix, Accuracy, and F1-Score.

3. Results and Discussion

As a follow-up to the review of previous studies, this research explicitly provides a comparison with several earlier approaches that did not implement the Bidirectional Long Short-Term Memory (BiLSTM) architecture. The BiLSTM approach in this study offers a significant advantage in capturing the contextual meaning of user reviews, as it processes information in both forward and backward directions, thereby improving sentiment classification accuracy compared to the unidirectional models used in prior studies. Moreover, this research analyzes user reviews written in 49 different languages, making the proposed model more robust and applicable to multilingual sentiment analysis.

a. Data Collection

This research utilizes the Spotify application review dataset, which was collected by scraping. The Spotify reviews were gathered within the time frame of April 18, 2022, to January 13, 2023, and the scraping process took place on January 31, 2023, at 10:44. This dataset is stored in .csv format and comprises 12 attributes, including source, review_id, user_name, review_title, review_description, rating, thumbs_up, review_date, developer_response, developer_response_date, language_code, and country_code. In total, there are 61,594 records of sentiment data. Review Description refers to the raw content of the review submitted by the user. This attribute is multilingual, consisting of 49 languages, including Japanese, Indonesian, Catalan, Norwegian, Hebrew, Welsh, Macedonian, Tagalog, Romanian, Kannada, Ukrainian, Portuguese, Marathi, Telugu, French, Swahili, Russian, Turkish, Hungarian, Punjabi, Korean, Greek, Gujarati, Czech, Hindi, Arabic, Nepali, Lithuanian, Tamil, German, Bulgarian, Finnish, Italian, Slovak, Malay, and many others.

b. Data Preparation

In the 'rating' attribute, it was observed that the distribution is bimodal or exhibits two distinct peaks. The distribution results are illustrated in Figure 2.

The distribution pattern depicted in Figure 2 indicates that the dataset is imbalanced.

Consequently, the 'rating' attribute is simplified into two classes, namely 'positive' and 'negative,' based on the mean rating of 3.15. This simplification results in ratings 1 to 3 being classified as 'negative' and ratings 4 to 5 being classified as 'positive.' The total data resulting from this class simplification process amounts to 31,657 records for the 'negative' class and 29,937 records for the 'positive' class.

Figure 1. Rating

c. Text Preprocessing

In this stage, the research comprises two steps: data cleaning and text tokenization using the BERT Tokenizer. The workflow is illustrated in Figure 3.

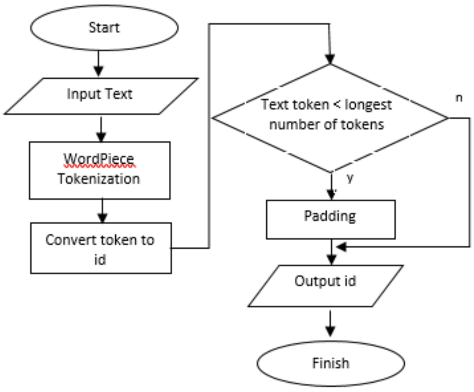

Figure 3. Text Preprocessing

First, input sentences or reviews are segmented into subwords using the WordPiece tokenization process. These tokens or subwords are then mapped to ID values, with each ID corresponding to the word numbering in the vocabulary list maintained by the BERT Tokenizer. Since the pre-trained BERT model utilized in this study is M-BERT, the maximum token limit should not exceed 512 tokens. For reviews with a token count below this limit, padding is applied. Only two attributes from the dataset are utilized: 'rating' and 'review_description,' as illustrated in Table 1.

Table 1. The function of Power Supply Components

No	Sentiment	Rating
1	"BEAUTIFUL SOUND'S IS GOOD MUSIC TO U'RE EAR'S AND dTHAT'S ALL GOOD, 5 TRIPLE STAR'S PLUS 4SHO"!!!	5
2	Bruh Y can't I listen to the music I searched up and pressed play on?	3
3	Amazing app....	5
4	There is no way to add podcast episodes to my queue on my phone. It's also very easy to accidentally swipe and skip episodes or clear the queue. Other apps like PocketCasts are much easier to use	2
5	It's a great music play but or at least for me when I logged in with my new phone it didn't let me play the song I wanted it picked a random song from my playlist. I want them to fix this it also has a thirdy second ad for almost every song.	4

Meanwhile, the attributes source, review_id, user_name, review_title, thumbs_up, review_date, developer_response, developer_ response_date, language_code, and country_ code are excluded from this study as they do not play a significant role.

1. Case Folding

   In text review datasets, there is often a mixture of uppercase and lowercase letters. The objective of case folding is to convert all letters in the reviews to lowercase, ensuring that the machine does not differentiate the same word as different words.

2. Punctuation Removal

   In the review dataset, punctuation marks are often present in the text. However, they do not significantly impact the meaning of the reviews. In this study, certain punctuation marks that do not significantly impact the text are removed. These include: ! " # $ % & ' ( ) * + , - . / : ; < = > ? @ [\ ] ^ _ ` { | } ~."

3. Stopwords Removal

   In the next step, we perform stop words removal. Stop words are commonly used words that typically do not contribute valuable information in sentiment analysis. For example, in English, stop words include words like 'a,' 'the,' 'is,' 'are,' and so on.

   To focus the analysis on more meaningful words, we need to eliminate stop words. Since the text review dataset used in this study is multilingual, stop words in several languages, including Arabic, Azerbaijani, Basque, Catalan, Bengali, Danish, Dutch, English, Finnish, French, German, Greek, Hebrew, Hinglish, Hungarian, Indonesian, Italian, Kazakh, Nepali, Norwegian, Portuguese, Romanian, Russian, Slovene, Spanish, Swedish, Tajik, and Turkish, should be removed.

4. Tokenization Wordpiece

After the data undergoes the data cleaning process, the next step is tokenization, where the text is broken down into smaller parts. In this research, we utilize the BERT Tokenizer employing the WordPiece technique. This involves dividing words in the text into smaller units known as tokens.

5. Converting Tokens to Id Values

Following the tokenization process, the next step is to convert the tokens into ID values by referring to the word numbering within BERT's vocabulary list. An example of this word-to-ID mapping is presented in Table 2.

Table 2. Token Conversion

Sentiment	Sentiment
beautiful,sounds,good,music,ure,ears,thats,good,5,triple,stars, plus,4sho	[3376, 1010, 4165, 1010, 2204, 1010, 2189, 1010, 24471, 2063, 1010, 5551, 1010, 2008, 2015, 1010, 2204, 1010, 1019, 1010, 6420, 1010, 3340, 1010, 4606, 1010, 1018, 22231]
bruh,cant,listen,music,searched,pressed, play	[7987,27225,1010, 2064, 2102, 1010, 4952, 1010, 2189, 1010, 9022, 1010, 4508, 1010, 2377]
amazing,app	[6429, 1010, 10439]

6. Padding

The dataset used in this study contains texts with varying lengths in each review. To train the model, it's necessary for all inputs to have the same sentence length. As a result, a padding process is applied to input sentences that are shorter than the predefined maximum token length. If an input sentence exceeds the maximum token length, it undergoes truncation.

The padding process involves adding elements of 0 to fill the length up to the maximum token. During the training process, text reviews are grouped into batches, with each batch containing 32 reviews. Each batch may have a different maximum token count. For instance, in the first batch, 32 reviews may have a maximum token count of 7. This means that if the reviews in the batch have fewer than 7 tokens, they will receive additional padding.

d. Data Splitting

In this stage, the data is split into two parts: the training data, which accounts for 80% of the dataset, and the testing data, which accounts for the remaining 20% (Asghar et al. 2021). This division is determined based on a batch size of 32, which is a recommended size to enhance BERT-Fine-Tuning potential from its transfer learning model.

For a total dataset size of 61,594, this results in 1928.0625 batches (rounded down to 1928 batches). Consequently, 80% of 1928 batches equals 1542 batches, or 49,344 data points, allocated for the training data, while 20% of 1928 batches equals 385 batches, or 12,320 data points, assigned to the testing data.

e. Application of BiLSTM

The model employed in the implementation of BiLSTM is founded on a recurrent neural network (RNN) architecture. The model's framework is depicted in Figure 4.

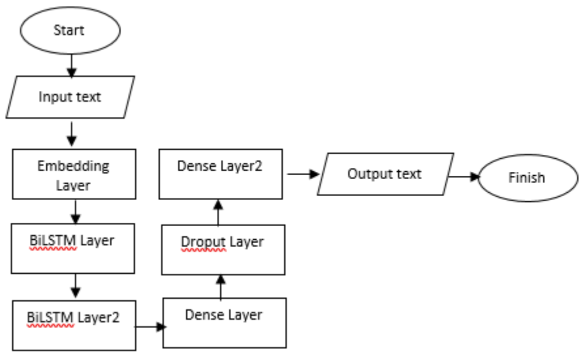

Figure 4. BiLSTM

1. Embedding layer

The Embedding Layer has a parameter called input_dim, which represents the size of the vocabulary, and output_dim, which specifies the dimensionality of the dense embedding, set at 200. This layer will generate an output in the form of a 3D floating-point tensor that consists of samples, sequence length, and embedding dimensionality.

2. Bidirectional LSTM layer

The first Bidirectional LSTM layer employs 64 units with the 'return_sequences' parameter set to true, while the second layer uses 32 units with 'return_sequences' set to false. In this configuration, for a sentence example like 'the cat jumps over the wall,' the input sentence is processed both from left to right and from right to left. For instance, 'the cat jumps over the wall' is processed in the order of 'the' → 'cat' → 'jumps' → 'over' → 'the' → 'wall' and also 'the' ← 'cat' ← 'jumps' ← 'over' ← 'the' ← 'wall.' This process enhances our understanding of the sentence context.

3. Dense Layer

The first dense layer employs 64 units with a ReLU activation function, whereas the second dense layer (following the dropout layer) utilizes 1 unit with a sigmoid activation function.

4. Dropout layer

The rate is set to 0.5. Its purpose is to prevent overfitting in the model, a condition where the model learns the patterns in the training data too precisely, thus hindering its ability to generalize to new data.

f. Training Model

The Binary Cross Entropy loss function is utilized to calculate the cross-entropy loss value between the predicted sentiment and the actual sentiment. This loss function represents the performance of the trained model.

Adaptive Moment Estimation (Adam) optimizer with a learning rate of 1e-4 is employed to minimize the model's loss value, enabling faster sentiment predictions.

The number of epochs is set to 5 to expedite the training process. Training is conducted in batches rather than processing all samples in a single iteration. This batching approach is aimed at balancing accuracy and training time.

The model training process in this study was carried out using 1542 batches of training data, totaling 49,344 data points.

g. Testing Model

To assess the effectiveness of the constructed model, a testing process was conducted using separate test data. The test results are determined by the accuracy value obtained, which is calculated based on the test data that was previously separated from the training data.

The model testing used a predefined test dataset, which constitutes 20% of the total dataset, equivalent to 385 batches or approximately 12,320 data points.

h. Model Evaluation

Model evaluation is a critical aspect of this research. In this context, we will assess the performance of the model constructed using Bidirectional LSTM and BERT Tokenizer by employing the Spotify application dataset for text sentiment analysis. The metrics used for model evaluation include the Confusion Matrix, Accuracy, and F1-Score.

The Confusion Matrix is used to calculate the predicted and actual values processed, and since there are only 2 classes, a 2x2 confusion matrix is obtained with TP = 7732, TN = 2558, FP = 1502, and FN = 496. Figure 5 shows the result of the confusion matrix.

The result of the confusion matrix in Figure 5 produced:

Recall = TP / (TP + FN) = 7732 / (7732 + 496) = 0.9396

Precision = TP / (TP + FP) = 7732 / (7732 + 1502) = 0.8375

F1-Score = 2 x Precision x Recall / (Precision + Recall) = 2 x 0.8375 x 0.9396 / (0.8375 + 0.9396) = 0.8856

Accuracy = (TP + TN) / (TP + FN + TN + FP) = (7732 + 2558) / (7732 + 496 + 2558 + 1502) = 0.8374

Thus, the f1-score value from the confusion matrix result is 0.8852, recall value is 0.9396, precision value is 0.8375, and accuracy value is 0.8374.

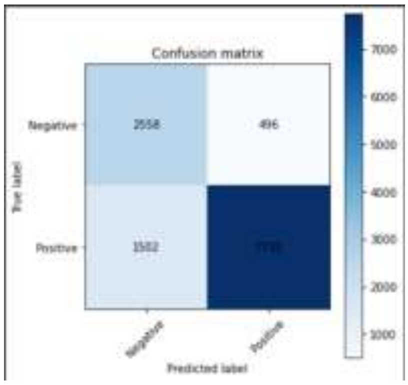

Figure 5. Confusion matrix

4. Conclusion

This study demonstrates that the combination of BERT Tokenizer and Bidirectional LSTM is effective for multilingual sentiment analysis of user reviews on the Spotify application. The integration of BERT's contextual word embeddings and BiLSTM's bidirectional sequence processing significantly enhances the model's ability to understand and classify sentiments across 49 different languages. The experimental results showed improved accuracy over successive training epochs, indicating that the proposed hybrid approach can successfully capture nuanced expressions of sentiment. These findings affirm that the model provides a robust solution for sentiment classification in diverse linguistic contexts.

Reference

Aldabbas, Hamza, Abdullah Bajahzar, Meshrif Alruily, Ali Adil Qureshi, Rana M. Amir Latif, and Muhammad Farhan. 2020. "Google Play Content Scraping and Knowledge Engineering Using Natural Language Processing Techniques with the Analysis of User Reviews." *Journal of Intelligent Systems* 30(1):192–208. doi: 10.1515/jisys-

2019-0197.

Anhar, Refany, Teguh Bharata Adji, and Noor Akhmad Setiawan. 2019. "Question Classification on Question-Answer System Using Bidirectional-LSTM." *Proceedings - 2019 5th International Conference on Science and Technology, ICST 2019* 1–5. doi: 10.1109/ICST47872.2019.9166190.

Asghar, Muhammad Zubair, Fazli Subhan, Hussain Ahmad, Wazir Zada Khan, Saqib Hakak, Thippa Reddy Gadekallu, and Mamoun Alazab. 2021. "Senti-ESystem: A Sentiment-Based ESystem-Using Hybridized Fuzzy and Deep Neural Network for Measuring Customer Satisfaction." *Software - Practice and Experience* 51(3):571–94. doi: 10.1002/spe.2853.

Chinnalagu, Anandan, and Ashok Kumar Durairaj. 2021. "Context-Based Sentiment Analysis on Customer Reviews Using Machine Learning Linear Models." *PeerJ Computer Science* 7. doi: 10.7717/PEERJ-CS.813.

David, Jeniffer, Jiarong Cui, and Fatemeh Rahimi. 2020. "Classification of Imbalanced Dataset Using Bert Embeddings."

Fhadli, Muhammad, Alfanugrah A. Hi Usman, Amal Khairan, Universitas Khairun, Jl Pertamina Kampus, I. I. Unkhair, Gambesi Kota, Ternate Selatan, and Nama Nama. 2022. "Pelatihan Machine Learning Menggunakan Bahasa Pemrograman Python Di Lingkungan Komunitas Teknologi Informasi Di Kota Ternate." *TRIDARMA : Pengabdian Kepada Masyarakat* 5(2).

Firdaus, Ali, and Wahyu Istalama Firdaus. 2021. "Text Mining Dan Pola Algoritma Dalam Penyelesaian Masalah Informasi : (Sebuah Ulasan)." *Jurnal JUPITER* 13(1):66.

Heryanto, A., and R. Pramudita. 2020. "Opini Media Sosial Facebook Terhadap Produk Hijab Menggunakan Metode Text Mining." *Information System for …* 4(2):168–77.

Imrana, Yakubu, Yanping Xiang, Liaqat Ali, and Zaharawu Abdul-Rauf. 2021. "A Bidirectional LSTM Deep Learning Approach for Intrusion Detection." *Expert Systems with Applications* 185(July):115524. doi: 10.1016/j.eswa.2021.115524.

Indrawati, Ariani. 2021. "Penerapan Teknik Kombinasi Oversampling Dan Undersampling Untuk Mengatasi Permasalahan Imbalanced Dataset." *JIKO(Jurnal Informatika Dan Komputer)* 4(1):38–43. doi: 10.33387/jiko.

Jahangir, Hamidreza, Hanif Tayarani, Saleh Sadeghi Gougheri, Masoud Aliakbar Golkar, Ali Ahmadian, and Ali Elkamel. 2021. "Deep Learning-Based Forecasting Approach in Smart Grids with Micro-Clustering and Bi-Directional LSTM Network." *IEEE Transactions on Industrial Electronics* 68(9):8298–8309. doi: 10.1109/TIE.2020.3009604.

Josi, Gabriel Putra, Weni A. Arindawati, and Nurkinan. 2020. "Motif Penggunaan Aplikasi Musik Spotify Pada Generasi-Z Di SMA XYZ Bekasi." *Warta ISKI* 3(02):154–59. doi: 10.25008/wartaiski.v3i02.64.

Karim, Md Rezaul, Bharathi Raja Chakravarthi, John P. McCrae, and Michael Cochez. 2020. "Classification Benchmarks for Under-Resourced Bengali Language Based on Multichannel Convolutional-LSTM Network." *Proceedings - 2020 IEEE 7th International Conference on Data Science and Advanced Analytics, DSAA 2020* 390–99. doi: 10.1109/DSAA49011.2020.00053.

Khan, Lal, Ammar Amjad, Kanwar Muhammad Afaq, and Hsien Tsung Chang. 2022. "Deep Sentiment Analysis Using CNN-LSTM Architecture of English and Roman Urdu Text Shared in Social Media." *Applied Sciences (Switzerland)* 12(5). doi: 10.3390/app12052694.

Liu, Gang, and Jiabao Guo. 2019. "Bidirectional LSTM With Attention Mechanism and Convolutional Layer for Text Classification." *Neurocomputing* 337:325–38. doi: 10.1016/j.neucom.2019.01.078.

Locarso, George Kenneth. 2022. "Analisis Sentimen Review Aplikasi Pedulilindungi Pada Google Play Store Menggunakan NBC." *Jurnal Teknik Informatika Kaputama (JTIK)* 6(2):353–61.

Otter, Daniel W., Julian R. Medina, and Jugal K. Kalita. 2021. "A Survey of the Usages of Deep Learning for Natural Language Processing." *IEEE Transactions on Neural Networks and Learning Systems* 32(2):604–24. doi: 10.1109/TNNLS.2020.2979670.

Pandika Pinata, Ngakan Nyoman, I. Made Sukarsa, and Ni Kadek Dwi Rusjayanthi. 2020. "Prediksi Kecelakaan Lalu Lintas Di Bali Dengan XGBoost Pada Python." *Jurnal Ilmiah Merpati (Menara Penelitian Akademika Teknologi Informasi)* 8(3):188. doi: 10.24843/jim.2020.v08.i03.p04.

Prihatno, Aji Teguh, Himawan Nurcahyanto, Md Faisal Ahmed, Md Habibur Rahman, Md Morshed Alam, and Yeong Min Jang. 2021. "Forecasting PM2.5 Concentration Using a Single-Dense Layer BiLSTM Method." *Electronics (Switzerland)* 10(15). doi: 10.3390/electronics10151808.

Rachman, Adhe Dezty Chajannah, Rito Goejantoro, and Fidia Deny Tisna Amijaya. 2020. "Implementasi Text Mining Pengelompokkan Dokumen Skripsi

Menggunakan Metode K-Means Clustering." *Jurnal EKSPONENSIAL* 11(2):167–74.

Rahayu, Ayu Sri, Ahmad Fauzi, and Rahmat. 2022. "Komparasi Algoritma Naïve Bayes Dan Support Vector Machine (SVM) Pada Analisis Sentimen Spotify." *Jurnal Sistem Komputer Dan Informatika (JSON)* 4:349–54. doi: 10.30865/json.v4i2.5398.

Ratna, Silvia. 2020. "Pengolahan Citra Digital Dan Histogram Dengan Phyton Dan Text Editor Phycharm." *Technologia: Jurnal Ilmiah* 11(3):181. doi: 10.31602/tji.v11i3.3294.

Varghese, Akson Sam, Saleha Sarang, Vipul Yadav, Bharat Karotra, and Niketa Gandhi. 2019. "Bidirectional LSTM Joint Model for Intent Classification and Named Entity Recognition in Natural Language Understanding." *International Journal of Hybrid Intelligent Systems* 16(1):13–23. doi: 10.3233/his-190275.

Verma, Sanjeev. 2022. "Sentiment Analysis of Public Services for Smart Society: Literature Review and Future Research Directions." *Government Information Quarterly* 39(3):101708. doi: 10.1016/j.giq.2022.101708.

Wahyudi, Rizki, and Gilang Kusumawardana. 2021. "Analisis Sentimen Pada Aplikasi Grab Di Google Play Store Menggunakan Support Vector Machine." *Jurnal Informatika* 8(2):200–207. doi: 10.31294/ji.v8i2.9681.

Yu, Y., J. Chen, F. Mehraliyev, S. Hu, S. Wang,2024. "Exploring the Diversity of Emotion in Hospitality and Tourism from Big Data: A Novel Sentiment Dictionary." *International Journal of ….* doi: 10.1108/ijchm-08-2023-1234.