Advance Sustainable Science, Engineering and Technology (ASSET)
Vol. 6, No.4, October 2024, pp. 02404018-01 ~ 02404018-08
ISSN: 2715-4211 DOI: https://doi.org/10.26877/asset.v6i4.934

Implementing Long Short Term Memory (LSTM) in Chatbots for Multi Usaha Raya

Ilham Dwi Raharjo[1*], Egia Rosi Subhiyakto[1]

[1]Faculty of Computer Science, Universitas Dian Nuswantoro Semarang, Jl. Imam Bonjol No. 207 Semarang, Central Java, Indonesia

*111202012889@mhs.dinus.ac.id

Abstract. The furniture industry is an important sector in Indonesia that supports the economy and provides quality furniture. An in-depth understanding of the furniture business is essential for industry players to improve operational efficiency and customer satisfaction. This research aims to develop a chatbot for Multi Usaha Raya furniture company to improve customer service and operational efficiency. In its development, the Machine Learning Model Development Life Cycle (MDLC) and deep learning approach using the Flask platform are employed. LSTM, a type of recurrent neural network (RNN) architecture capable of handling long-term dependencies, is utilized in this chatbot model. The model training results show an accuracy of 99%, validation accuracy of 96%, loss of 0.1%, and validation loss of 0.2% after 200 epochs, demonstrating the effectiveness of the LSTM algorithm for developing a chatbot in this company.

Keywords: *Multi Usaha Raya, furniture, chatbot, MDLC, Long Short-Term Memory, Flask, Deep Learning, Oprational Efficiency*

(Received 2024-08-08, Accepted 2024-08-14, Available Online by 2024-10-17)

1. Introduction

The advancement of the times has driven an acceleration in technological development, especially in the field of artificial intelligence. One of the major achievements in this field is the ability of machines to interact like humans, made possible through Natural Language Processing (NLP) technology. This NLP technology has been applied in various applications, such as Google Translate for language translation, personal assistants like Siri, language accuracy checking tools like Grammarly, and also in the development of chatbots.

Furniture is furniture or equipment used to support various human activities such as sitting, sleeping, and storing goods. Furniture includes various types of products such as chairs, tables, cabinets, beds, and shelves. Besides its main function, furniture also plays an important role in the aesthetics of the room and reflects the style and personality of the owner[1].

A chatbot is a computer program designed to simulate human conversation via text or voice, using artificial intelligence and Natural Language Processing (NLP) technologies. In general, chatbots are also often referred to as automated conversational agents[2]. Chatbots can operate autonomously or through instant messaging platforms and apps, providing relevant automated responses based on user input. The main functions of chatbots include customer service, technical support, purchase guidance, and social interaction. These programs are often used in various situations such as customer service and information provision. Chatbots have been used extensively in various fields, including entertainment, education, tourism sector, and many others[3]. Chatbots can save time and reduce several types of costs. Based on survey results from Accenture, chatbots can help organizations reduce operational costs by up to 30%. In addition, users feel satisfied because they get instant access 24/7 to the answers they need[4].

A chatbot is used to collect and store data through a question and answer system, which can then be applied in a Python program. The dataset that will be used in this program is the Cornell Movie Dialog Corpus, a dataset containing fictional conversations with a lot of metadata, taken from movie scripts[5]. In addition, the research aims to improve communication between citizens and government, an issue that has long been a challenge in the public sector[6].

In the study mentioned in reference[7], successfully implemented the sentence into a chatbot that serves as the main source of information on cybersecurity. This chatbot provides answers as well as suggestions and strategies to protect internet users from cyber threats. The chatbot model was trained using the LSTM algorithm, which resulted in optimal performance without overfitting or underfitting problems, with accuracy reaching 100% and a loss value of 3.09%. In addition, the chatbot was also successfully integrated into a web-based application.

Research conducted by [8] developed a chatbot for Frequently Asked Questions (FAQ) aimed at providing answers to student questions regarding academic aspects at the Kosgoro Institute of Business and Informatics 1957. In training the model using the LSTM method, an accuracy of 99.20% was achieved after 90 repetitions (epochs).

Methods of creating chatbots are increasingly varied. Among the methods that are often applied are Recurrent Neural Network and Long Short-Term Memory (RNN-LSTM)[5], Bidirectional Long Short-Term Memory [6], and Natural Language Processing[9]. The Long Short-Term Memory (LSTM) method allows computers to process natural language, making it easier for users to communicate with computers using everyday language. LSTM provide superior performance over traditional methods and are very suitable for sentiment analysis [10]. LSTM is often used in chatbot research and development due to its ability to receive and generate data in the form of sequences. It is an improvement over the more conventional Recurrent Neural Network (RNN) method.

LSTM, or Long Short-Term Memory, is a type of neural network architecture that is part of the Recurrent Neural Network (RNN) category. LSTMs were created to address the problem of managing long-term data and maintaining long-term memory[11]. LSTM is a type of recurrent neural network (RNN) that is designed to store information over long periods of time, and is able to overcome various challenges that arise when processing sequential data[12].

Chatbot programs have made rapid progress in the Indonesian market, serving as online customer service representatives capable of providing instant responses and interacting with customers using Natural Language Processing (NLP) technology[13].In Indonesia, the application of chatbots is still relatively lacking. According to a survey conducted by Pancake on Micro, Small Medium Enterprise (MSMEs) in Indonesia, only 15% of MSMEs have implemented chatbots [4]. It can be concluded that there are still many organizations and companies that have not utilized this technology to facilitate business, one of which is Multi Usaha Raya (MURTEAK). Multi Usaha Raya still runs conventional activities in terms of communication with customers. Customers are accustomed to asking staff directly by phone or physical visit to the office regarding questions about products and services. When customers request additional information or specific services, they usually have to send an email or call the phone number provided, then the staff will respond manually.

This conventional process certainly takes a lot of time, especially if the need is urgent. This is of course a little inconvenient, especially in today's digital era where customers want fast and responsive answers that are easily available anywhere and anytime. To overcome this problem, a chatbot is needed that can produce the information and answers needed with a good level of accuracy. This research uses the LSTM algorithm which is a Deep Learning method suitable for data sequences. Deep Learning is a branch of Machine Learning whose algorithms are inspired by the structure of the human brain. These structures are known as Artificial Neural Networks (ANN).[14] This research is expected to provide solutions to some of these problems. This research is expected to produce a chatbot that can facilitate users, especially Multi Usaha Raya customers, to get information about products and services more quickly and efficiently.

2. Methods

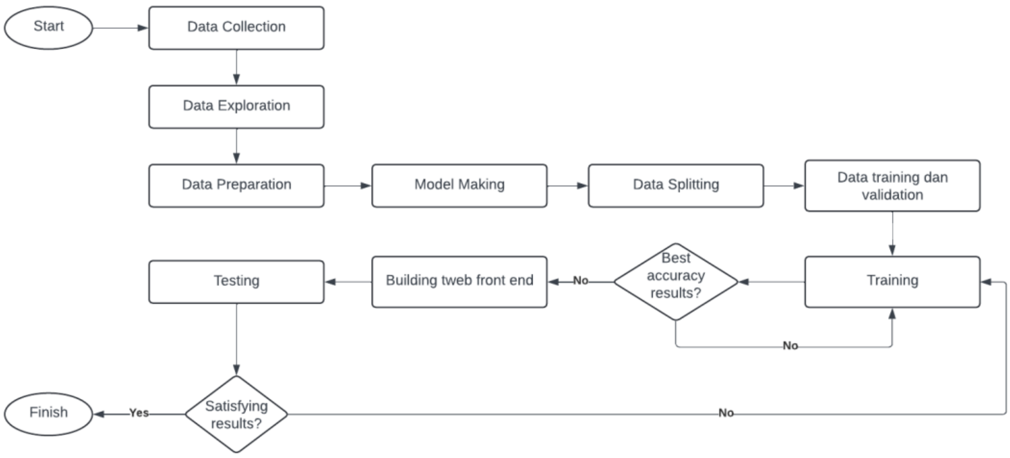

Figure 1. Flowchart of Research Methods

This research follows the machine learning model development cycle (MDLC) as a guide for each stage. MDLC is a complete guide that covers the entire process of developing a machine learning model from start to finish. The main stages in MDLC include exploratory data collection and analysis, data preparation, model building, and model operation [15]. An overview of the stages of this research can be seen in Figure 2.

2.1. Data Collection

The first step that needs to be done is collecting data. In this stage, the data is taken from its original source and put into a predefined repository for further processing and analysis. Once the data is collected, it is explored by understanding and analyzing it to find patterns that can generate new ideas and knowledge useful for modeling.

2.2. Data Exploration

This step is the initial stage before conducting more in-depth research to develop the model. In this phase, the process includes collecting data and understanding the type of data. The information collected includes requirements, flow, procedures, and related information on the company. This data will be used to compile the dataset. Questions will be created based on the data collected, by conducting interviews with employees and owners.

2.3. Data Preparation

Data preparation is one of the most challenging and time-consuming steps in a machine learning project. In this stage, raw data is processed into data that is ready to be used for training machine learning models. This process involves various steps, including transforming the data to make it suitable for the next step, cleaning the data from irrelevant queries, performing tokenization, and indexing each tokenized word. In addition, this step also involves adding SOS (Start of Sequence) and EOS (End of Sequence) tokens to the answers, as well as OUT on words that are not in the vocabulary. The indexed vocabulary is then flipped, the text is converted into a sequence of numbers, and padding is added to the sequence. Finally, the labels are converted into binary vectors for further training process.

2.4. Model Making

The next step is to build the model. First of all, the data will be divided into two parts, namely training data and validation data. At this stage, part of the data is used to find the best model parameters in machine learning, which aims to minimize the error in the data set. The validation data is then used to test the ability of the model that has been built. This process is repeated several times (epochs) to improve the accuracy and performance of the model. This data division is done with 80% for training and 20% for validation. After that, the next step is to determine the metrics that will be used to measure the performance of the model, determine the model structure, and then train it. The model structure to be used includes Embedding, LSTM, and Output layers. Since this model uses multiclass classification, the loss function used is categorical_crossentropy with optimization using the "Adam" algorithm. The model will be evaluated using the "accuracy" metric.

2.5. Deployment

Before the model that has been created can be tested by users, the first step is to deploy and host the model so that it can be accessed online. In this research, the deployment process is done through a website built using the Python programming language and the Flask framework. To create an interactive and user-friendly interface, HTML, JavaScript, and CSS were used. The website is designed simply, consisting of only one main page that displays a bubble. When the user clicks on the bubble, a chat menu will appear that allows them to ask questions about various company information.

3. Results and Discussion

3.1. Reasults

Data obtained there are 18 pieces of important information that will be used as answers. This data is data that is often sought and asked by custemers to the admin. Data obtained from the admin and also the results of direct interviews with the owner and company staff. The files obtained are doc or docx files.

After obtaining company information data, then create question data based on the answer data obtained. Questions are made by themselves based on answers with input from the results of interviews given to the owner and staff workers. The data obtained consists of several types, namely data about the company, company services and product information.

After collecting company information data, the next step is to compile question data based on the answers that have been obtained. These questions are made by taking into consideration the answers given, as well as input from custemers filled in through the admin.

Once the data is obtained and understood, the next step is to prepare the data. The data consisting of questions and answers is converted into a single table with columns "question" and "answer" in a JSON file. This file will then be processed using Python. The dataset contains 148 samples with 18 pieces of information each. The data is again converted into a dataframe format in Python using the Pandas library. To make it easier to process the question and answer data, the two are separated and converted into a list.

The question data is converted into a list and then cleaned using the NLTK library. The cleaning process involves several steps, including converting all letters to lowercase, removing unnecessary symbols, and using stopwords to remove unimportant or meaningless words. The purpose of data cleaning is to ensure that all questions have a consistent format and are free of unnecessary symbols, so that the number of vocabularies can be reduced. Thus, the model training process becomes faster and the model results become better.

SOS is Start of Sequence, while EOS is End of Sequence, and OUT is Out of Vocabulary. SOS is used at the beginning of each answer or label, while EOS is given at the end of each answer or label to indicate the start and end boundaries of an answer. OUT is used to mark words that are not in the vocabulary. All these marks, namely SOS, EOS, and OUT, are then entered into the vocabulary.

The precompiled vocab is a dictionary data type with words as keys and numbers as values. The purpose is to translate the output prediction results in the form of index numbers into understandable words. In this process, words that were originally dictionary keys are converted into index numbers, and values that were originally indexes are converted into words.

Once we finish creating a vocabulary dictionary that lists the words along with their indexes, the next step is to create an integer sequence. This process involves converting the sequence of words into a sequence of integers. To perform this conversion, we use the dictionary we created earlier. This dictionary allows us to replace each word with its corresponding index, resulting in an integer sequence that represents the original word sequence.

Padding is a technique to equalize the length of each different sequence into a uniform length. This is important so that each input into the embedding layer has a consistent length.

In this research, a model structure consisting of several layers is used to achieve the desired results. In the first layer, there is an embedding layer that serves to represent each word using a 128-dimensional vector. Next, the second layer is the LSTM layer which has 256 perceptron units, designed to capture temporal patterns in the data. Finally, the output layer is the Dense Output layer which consists of 272 perceptron units and uses a softmax activation function to generate the final prediction. This structure is designed to optimize the model's performance in analyzing and processing data.

3.2. Discussion

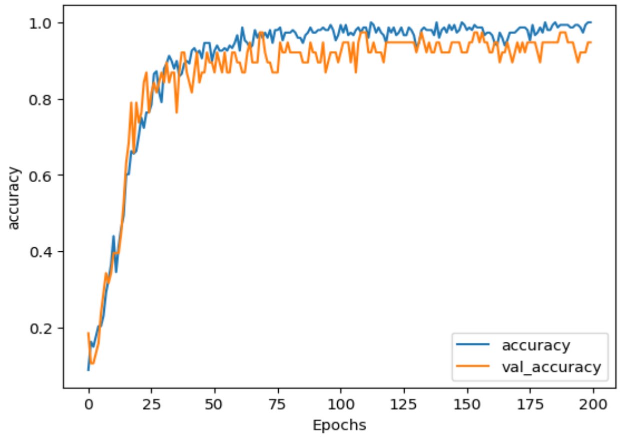

Figure 2. Training and Validation Accuracy Graph

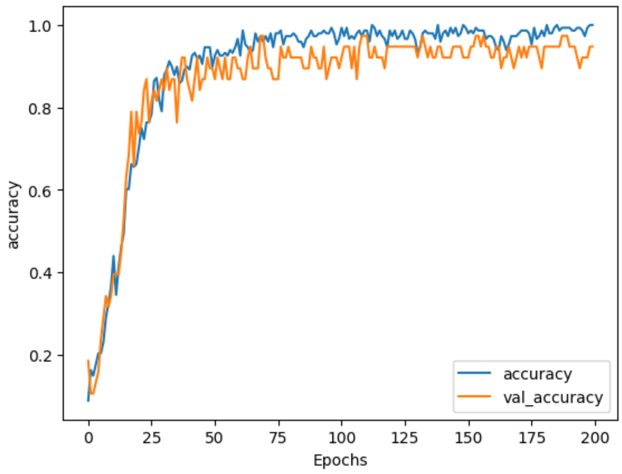

Figure 3. Training and Validation Loss Graph

This research involves multiclass classification using categorical_crossentropy (hard) loss function and "Adam" optimization function, as well as "accuracy" evaluation metric. The data was divided into 80% for training and 20% for validation. Training data was conducted with the previously created model structure for 200 epochs. The results of the training process show an accuracy rate of 99% and a validation accuracy of 96%, with a loss value of 0.1% and a validation loss of 0.2%. Graphs showing the results of accuracy, loss, validation accuracy, and validation loss at each epoch can be seen in Figure 2 and Figure 3.

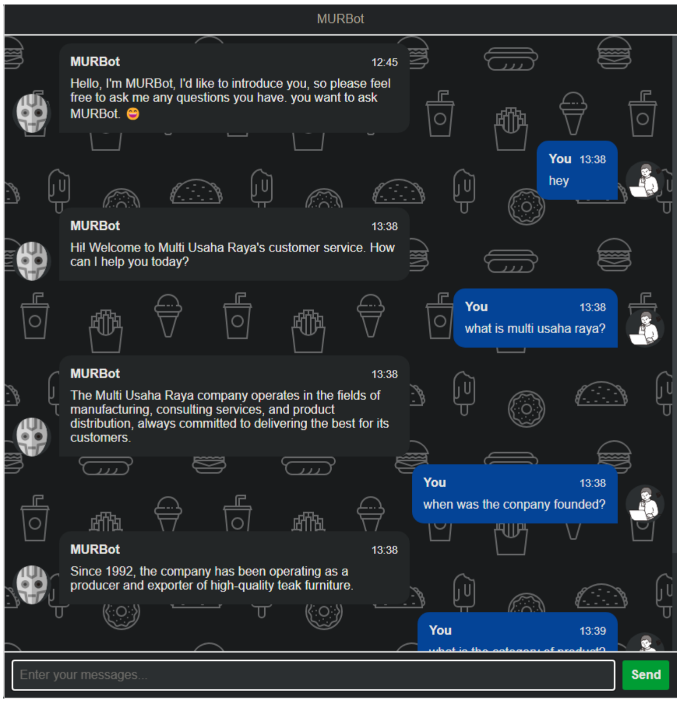

Figure 4. Conversation page after asking

The next stage is Deployment. This stage aims to make the chatbot model that has been created can be used by users with an interface that is similar to that during model testing. The deployment process is carried out using the Python programming language and the Flask framework, while the interface is built using HTML, CSS, and JavaScript. On the website that was created. If the user enters a question about furniture information, the system will respond as shown in Figure 4.

The last stage in this process is the testing stage, which is conducted through the user validation method. In this method, users are invited to try the chatbot that has been built and provide an assessment of whether the results provided by the chatbot match their needs. Users will receive a trial model as well as a list of question topics and supposed answers. This test involved 10 employees from the company. Each user was given five question and answer topics, but they were also allowed to ask questions outside of these five topics.

However, it's important to recognize that these results were obtained in a controlled environment. While the model excels with the current dataset, real-world scenarios often involve more variability and complexity. Factors such as diverse user inputs and ambiguous queries may impact performance. Thus, while the model demonstrates high accuracy, further testing in real-world conditions is necessary to fully assess its effectiveness.

The LSTM model addresses the limitations of traditional RNNs, such as the vanishing gradient problem, by using gating mechanisms to manage long-term dependencies, resulting in high accuracy and low loss. While Transformer models like BERT and GPT excel in handling complex language patterns through attention mechanisms, potentially offering superior performance in capturing nuanced contexts, our LSTM model remains effective. Future research could explore hybrid approaches, combining LSTM and Transformer techniques to leverage their strengths, potentially enhancing chatbot performance across a broader range of queries and interactions.

4. Conclusion

This research successfully developed and implemented a chatbot using the LSTM algorithm, which demonstrated high accuracy in handling customer queries. The findings highlight the effectiveness of the LSTM model in managing sequential data and providing responsive customer service. However, this research also underscores the potential for further improvement by integrating more advanced models, such as Transformers, which can offer superior performance in understanding complex language patterns and larger contexts.

With the advancement of AI technology, businesses can significantly improve customer service efficiency and user satisfaction by adopting these advanced methods. Future work should explore the combination of LSTM and Transformer models or other hybrid approaches to leverage the strengths of both, potentially setting new benchmarks in chatbot performance. This continued exploration will be critical in driving innovation and keeping pace with the increasing demands of the digital customer service environment.

References

[1] E. A. Risti, "Implementasi Pengolahan Sistem Penjualan Furniture Menggunakan Metode Design Thinking (Studi Kasus : Furniture Jati Sungu Bandar Lampung)," *Jurnal Informatika dan Rekayasa Perangkat Lunak*, vol. 3, no. 4, pp. 435–4459, 2022, [Online]. Available: http://jim.teknokrat.ac.id/index.php/informatika

[2] P. Suta, X. Lan, B. Wu, P. Mongkolnam, and J. H. Chan, "An overview of machine learning in chatbots," *International Journal of Mechanical Engineering and Robotics Research*, vol. 9, no. 4, pp. 502–510, 2020, doi: 10.18178/ijmerr.9.4.502-510.

[3] F. Zakariya, J. Zeniarja, and S. Winarno, "JURNAL MEDIA INFORMATIKA BUDIDARMA Pengembangan Chatbot Kesehatan Mental Menggunakan Algoritma Long Short-Term Memory," 2024, doi: 10.30865/mib.v8i1.7177.

[4] P. B. Wintoro, H. Hermawan, M. A. Muda, and Y. Mulyani, "Implementasi Long Short-Term Memory pada Chatbot Informasi Akademik Teknik Informatika Unila," *EXPERT: Jurnal Manajemen Sistem Informasi dan Teknologi*, vol. 12, no. 1, p. 68, Jun. 2022, doi: 10.36448/expert.v12i1.2593.

[5] P. Anki, A. Bustamam, H. S. Al-Ash, and D. Sarwinda, "Intelligent Chatbot Adapted from Question and Answer System Using RNN-LSTM Model," in *Journal of Physics: Conference Series*, IOP Publishing Ltd, Mar. 2021. doi: 10.1088/1742-6596/1844/1/012001.

[6] I. M. Untari, "Chatbots and Government Communications in Covid-19 Pandemic."

[7] H. Anbiyani, F. Muhyidin, and L. Venica, "Jurnal Informatika dan Rekayasa Perangkat Lunak Pengembangan Chatbot untuk Meningkatkan Pengetahuan dan Kesadaran Keamanan Siber Menggunakan Long Short-Term Memory," vol. 5, no. 2, pp. 152–161, 2023.

[8] A. Silvanie and R. Subekti, "APLIKASI CHATBOT UNTUK FAQ AKADEMIK DI IBI-K57 DENGAN LSTM DAN PENYEMATAN KATA," *Jurnal Informatika dan Komputer) Akreditasi KEMENRISTEKDIKTI*, vol. 5, no. 1, 2022, doi: 10.33387/jiko.

[9] V. R. Prasetyo, N. Benarkah, and V. J. Chrisintha, "Implementasi Natural Language Processing Dalam Pembuatan Chatbot Pada Program Information Technology Universitas Surabaya," *Teknika*, vol. 10, no. 2, pp. 114–121, Jul. 2021, doi: 10.34148/teknika.v10i2.370.

[10] H. Jelodar, Y. Wang, R. Orji, and H. Huang, "Deep Sentiment Classification and Topic Discovery on Novel Coronavirus or COVID-19 Online Discussions: NLP Using LSTM Recurrent Neural Network Approach," Apr. 2020, [Online]. Available: http://arxiv.org/abs/2004.11695

[11] Y. Astari and S. Wahib Rozaqi, “Analisis Sentimen Multi-Class pada Sosial Media menggunakan metode Long Short-Term Memory (LSTM),” 2021.

[12] M. A. Amrustian, W. Widayat, and A. M. Wirawan, “Analisis Sentimen Evaluasi Terhadap Pengajaran Dosen di Perguruan Tinggi Menggunakan Metode LSTM,” *JURNAL MEDIA INFORMATIKA BUDIDARMA*, vol. 6, no. 1, p. 535, Jan. 2022, doi: 10.30865/mib.v6i1.3527.

[13] L. Sanny, A. C. Susastra, C. Roberts, and R. Yusramdaleni, “The analysis of customer satisfaction factors which influence chatbot acceptance in Indonesia,” *Management Science Letters*, vol. 10, no. 6, pp. 1225–1232, 2020, doi: 10.5267/j.msl.2019.11.036.

[14] M. Riziq sirfatullah Alfarizi, M. Zidan Al-farish, M. Taufiqurrahman, G. Ardiansah, and M. Elgar, “PENGGUNAAN PYTHON SEBAGAI BAHASA PEMROGRAMAN UNTUK MACHINE LEARNING DAN DEEP LEARNING,” 2023.

[15] F. Alfiansyah, S. Lina, and M. Sitio, “Implementasi Metode Multimedia Development Life Cycle (Mdlc) Pada Aplikasi Edukasi Interaktif Pengenalan Mental Health Kepada Masyarakat Berbasis Mobile.” [Online]. Available: https://journal.mediapublikasi.id/index.php/logic

[16] A. S. Dewantara and J. Aryanto, “Implementation Of A Web-Based Chatbot Using Machine Learning For Question And Answer Services In Universities,” *Advance Sustainable Science, Engineering and Technology*, vol. 6, no. 1, p. 0240106, Dec. 2023, doi: 10.26877/asset.v6i1.17590.

[17] A. N. Cahyani, J. Zeniarja, S. Winarno, R. T. E. Putri, and A. A. Maulani, “Heart Disease Classification Using Deep Neural Network with SMOTE Technique for Balancing Data,” *Advance Sustainable Science, Engineering and Technology*, vol. 6, no. 1, p. 0240108, Dec. 2023, doi: 10.26877/asset.v6i1.17521.

[18] A. Daud, D. Irwanto, M. Said, M. Mubyl, and M. Mustamin, “Identification Of Chatbot Usage In Online Store Services Using Natural Language Processing Methods,” *Advance Sustainable Science, Engineering and Technology*, vol. 6, no. 2, p. 0240206, Mar. 2024, doi: 10.26877/asset.v6i2.18309.

[19] 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.

[20] N. Aziza and F. B. Setiaji, “PENGENDALIAN KUALITAS PRODUK MEBEL DENGAN PENDEKATAN METODE NEW SEVEN TOOLS,” *Teknika : Engineering and Sains Journal*, vol. 4, no. 1, pp. 27–34, 2020.