Enhancing Durrotalk Chatbot Accuracy Utilizing a Hybrid Model Based on Recurrent Neural Network (RNN) Algorithm and Decision Tree

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Abstract – DurroTalk, a chatbot for new student admissions at Pondok Pesantren Durrotu Ahlissunnah Waljamaah, Semarang, integrates a hybrid model with Recurrent Neural Network (RNN) and Decision Tree. RNN, the base model, employs Natural Language Processing (NLP) to understand sentence structure and context, overcoming vanishing gradient through LSTM layers. The Decision Tree normalizes words, addressing slang and synonyms. The hybrid model boosts chatbot accuracy by 9%, reaching 77% from the initial 68%. This research signifies progress in integrating artificial intelligence into traditional education, showcasing a chatbot adept at handling non-standard language. Decision Tree integration enhances overall performance, making the chatbot proficient in understanding user inputs and generating contextually relevant responses. This study exemplifies the potential of AI, particularly chatbot technology, in modernizing educational processes at traditional institutions.

Keywords: Chatbot, Artificial Intelligence, Recurrent Neural Network, Decision Tree, Natural Language Processing

I. INTRODUCTION

Artificial Intelligence (AI) has rapidly evolved in the era of the fourth industrial. AI focuses on creating intelligent machines capable of learning, reasoning, communicating, and making decisions like humans [1]. However, the utilization of AI in Indonesia, especially in Islamic boarding schools (pesantren), remains limited [2]. The admission process for new students in traditional pesantren often relies on less organized methods [3]. Information related to new student admissions is disseminated manually through announcements and brochures, slowing down the process and requiring direct communication with prospective students [4].

Chatbots, programs simulating human-computer conversations, can be a solution to enhance the efficiency of the new student admission process in pesantren [5]. Through the use of Recurrent Neural Network (RNN) and Decision Tree algorithms, this research aims to improve the accuracy of a chatbot integrated with Telegram Bot for distributing information about new student admissions at Pondok Pesantren Durrotu Aswaja, Semarang City.

This research refers to several pieces of literature related to chatbot development methods and utilized models. These pieces provide insights into the chatbot development process, serving as a foundation for the researcher to gain an in-depth understanding. The following are five previous studies used as references, showcasing the novelty of this research.

Ref. [6] developed an AI-based chatbot to predict diseases based on symptoms. They employed two classification algorithm models, Decision Tree, and KNN, focusing on question-answer features through text conversations and text-to-speech. Then [7] investigated the development of a chatbot for student admission information services at Telkom University. The study focused on developing a chatbot for sequential data modeling using Natural Language Processing (NLP) approaches. In 2021 [8] discussed the chatbot development process, covering architecture design to system implementation. They highlighted the roles of artificial intelligence and machine learning technologies in chatbot creation, emphasizing data preprocessing using NLP approaches.

Researcher [9] utilized the RNN-LSTM model in chatbot development. The choice of the RNN model was based on its high performance. With the Cornell movie dialog corpus dataset, the researchers achieved an accuracy of 0.994. Ref. [10] implemented the RNN algorithm in a chatbot for new student registration at Pakuan University. They outlined three stages of chatbot development with a dataset containing 300 text samples obtained from interviews.

This research identifies a gap in the adoption of chatbots within Islamic boarding schools (pesantren), where the utilization remains limited. The majority of pesantren continue to rely on conventional methods for handling new student admissions. Consequently, this study aims to bridge this gap by introducing the DurroTalk chatbot, streamlining the new student admission process at the traditional Islamic boarding school of Durrotu Aswaja.

Building on the insights from the literature, this research endeavors to pioneer the implementation of chatbots in the context of salaf Islamic boarding schools, characterized by restrained technology use. The distinctiveness of this endeavor lies in seamlessly integrating RNN and Decision Tree models within the DurroTalk chatbot, anticipating heightened efficiency in the new student admission procedures.

II. METHOD

A. Data Collection and Preprocessing.

The preparation of the dataset is a crucial aspect of this research, particularly in the context of chatbot development. The primary dataset is derived from the experiences of the admission committee for new students at Pondok Pesantren Durrotu Ahlissunnah Waljamaah in Semarang. It includes question intent, sample question text, and chatbot responses. Sample text represents common questions from prospective students, while chat responses are derived from official information on new student registration.

The researcher also compiles a specific dataset containing slang/synonym words frequently used in user inputs. This dataset is an integral part of training the chatbot model to understand everyday language, even when using informal expressions. After gathering the necessary data, the preprocessing stage is implemented using natural language processing approaches, including case folding, tokenizing, word normalization, filtering, and vectorization, to prepare the dataset for model training [11]-[13].

B. Model Design.

1) Base Model: The base model, constructed using RNN architecture, serves as a foundational comparison for the hybrid model. It acts as a benchmark to assess the hybrid model's success in improving accuracy. The RNN model consists of three main layers: Embedding Layer, LSTM Layer, and Dense Layer. The training and testing processes are crucial in both machine learning (ML) and deep learning (DL) stages, playing a pivotal role in artificial intelligence development. Training involves the model learning from prepared data without explicit instructions. The flowchart of the base RNN model training process is depicted in Fig. 1.

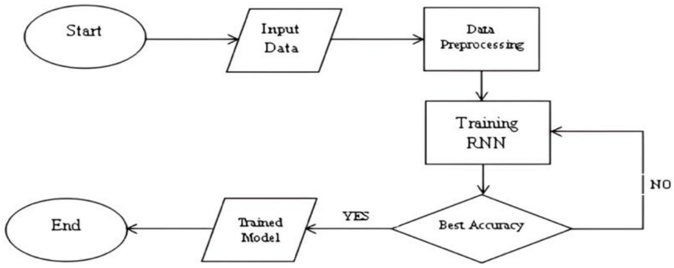

Fig. 1 Training base model flow

2) Hybrid Model: Following the successful design of the base model, the researcher integrated a Decision Tree into the RNN model to create the hybrid model. The Decision Tree model takes the initial step in detecting slang words or synonyms, transforming them into standardized words based on the available slang word /synonym dataset. The researcher employed the stacking method to construct this hybrid model chatbot [14]. The stacking process begins by using the Decision Tree model for text preprocessing, converting slang words into standard words. The output from this model is then fed into the RNN model. The RNN processes the input sequence, classifying the labels responses. The training process for the hybrid model mirrors that of the base model, with the addition of the Decision Tree model positioned above the RNN model. The training data for the Decision Tree model involves the slang/synonym dataset, facilitating the conversion of slang/synonymous words into predefined standard words. Fig. 2 illustrates the flowchart of the hybrid model training process.

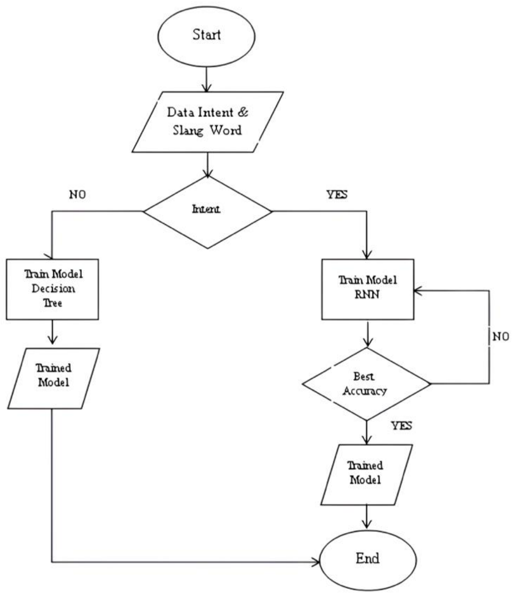

Fig. 2 Training hybrid model method flow

C. Evaluation Matrix

Results analysis is a crucial phase in this research. It involves evaluating the accuracy of both the non-hybrid and hybrid chatbot through testing with 53 participants. Accuracy is defined as the comparison of correct predictions to the actual values in a dataset [10]. Correct predictions encompass the sum of true positives and true negatives derived from the confusion matrix analysis process. The equation used to calculate accuracy is (1).

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

Conclusions are drawn based on the comparison of evaluation matrix between the hybrid and base models. The success of the hybrid model is determined when its accuracy surpasses that of the base model.

III. RESULT AND DISCUSSION

A. Dataset Result

The datasets generated in this study consist of two sets: the intent dataset and the slang word dataset. Both datasets were created using Microsoft Excel. The intent dataset, which compiles data from frequently asked questions by prospective students to the admission committee of Pondok Pesantren Durrotu Ahlissunnah Waljamaah, has a column format structure comprising columns for conversation intent/topics, sample text questions, and responses. Meanwhile, the slang word dataset is structured with columns for standard words, synonymous words, and frequently used slang words in conversations. The results show that there are 3,500 sample text questions related to new student registrations distributed across 60 conversation intents or topics. An example of the intent dataset is listed in Table I.

The creation of the slang and synonym dataset resulted in a total of 367 slang words and synonyms, with 33 standard words. Sample data for slang and synonyms are displayed in Table II.

TABLE I
SAMPLE INTENT DATASET

Intent	Sample Text 1	Sample Text 2	Sample Text 3	Respon
Salam	*assalamualaikum*	*assalamualaikum chatbot aswaja*	*assalamualaikum wr.wb, mau tanya-tanya boleh?*	*periode pendaftaran di pondok durrotu aswaja sudah dan masih dibuka sampai sekarang lho, yuk buruan daftar.*
Periode Pendaftaran	*mau tanya terkait dengan periode pendaftaran di aswaja*	*kapan periode pendaftaran santri barunya dimulai?*	*periode pendaftaran santri baru di aswaja masih dibuka nggak ya?*	*waalaikumussalam, kenalin aku durro, santri aswaja yang siap menjawab semua pertanyaanmu terkait pendaftaran santri baru di ponpes aswaja, kamu mau tanya apa nih?* □
Oot	*makanan yang enak apa ya?*	*di sini yang jualan ayam geprek di mana ya?*	*info penjual sate deket kampus dong*	*mohon maaf durro hanya bisa menjawab pertanyaan seputar pendaftaran di pondok pesantren durrotu aswaja.* □

TABLE II
SAMPLE SLANG DATASET

Slang/Synonym Words	Standard Words
salamlekom	*assalamualaikum*
akuuuuu	*aku*
sayaaa	*saya*
klo	*kalau*
pendaftran	*pendaftaran*

The collected data is processed to make it accessible and acceptable by the machine, a step known as data preprocessing. This includes tokenization, vectorization, and padding. Tokenization is the process of breaking down text or sentences into smaller units to facilitate the model's understanding and analysis of the text's structure and meaning [12]. Vectorization involves transforming text data into vector representations, a crucial step in natural language processing, as unprocessed data cannot be effectively handled by the model [15]. The transformed dataset in vector form is then shaped into training data for processing in the machine learning model through sequence padding. Padding sequences ensure that the processed data sequences have the same length [16]. Fig. 3 illustrates the Padding Sequence process.

B. Chatbot Model

1) Base Model: The base model is an RNN model composed of three main layers: the Embedding Layer, LSTM Layer, and Dense Layer [17] [2]. The Embedding Layer is responsible for constructing word vectorization [15]. It is designed to recognize 1824 unique tokenized words and can handle word sequences with a maximum size of 17 words. The output from this layer is an array representing a sentence with a length of 17 words, where each word has a vector space dimension of 100. This process allows the model to understand the relationships between words in the context of a sentence before engaging in the LSTM layer. The second layer is LSTM, which aims to address vanishing gradient issues or long-term dependencies in the RNN model. LSTM can decide which information to store and retain in the memory cell and which information needs to be forgotten. LSTM has three gates regulating the flow of information, the forget gate, input gate, and output gate. The LSTM layer requires configuration to determine the number of neurons used in the LSTM layer. This number of neurons indicates how complex and expressive the LSTM model is. A larger number of units imply more model capacity to learn complex patterns in data. However, an excessively large number of units can lead to overfitting and increased computational requirements. To determine the number of neurons applied to the LSTM hidden layer, testing is performed to identify the optimal number through random experimentation until finding the optimal amount [18]. Table III shows the test results to determine the number of neurons in the LSTM hidden layer.

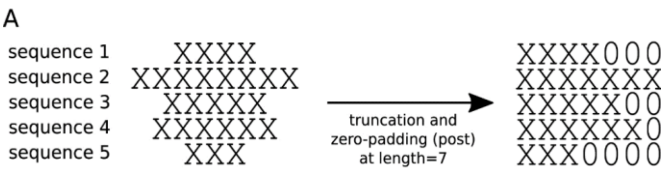

Fig. 3 Padding sequence process [16]

TABLE III
EXPERIMENT NUMBER OF NEURONS

Experiment No	Number of Neurons	*Epoch*	Training Accuracy
1	128	5	38 %
2	100	5	20,6 %
3	156	5	38 %
4	172	5	36 %
5	**64**	**5**	**53 %**
6	32	5	49 %
7	70	5	36 %
8	60	5	39 %
9	32	5	44%
10	64	**5**	**52 %**

Based on Table III Testing the number of neurons in the LSTM hidden layer, with a training iteration of 5 epochs, the 5th and 10th Tests with 64 neurons resulted in optimal and consistent training accuracy, with an average accuracy of 52.5%. Therefore, the number of neurons used in the LSTM hidden layer is 64 neurons. The third layer is a dense layer, Dense layer represents the number of labels in the data. In this study, the number of labels in the data is 60 labels. This layer uses the softmax activation function. The softmax activation function is used here because the model is used for multi-class classification. Softmax generates probabilities for each class, so the dense layer will produce output in the form of a probability distribution of labels for a sentence. After testing the number of neurons to be used in the hidden state LSTM layer, the next step is to test the number of epochs (a hyperparameter that determines how many times the learning algorithm iterates over the entire training dataset) against the accuracy rate of testing the LSTM model created. Table IV shows the results of the epoch testing.

Based on Table IV, using 64 neurons and 32 epochs, the highest accuracy value during the training process is 98%. Therefore, the number of epochs used in the model training process is 32. During training, the Adaptive Moment Estimation (ADAM) method is employed to optimize the training process. This function works by minimizing the loss at each training step. The implementation of this method is provided by Keras.

TABLE IV
EXPERIMENT NUMBER OF EPOCH

Experiment No	Number of Neurons	*Epoch*	Training Accuracy
1	64	16	91 %
2	64	5	53 %
3	64	10	76 %
4	64	24	93 %
5	64	32	98 %

After successfully completing all stages, the final step is the prediction phase of the base model chatbot responses. The prediction phase involves the loaded model processing preprocessed sample text to generate appropriate responses. Table V provides an example of input sample text and responses displayed by the base model chatbot.

Based on Table V, it is evident that the base model chatbot can provide satisfactory answers to questions, although there are some shortcomings. One of the limitations is observed when users input slang words or make typos; the chatbot may deliver less accurate responses. The columns shaded in gray represent examples of incorrect responses given by the chatbot when there is a typo in the user's question. These issues will be addressed and improved upon by the hybrid model.

TABLE V
BASE MODEL PREDICT

Input	Respon Predict
halo chatbot	*Halo, namaku Durro, santri aswaja yang bertugas untuk memberi informasi terkait penerimaan santri baru. silahkan ajukan pertanyaanmu* □
mikuum	*oke, apakah masih ada yang perlu kamu tanyakan?* □ *kalau masih ada langsung disampein aja ya*
pondoj aswaja di mana	*Mohon maaf Durro hanya bisa menjawab pertanyaan seputar pendaftaran di Pondok Pesantren Durrotu Aswaja.* □

2) Hybrid Model: The hybrid model is a combination of the base RNN model and an additional model, namely the Decision Tree model. The Decision Tree model is used for data preprocessing to normalize slang words into standard words. Additionally, the Decision Tree model is employed to predict the appropriate response based on the label predictions issued by the base RNN model. The Decision Tree model is formed using the 'Gini' criterion as the parameter. The 'Gini' criterion measures the quality of the split at each node in the Decision Tree. In this context, 'Gini' is a method of measuring impurity within a node [19]-[20]. The Decision Tree algorithm aims to reduce impurity at each node during the training process. Furthermore, there is the Max Depth parameter that determines the maximum depth of the Decision Tree. If Max Depth is set as None, the tree will continue to grow until each leaf has zero impurity or until the minimum sample count required to split the node is met. Here is Fig. 4 illustrating the Decision Tree successfully formed in the training process with a Max Depth of 3 nodes to transform slang words into standard words.

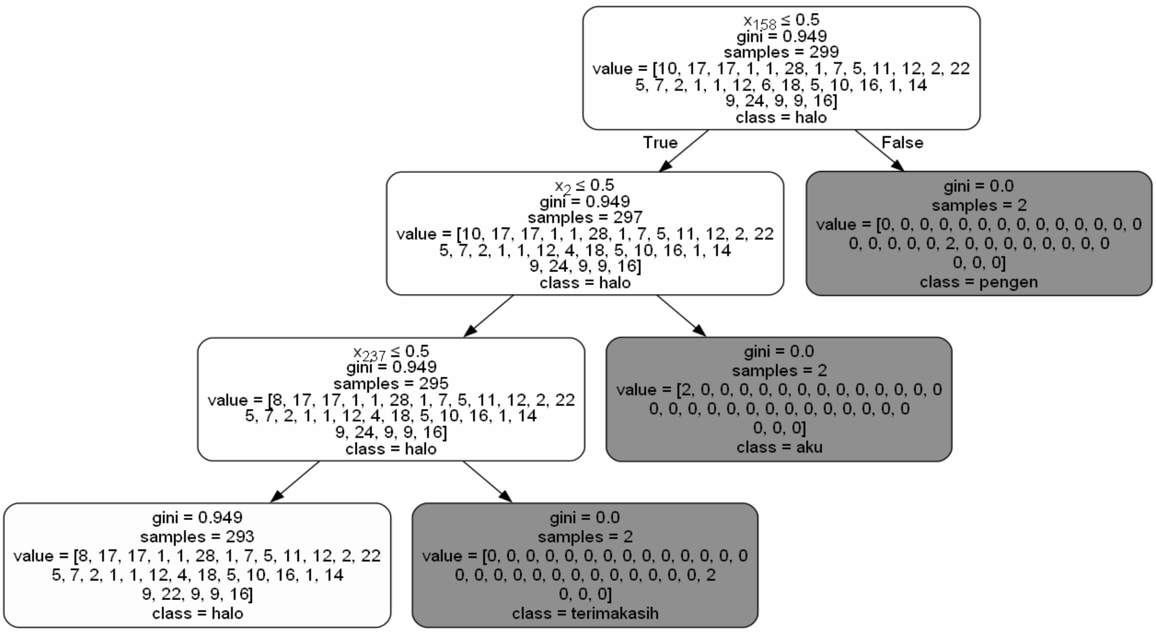

Fig. 4 Illustration of decision tree

The prediction process of the hybrid model chatbot begins by inputting a question, referred to as sample text in this study. The sample text used is the same as that inputted into the base model chatbot. Subsequently, the inputted sample text undergoes tokenization, case folding, vectorization, and padding stages to ensure it can be processed by the machine. The next step involves the cleaning process of the sample text using the Decision Tree model. Cleaning the sample text entails converting words detected as slang by the Decision Tree model into their standard form. The output from the Decision Tree model is then fed into the base model for further processing to generate the chatbot's prediction response. Table VI provides an example of input sample text, the output from the Decision Tree model, and the response displayed by the hybrid model chatbot.

Based on Table VI, the gray-colored column indicates the accurate response of the hybrid model even in the presence of typos in the user's input, demonstrating that the hybrid model successfully addressed the shortcomings of the base model chatbot.

C. Evaluation Matrix

The final stage of this research involves evaluating both the base and hybrid models of the chatbot. Evaluation data is obtained from the chatbot prediction results stored in the logchat. The objective of this stage is to measure the chatbot's performance through the calculation of a confusion matrix, including True Positives, True Negatives, False Negatives, and False Positives. These matrixes will be analyzed to determine the accuracy of both models. To ensure a comprehensive evaluation, the testing process is delegated to 53 testers, consisting of students from Pondok Pesantren Durrotu Aswaja, involving 600 data points. Fig. 5 provides a comparison of the confusion matrix for the base model.

TABLE VI
PREDICT HYBRID MODEL

Input	Cleaned Input	Respon Predict
halo chatbot	*halo chatbot*	*Halo, namaku Durro, santri aswaja yang bertugas untuk memberi informasi terkait penerimaan santri baru. silahkan ajukan pertanyaanmu* □
mikuum	*assalamualaikum*	*Walaikumussalam, Kenalin aku Durro, santri Aswaja yang siap menjawab semua pertanyaanmu terkait pendaftaran santri baru di Ponpes Aswaja, kamu mau tanya apa nih?* □
pondoj aswaja di mana	*pondok aswaja dimana*	*Aku kasih tau alamat pondoknya nih ya...* *1. Pondok Pesantren Durrotu Aswaja 1 (Pusat) bertempat di Jl. Kalimasada Gg. Abimanyu II No. 11A Banaran RT/RW. 08/05 Sekaran Gunungpati, Kota Semarang 50229 (Komplek Kampus Unnes)* *2. Pondok Pesantren Durrotu Aswaja 2 Li Tahfidzil Qur'an (PAUD, TK, dan SD Islam Ya Waladi) bertempat di Jl. Kalimasada VI Jl. Raya Banaran, Sekaran Gununugpati, Kota Semarang (600 m dari Pondok Aswaja 1)*

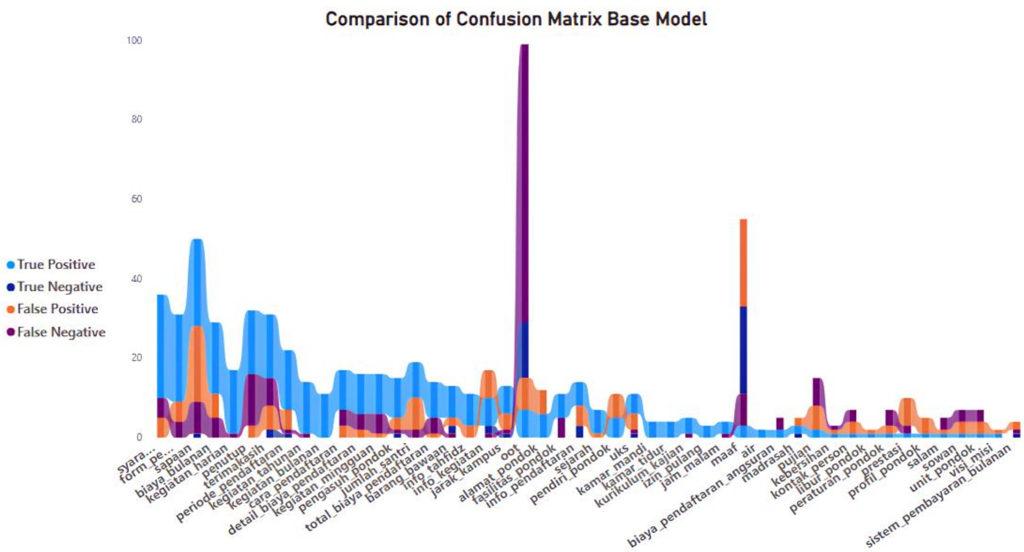

Fig. 5 Comparison of confusion matrix base model

Similarly, the hybrid model undergoes evaluation using the confusion matrix in the same stage. This aims to provide insights into whether the hybrid model successfully improves the accuracy compared to the base model. Fig. 6 presents a comparison of the confusion matrix for the hybrid model.

Based on the distribution of true positive and true negative cases for each intent, it can be observed that the hybrid model is more consistent and exhibits a better trend compared to the base model in predicting responses to the given input. The values of true positive and true negative cases will then be used to calculate the accuracy of both models, as described in (1), by summing up the true positive and true negative values and then comparing them with the total number of data points.

In the realm of Artificial Intelligence-based Chatbot development, similar research endeavors are still relatively scarce, especially in Indonesia. This scarcity posed challenges for researchers in accessing datasets and sample model structures. As a result, the researcher opted to create two chatbot models for comparison and gathered primary data through direct surveys with students at Pondok Pesantren Durrotu Aswaja in Semarang City.

To strengthen the researcher's references in developing the chatbot, several prior studies with similarities to the ongoing research were also cited, encompassing resemblances in both dataset structure and algorithms utilized in the chatbot development. These include the development of chatbot by Zuraiyah et al. in 2019 [10], Purwitasari & Soleh in 2022 [21], Wintoro et al. in 2022 [2], and Hikmah et al. in 2022 [22]. Table VII shows a comparison of the accuracy obtained by the base model chatbot and the hybrid model chatbot developed by the researcher.

The research findings presented on Table VII indicate that the hybrid model exhibits superior accuracy and capabilities compared to the base model, with a 9% difference in accuracy. The hybrid model in this study demonstrates proficiency in providing accurate responses, even in the presence of slang words or typos in user inputs. The combination of two models, namely RNN and Decision Tree, not only enhances overall performance but also complements each other to address potential weaknesses inherent in each model.

However, despite the advantages demonstrated by the hybrid model in this study, there are still notable limitations. One primary drawback lies in the limitation of the data used in the research. Insufficient representativeness or inadequate coverage of variations in the data may affect the model's performance, particularly in recognizing and handling slang words or typos that are not included in the training dataset.

TABLE VII
COMPARISON OF ACCURACY MATRIX BETWEEN THE BASE MODEL AND HYBRID MODEL

Model	Dataset	Accuracy
Base model	Dataset Informasi Pendaftaran Santri Baru	68%
Hybrid model	**Dataset Informasi Pendaftaran Santri Baru dan Dataset Kata Slang & Baku**	**77%**

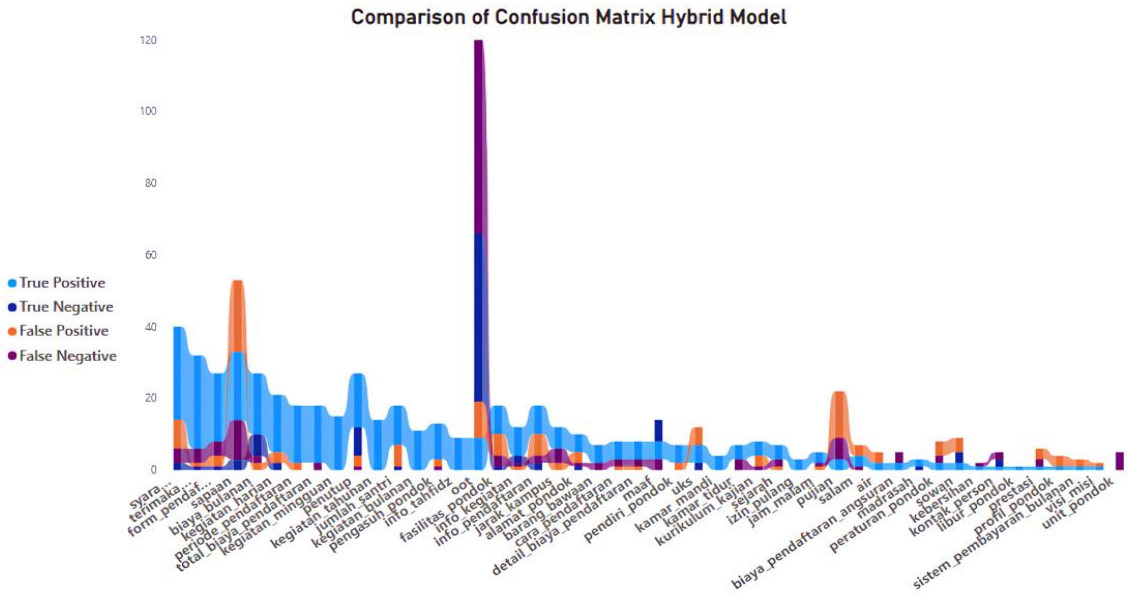

Fig. 6 Comparison of confusion matrix hybrid model

IV. CONCLUSION

Based on the research, this study aims to enhance the development of the DurroTalk chatbot within the new student admission information system at Pondok Pesantren Durrotu Ahlissunnah Waljamaah, Semarang City. It employs a hybrid model of RNN and Decision Tree, combined through stacking to mitigate individual weaknesses. The Decision Tree preprocesses data by identifying and standardizing slang words before feeding them into the RNN model. This hybrid model significantly improves the chatbot's accuracy by 9%, from 68% to 77%, particularly in accurately responding to slang-laden chats or queries. Thus, the study positively impacts the chatbot's development, thereby enhancing the efficiency of the new student admission information system. Furthermore, the researchers suggest that in future iterations of constructing this hybrid model, it is advisable to explore combining other deep learning models with similar structural and layer characteristics to the RNN model. Additionally, there is a need to augment the dataset with more references to be utilized during model training to yield a more robust chatbot model.

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