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Chatbot-based Information Service using RASA Open-Source Framework in Prambanan Temple Tourism Object

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Abstract

The pandemic has caused a shift in the tourism industry's drive towards comprehensive digitization. This approach is used to prevent the spread of the Covid-19 virus. The impact of Pemberlakuan Pembatasan Kegiatan Masyarakat (PPKM) limiting the mobility of tourists who will vacation in Indonesia causes losses and foreign exchange earnings of the state in the tourism industry sector of 20.7 billion. So, to survive in the current situation, industry players must be able to adapt and rise by providing more effective innovations. This study aims to develop a Question Answering System or a digital question and answer system using a chatbot (ChatterBot). The chatbot is used as an information service provider that can make it easier for tourists who are looking for information about tourist attractions. Chatbot-based information service systems can work 24 hours or all day, reducing the intensity of direct physical contact with officers and saving operational costs. The chatbot implementation is built on the Machine Learning Framework using RASA Open Source with the Python programming language. The knowledge base of the chatbot system is trained based on the FAQ (Frequently Asking Question) dataset with a case study of the Prambanan Temple tourist attraction as a sample of Indonesian tourism. The results of the evaluation and system performance based on data testing obtained the level of model accuracy is 0.91. Furthermore, the weighted average value in the Confusion Matrix produces a precision of 0.97, a recall of 0.94, and an F1-score of 0.95. The training and testing model processes locally using the Visual Studio Code software.

Keywords: *Covid-19, Chatbot, Machine Learning, RASA Open Source, Prambanan Temple*

1. Introduction

World Health Organization (WHO) officially declared on March 11, 2020 that the corona virus or Coronavirus Disease 2019 (Covid-19) as the global pandemic. On May 31st 2021, the number of spreads increased rapidly to 219 countries/territories with the total global infections of more than 171.5 million cases and 3.7 million deaths. The rapid spread of the epidemic has caused enormous effect on all countries both in the aspect of health, social and welfare, as well as the economy.[1].

As the impact of COVID-19 pandemic, many sectors experienced massive deficits and losses, one of which was the tourism industry. The number of visits as recorded by PT Taman Wisata Candi (TWC) Borobudur, Prambanan, and Ratu Boko for one year was only around 1.3 million people or only 22% compared to 2019.[2]. It was recorded that state revenue in the tourism industry sector decreased by Rp. 20.7 billion due to Large-Scale Social Restrictions (PSBB) and the closure of travel access to Indonesia. This policy has impacted the tourism industry sector for a long time because most tourists reduce their activities for traveling. From January to November 2021, the number of foreign tourist visits to Indonesia was 1.48 million visits. The number of foreign tourist visits has decreased drastically to 61.82% compared to the period in 2020 [3].

The decreasing number of tourist visits has encouraged players in the tourism industry to innovate in order to survive in the midst of the pandemic. The concept of Online Experience-based service system is one of the alternative innovations that can be used to deal with crisis conditions in the midst of the current pandemic. The digital acceleration process gave birth to a new trend, namely Contactless Tech Adoption, which provides a different experience for Customer Journeys of the tourists. System implementation with the principle of "Contactless" is used to create digital service programs by adopting automation technology that is growing rapidly. The changes in consumer behavior, which are increasingly adapting to

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technological developments, they are no longer becoming a gap to realize an all-online tourism industry sector. This trend can continue to be used during the pandemic and post-pandemic[4].

One of the latest technologies that support the digital transformation process in the tourism sector is Artificial Intelligence (AI). AI is used to build intelligent systems as a digital information service center in the form of a Chatbot (ChatterBot). With the ease of access provided, chatbots can be the technology supporting the creation of social sustainability through inclusive access of information. Chatbots have also become one of the 4.0 Industrial Revolution technologies that support the formation of Society 5.0. As conceptually it can be a solution for solving health problems and supporting the achievement of the Sustainable Development Goals (SDGs). In addition, the practical implications of the study also state that the use of chatbots can be further developed to overcome other problems. The use of chatbots can have an impact on improving the economy during the Covid-19 pandemic. Chatbot technology can continue to be optimized even though the Covid-19 pandemic crisis period is over[5].

Chatbot development is increasingly popular among the software developer community because it is widely used by entrepreneurs and governments to save time and operational costs. However, developers must also be careful in choosing the best platform according to the problems needed. In the research about evaluating the performance of chatbot systems using IBM Watson, Google Dialogflow, RASA, and Microsoft LUIS, it is concluded that IBM Watson is the NLU with the best performance for the intent classifier category, with F1-Score of > 84%. Moreover, in the next assessment, the RASA Framework obtained the top position with the best average confidence scores of more than 91%. The last assessment regarding the entity extraction process shows that Microsoft LUIS and IBM Watson are the best[6].

The next research explains about the implementation of RASA Open Source Chatbot which can be integrated with database, API, conversational flow, interactive learning with Reinforcement Neural Network. The various features provided by RASA Framework can be used to execute chatbot task that getting more complex. [7]. The Chatbot uses FRASA Open-Source Framework is developed with deep learning model, especially LSTM. LSTM (Long Short-Term Memory) not only can efficiently save some memories needed, but also it will also delete the unnecessary memories. The model in RASA Framework is arranged using DIET Classifier which can predict with the accuracy of 96% based on the research[8]. Furthermore, the chatbot model is proven using weighted average value results for precision 0,995, recall 0,995 dan F1-Score 0,995. While the dialogue model evaluation shown the accuracy rate of 0.70, precision score of 0,72 and F1-*Score* of 0,70 which represent the chatbot performance in predicting the response is right for the users [9].

This research aims to continue the study of developing a Chatbot-based Question Answering System used as the digital information service system regarding tourism objects. The research case study was carried out at the Prambanan Temple tourist attraction as an ambassador for Indonesian tourism [10]. The chatbot system was designed using RASA Open-Source Framework and Python program language.

2. Research Methods

This study was compiled using the CRISP-DM method. The method is a set of processes or work systems that are used as guidelines for creating a complete AI/ML project [11]. This study was compiled using the CRISP-DM method. The method is a set of processes or work systems that are used as guidelines for creating a complete AI/ML project.

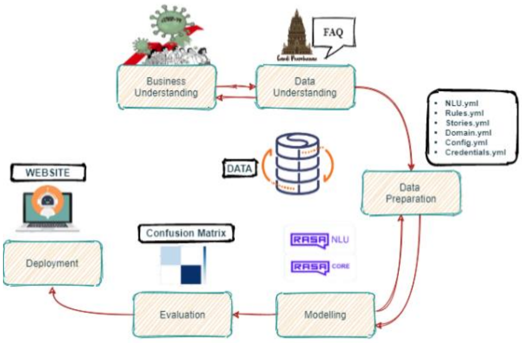

Figure 1. Research's CRISP-DM Block Diagram

The explanation of each stage of CRISP-DM according to the research can be written as:

2.1. *Business Understanding*

The understanding of the economic problems faced by the Indonesian tourism industry sector became the research study due to the declining of state income. Several things were done at the business understanding stage, starting with understanding the needs of the tourists and conducting an analysis in the form of defining the problems encountered. After that, plans and strategies that produce solutions to achieve data mining business goals were defined.

2.2. *Data Understanding*

The process of developing Contextual Chatbot with Machine Learning technology where the system required a number of datasets to train the chatbot model. Dataset was an important material or component in AI/ML project research case studies that can be obtained from various data collection or acquisition methods. This study used the type or method of data

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acquisition based on surveys and observations, namely by collecting questions in Frequently Asked Questions (FAQ) as chatbot training data. Based on the surveys and observations, the FAQ dataset contained questions about the Prambanan Temple tourist attraction. The following types of input message categories that were managed for the definition of intent and response based on FAQ questions as chatbot training data were presented in Table 1.

Table 1. Dataset of FAQ Chatbot

No	Type of Intent	Message Description	Number of Samples
1	*greet*	Greetings of conversation	32
2	kabar	Users asking how is ARTour	11
3	bantuan	Users asking for helps	14
4	*affirm*	Good response or agreement	28
5	*deny*	Bad response or disagreement	22
6	candi	Information about Prambanan Temple	17
7	Lingkungan _candi	Information about the surrounding of Prambanan Temple Complex	9
8	lokasi	Location of Prambanan Temple	10
9	waktu	Operating hours of Prambanan Temple	8
10	tiket	Ticket price of Prambanan Temple	13
11	pesan	Information about ticket reservation of Prambanan Temple	14
12	akomodasi_ kendaraan_ pribadi	Private vehicle route to Prambanan Temple	13
13	akomodasi_ bus	Bus route to Prambanan Temple	12
14	akomodasi_ kereta_api	Train route to Prambanan Temple	9
15	akomodasi_ pesawat	Plane route to Prambanan Temple	12
16	kuliner	Food recommendations around Prambanan Temple	19
17	souvenir	Souvenirs of Prambanan Temple	10
18	covid	Health protocol in Prambanan Temple area	10
19	*bot_ challenge*	Users asking who is Artour	10
20	Artourist	Users asking name of Artourist	6
21	*goodbye*	End of Conversation	12
	Total Samples		291

The number of sample messages used as the training dataset is 291 sentences with 21 types of intent variations based on different categories.

2.3. *Data Preparation*

The Prambanan Temple chatbot information service system built using the RASA Open-Source Framework requires several configuration files as a training dataset. Figure 2 shows the data components configured as training data.

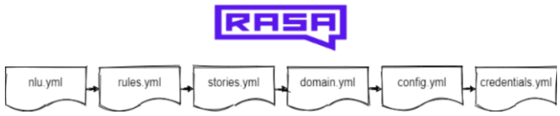

Figure 2. Components of *RASA Framework Dataset*

The explanation of each configurated dataset component were written as the following[12]:

1. *Natural Language Understanding* (NLU)

NLU data in RASA Framework contained the sample messages from the users labelled with the intent based on each category. In the advanced level, the NLU data can be combined with entity addition, synonym and Lookup tables.

2. *Rules*

The data of rules in RASA Framework contained the conversation snippets which must be fit between the intent and the given response.

3. *Stories*

The data of stories in RASA Framework contained the conversation snippets which were able to generalize new conversation or something which had never been trained before.

4. *Domain*

The data of domain in RASA Framework contained the conversation universe such as action, intents, entities and slot. The definitions of actions and responses were used as the answer template of chatbot.

5. *Config*

The data of config in RASA Framework contained the language, pipeline and policy configurations which used to train the model.

6. *Credentials*

The data of credentials in RASA Framework contained the activation token so that the model that had been trained can be used and connected with Facebook, slack, Twilio, telegram, google hangouts chat, website, etc.

2.4 Modelling

The model configuration in RASA Open-Source Framework required three stages as the main components, they were language, pipeline and policies. Those components were used as the model rules to comprehend the user's input message and to determine the suitable response or output [13]. In Figure 3, some of file configurations of Config model that used in the research.

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```
# Configuration for Rasa NLU.
# https://rasa.com/docs/rasa/nlu/components/

recipe: default.v1
language: id
pipeline:
  - name: WhitespaceTokenizer
    token_pattern: (?u)\b\w+\b
  - name: RegexFeaturizer
  - name: LexicalSyntacticFeaturizer
  - name: CountVectorsFeaturizer
  - name: CountVectorsFeaturizer
    analyzer: char_wb
    min_ngram: 1
    max_ngram: 4
  - name: DIETClassifier
    constrain_similarities: True
    epochs: 100
  - name: EntitySynonymMapper
  - name: ResponseSelector
    retrieval_intent: out_of_scope
    scale_loss: True
    epochs: 100
  - name: FallbackClassifier
    threshold: 0.5
    ambiguity_threshold: 0.3
```

Figure 3. Configuration of *Pipeline* Model

A series of special processes that used to detect intents and to extract entities known as "Pipeline". The language defined in Pipeline model configuration of the research is Indonesian Language or Bahasa Indonesia with the language code of "id". The pipeline model consisted with the process of Tokenization, Featurization, Intent Classification, Entity Extraction and Response Selectors.

Moreover, the "Policies" aimed to define the dialogue management process and the models used to define the answers (response) based on the user message input. Different from the Pipeline procedure which had sequences, the "Policies" procedure was done in parallel. Figure 4 shown the Policies configuration that used in chatbot model.

```
policies:
  - name: RulePolicy
    core_fallback_threshold: 0.5
    core_fallback_action_name: "action_default_fallback"
    enable_fallback_prediction: True
    max_history: 6
  - name: AugmentedMemoizationPolicy
  - name: TEDPolicy
    constrain_similarities: True
    max_history: 10
    epochs: 20
    batch_size:
    - 32
    - 64
```

Figure 4. Configuration of *Policies* Model

Based on the Figure 4, there were two types of components that used to arrange the configuration of Policies model, they were: (a). Rule-based Policies used as the model policies which was fixed in making prediction by following the rules that had been trained in the conversation. (b). *Machine-Learning Policies* used as the model policies which was flexible in making prediction based on the patterns that had been trained from the training data. The types of ML Policies which used in the research were: (1). TEDPolicy (*The Transformer Embedding Dialogue*), used to predict the response, actions and entity processing. (2). AugmentedMemoizationPolicy, used to memorize the previous data training as the guidance to generalize the new input message such as MemoizationPolicy.

2.5 Evaluation

The evaluation process of chatbot-based information service system using RASA open-source provided automatic testing features. The evaluation result of chatbot performance using RASA Open-Source Framework gave the NLU model report and dialogue model, as follows:

1. NLU Model Evaluation

NLU mode was evaluated based on the model training dataset when processing the unstructured user input message, such as: extracting entity and clarification process of user message intent based on the categories.

2. Dialogue Model Evaluation

Dialogue model was evaluated based on the response definition or the output of the chatbot based on the input message in the conversation. The given response as the user output which determined based on the understanding of the message and intent category classification in NLU model.

Model evaluation process created the table of Confusion Matrix which consisted of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). Each component could create value that used as the parameter to count the evaluation on the classification model as written [14]:

Accuracy

Parameter of *Accuracy* is used as the performance measurement which shown the accuracy rate of all the prediction created by the model. The formula equation can be calculated as written below:

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN} \tag{1}$$

Precision

Parameter of *Precision* was used as the accuracy rate of classification results of all documents in the system. The equation formula can be calculated as written below:

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Recall

Parameter of *Recall* shown the success rate of the system to recognize a category. The equation formula can be calculated as written below:

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

F1-measure

Parameter of *F1-measure* was the description of relativity between the *precision value* and *recall* or called as *harmonic mean*. The equation formula can be calculated as written below:

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$$F1 - score \ = 2 \ x \ \frac{(precision \ x \ recall)}{(\ precision + recall)} \qquad (4)$$

After that, the calculation of parameter evaluation in multi-class classification based on the mean value gained from Macro- and Weighted-average were as follows [14]:

1. Macro-Average was the calculation matrix that used independently in each class which then taken the mean value based on the total. The equation formula can be calculated as written below:

$$Macro \ Average \ Precision$$
$$= \frac{\sum_{k=1}^{K} Precision_k}{K} \qquad (5)$$
$$Macro \ Average \ Recall = \frac{\sum_{k=1}^{K} Recall_k}{K} \qquad (6)$$
$$Macro \ F1 - score$$
$$= 2 \ x \ \frac{(MacroAvgPrecision \ x \ MacroAvgRecall)}{(\ MacroAvgPrecision^{-1} + MacroAvgRecall^{-1})} \qquad (7)$$

2. Weighted-Average was the independent mean value calculation based on each class which weighted based on number of data size. The equation formula can be calculated as written below [15]:

$$Weighted \ Average \ Precision$$
$$= \frac{\sum_{i=1}^{l} Precisioni * N}{Total \ Data} \qquad (8)$$
$$Weighted \ Average \ Recall$$
$$= \frac{\sum_{i=1}^{l} Precisioni * N}{Total \ Data} \qquad (9)$$
$$Weighted \ Average \ F1\text{-}Score$$
$$= \frac{\sum_{i=1}^{l} F1 - scorei * N}{Total \ Data} \qquad (10)$$

2.6 Deployment

The implementation phase of RASA Open Source chatbot had the purpose to ease the users to access the chatbot in public. Here was the diagram that explained the implementation process of chatbot service system to end user. The process implementation in chatbot system can be illustrated in Figure 5.

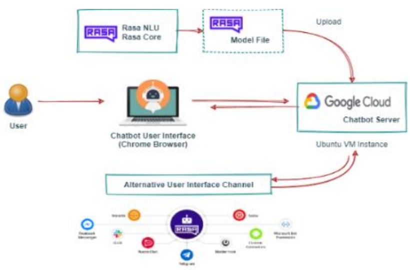

Figure 5. System Implementation of Chatbot

The configuration and dataset training phase were done using local computers so they created the chatbot model with the test evaluation above 80%. After succeeding the good evaluation criteria, the RASA chatbot model was sent to the server. It was done so that RASA chatbot model can be accessed publicly by the users or also known as hosting. The benefit of hosting by the server were a safer implementation of virtualization concept or secure and a guarantee of data backup or data recovery if the disaster or the system error happened. Moreover, the Ip address of external server can be configurated into static so to prevent changing from time to time so that it would be fit to be integrated in a wider scale. This research used the server service from Google Cloud Platform to build Virtual Machine with Ubuntu operating system. After the model was sent to the server, the chatbot system that built in Framework RASA Open Source could be accessed using "Web Browser" such as Google Chrome as User Interface (UI) of public information service of Prambanan Temple tourism object. The system implementation of chatbot service can be seen in Figure 6.

Figure 6. *User Interface of* Chatbot

These activities aimed to ease the users or tourists who needed the actual information about Prambanan Temple tourism object

3. Results and Discussions

The chatbot model was given the simulation test using data testing with the purpose to understand the performance when the system working. The testing process used RASA Open-Source Framework automatically produced the system reports which presented in the format of picture, json, and yml file. In Table 2, the evaluation result reports of conversation flow with the error in intent classification while making the prediction of user input message was presented in Table 2.

Table 2. *Report Error of Intent*

Input Message	*Intent*	*Intent Prediction*	*Confidence Level*
"ada candi prambanan dimana"	Lokasi	nlu_fallback	0.50
"mau pesen tiket kemana"	Pesan	nlu_fallback	0.50
"aku mau ke prambanan bareng keluarga"	akomodasi _kendaraan _pribadi	nlu_fallback	0.50
"jaraknya jauh?"	akomodasi _kereta_api	nlu_fallback	0.50
"mau nasi padang"	Kuliner	nlu_fallback	0.50
"salam kenal, raya"	Artourist	*greet*	0.93
"byee artour"	*Goodbye*	nlu_fallback	0.50
"artour km dimana"	Bantuan	lokasi	0.61
"hay"	*Greet*	*affirm*	0.77
"mau pesen tiket?"	Pesan	nlu_fallback	0.50

Based on the result of simulation test on Table 2, while doing the process of intent classification, there were 10 user messages that falsely predicted by system. It used data testing with the number of message inputs of 113 resulted in 103 sentences were rightly predicted. The score of evaluation result based on the accuracy rate of dialogue model was 0.91 or 91%. The accuracy value based on the rest result can be calculated using Equation 1 that is *accuracy multi-class classification* which can be written as:

$$Accuracy = \frac{103}{113} = 0,91$$

Then, the result of parameter evaluation based on Confusion Matrix consisted of the scores of precisions, recall and F1-score created based on the testing reports using data testing in RASA Open-Source Framework. In the Table 3, the Report Message of testing result is presented.

Table 3. *Report Message*

No	Message Category	Support	Precision	Recall	F1-score
1	Deny	2	1	1	1
2	utter_pesan	3	1	1	1
3	akomodasi_kendaraan_pribadi	2	1	0.5	0.666
4	Sourvenir	2	1	1	1
5	utter_lokasi	3	1	1	1
6	utter_kabar	2	1	1	1
7	utter_lingkungan_candi	3	1	1	1
8	utter_kendaraan_pribadi	2	1	1	1
9	Kuliner	3	1	0.666	0.8
10	Goodbye	2	1	0.5	0.666
11	utter_ask_nama	2	1	1	1
12	Waktu	3	1	1	1
13	lingkungan_candi	3	1	1	1
14	bot_challenge	2	1	1	1
15	utter_bantuan	4	0.8	1	0.888
16	utter_candi	4	1	1	1
17	action_listen	56	1	0.982	0.99
18	Kabar	2	1	1	1
19	Pesan	3	1	0.333	0.5
20	utter_waktu	3	1	1	1
21	utter_iambot	2	1	1	1
22	utter_bus	2	1	1	1
23	Affirm	2	1	1	1
24	utter_deny	2	1	1	1
25	akomodasi_pesawat	2	1	1	1
26	candi	4	1	1	1
27	Artourist	2	1	0.5	0.666
28	bantuan	3	0.666	0.666	0.666
29	utter_affirm	2	1	1	1
30	covid	2	1	1	1
31	akomodasi_bus	2	1	1	1
32	utter_kereta_api	2	1	1	1
33	utter_greet	7	1	1	1
34	utter_goodbye	2	1	1	1
35	utter_pesawat	2	1	1	1
36	lokasi	3	0.75	1	0.857
37	greet	7	0.875	0.857	0.933
38	akomodasi_kereta_api	2	1	0.5	0.666
39	utter_sourvenir	2	1	1	1
40	Tiket	3	0.75	1	0.857
41	utter_covid	2	1	1	1
42	utter_kuliner	3	1	1	1
43	utter_tiket	3	1	1	1
44	None	1	0	0	0
	macro_average	**170**	**0.95**	**0.90**	**0.91**
	weighted_average		**0.97**	**0.94**	**0.95**

The evaluation result in Table 3 created the mean value based on Macro Average of Precision evaluation with 0.95 or 95% that can be calculated using the Equation 5 as written below:

$$Macro\ Average\ Precision = \frac{41,84}{44} = 0,95$$

The evaluation score based on *Recall* was 0.90 or 90% which can be calculated using Equation 6, it can be written as:

$$Macro\ Average\ Recall = \frac{39,50}{44} = 0,90$$

the evaluation score based on *F1-score* was 0.91 or 91% that can be calculated using Equation 7, it can be written as:

$$Macro\ F1 - score = \frac{40,16}{44} = 0,91$$

The average evaluation of *Weighted Average* based on the evaluation of *Precision* was 0,97 or 97% which can be calculated using Equation 8, it can be written as:

$$Weighted\ Average\ Precision = \frac{164,82}{170} = 0,97$$

The evaluation score based on *Recall* was 0,94 or 94% which can be calculated using Equation 9, it can be written as:

$$Weighted\ Average\ Recall = \frac{158,99}{170} = 0,94$$

The evaluation score based on *F1-score* was 0,95 or 95% which can be calculated using Equation 10, it can be written as:

$$Weighted\ \ Average\ F1 - score = \frac{160,89}{170} = 0,95$$

The accuracy rate of the model that gained was 0.91 or 91%. The parameters were used as the indicators to evaluate the chatbot while operating the system based on the false or right result prediction. The accuracy rate of the system was affected by the number of Prambanan Temple FAQ dataset which used as the data training of chatbot model. However, in the case of supervised learning model classification, the accuracy rate was not the only matrix that used. The parameter of chatbot model evaluation can also be analyzed form the reports given by RASA Open-Source Framework, they were precision, recall and F1-score. The precision value of the chatbot model produced was 0.97 or 97% representing the accuracy rate between information needed by users and the answers or responses given by the chatbot system. The recall value of the chatbot model produced was 0.94 or 94% representing the success rate of user input message classification based on the data testing in chatbot system. Moreover, the

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parameter of F-1 score value of chatbot model produced was 0.95 or 95% representing the balance between the parameter value of precision and recall.

4. Conclusions

The chatbot built using RASA Open-Source Framework version 3.0 with Phyton language program was used as Question Answering System of Prambanan Temple tourism object. The learning process of chatbot system machine needed some of dataset configuration as the basis material of model training which consisted of NLU, Stories, Rules, Domain, Config and Credentials data.

The evaluation results of chatbot model in doing the intent classification and determining the action or response toward the user message given the accuracy rate of 0,91 and the parameter components based on Confusion Matrix given the average weighted value of precision with 0,97, recall with 0,94 and F-1 score with 0,95.

The chatbot-based information system can be the alternative for tourism industry which starting to transform and adopt digital technology. The chatbot feature can also be used to keep the communication with the customer by using "Contactless Tech Adoption" so that the spread of Covid-19 can be suppressed. The chatbot service system will help the work of customer service staffs since it can work for 24 hours. The chatbot can also be used well during the pandemic and post pandemic and can save the operational cost and can add the business value.

Recommendations

As for the next research, it is expected to use more data of user question data as the knowledge base material of chatbot system. The development of Actions response that connected with

REST API database can be used to create new system service such as ticket auto-creating as the solution to minimize the que in the locket. It will be better to provide the system in any different languages other than Indonesian language.

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