

# Service Provider Allocation and Customers' Service Requests Management System

<sup>1</sup>I.A.Kandamby, <sup>2</sup>A.W.S.G. Sasiprabha, <sup>3</sup>Perera K.G.I.D., <sup>4</sup>Mahaadikara M.D.J.T Hansika, <sup>5</sup>Arachchi T.L.P.,  
<sup>6</sup>Devanshi Ganegoda

<sup>1,2,3,4,5,6</sup>Faculty of Computing, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka

**Abstract** - Automated technology revolutionizes the service industry and is a prerequisite for quality service. There are several ways to expand the use of automated systems, boost customer services, and save money in our day-to-day operations. The main focus of this research is to provide people with their service requirements and making day-to-day life easier. This research aims to automate customer service request management and the allocation of service providers. "UTILIQUE" is designed to provide customers a way of reaching out to service providers effectively and possible solutions if no service provider is located in the vicinity of the area. Besides, it analyzes user reviews and rank services providers accordingly, estimates operating costs for customers before delivering the services, and provides automated solutions. This is a mobile application and customers can easily control the application using voice and speech. Automated solutions providing, cost prediction, and ranking based on feedback analysis are used for market opportunities that can draw more users than other service providing applications.

**Keywords:** Natural language processing, Voice detection, Feedback analysis, Cost Prediction, Random Forest, Machine Learning, Blockchain, Sentiment analysis.

## I. INTRODUCTION

The term ICTs is used to describe a variety of technology for information collection, storage, retrieval, processing, analysis, transmission, and communication in real-time. ICT applications have a profound impact on the political, economic, social, cultural, and everyday life of a huge number of citizens in the developing world. They affect education, governance, job market, and e-commerce and thus on economic growth and social systems.

In everyday life, people need minor services like fixing a broken pipe, changing a flat tire of a vehicle, etc. As the people in modern society are very busy, they won't be able to spend much time finding service providers to get these needs done and service providers may not be available whenever they are needed. As mentioned in [1] it is currently a common factor that mobile communication has become a significant part of human life and a major role player anywhere in the

world. The development of mobile and location-aware coordination system to find service providers and customers' service requirements management will be a valuable way of easing peoples' way of life

There is no way to provide 24/7 customer support, to locate service providers, to estimate the cost for tasks. It was then agreed to develop an application for service providers that overcome the limitations in existing applications. This paper explores the methodologies used to establish the application proposed. The new system is an automated system that connects service providers with customers and it offers temporary solutions, recommendations when there are no service providers nearby. Customers can monitor the service provider's location and get to know the time of arrival. Customers are provided with details of the estimated cost that will take to complete the task. Feedback from customers is taken as texts and evaluated to make suggestions for future customers.

## II. RESEARCH GAP

Gežinič, J. notes that system performance must be monitored both for understanding the requirements of the customer and for controlling the process and for implementing ongoing reform. The implementation of personalized, safe, and unique client service solutions has been the key to attracting and maintaining visitors and giving clients a good end-to-end experience [2]. Many systems do not permit customers to interact without a human agent in the management of customer service requests. But in 'Utilique' everything is automated and no human agent is required.

Natural Language Processing (NLP) is a branch of computer science and artificial intelligence (AI) concerned with processing and analyzing natural language data. Deep learning for NLP is one of the approaches that is improving the capability of the computer to understand human language. There are a few studies that try to incorporate customer written reviews in generating recommendations [3].

As an aspect-based recommender system, in [4] proposed a model called an aspect-based latent factor model that combines ratings and text reviews using a latent factor model.

Several other aspect-based recommender systems use semantic analysis. For example, [5] proposed a sentiment utility logistic model that uses sentiment analysis of user reviews where it predicts the sentiment that the user has about the item and then identifies the most valuable aspects of the user's possible experience with that item. The balance between price and quality of service is a major challenge for service providers [6].

In this application, sentiment analysis was used to analyze customer reviews and rank service providers. There are no previously developed service provider allocation systems to rank service providers by analyzing customer reviews. Although several applications have already developed to connect service providers and customers they provide only platforms for service providers and customers to post services and requests. Novel features in 'Utilique' are cost prediction, automated solution provision, and consultant service.

### III. METHODOLOGY

Basically, "UTILIQUE" has core functionalities such as service provider allocation, job scheduling & feedback analysis, automated system to provide solutions & suggestions, online consulting service system, and system for payment and forecasts.

#### A) Service providers' allocation, job scheduling, and feedback analysis

The core of this research is the allocation of a service provider for a customer according to his/her choice. Once the customer search for a service provider, using Google location API, the system captures the location of the customer and find nearby service providers that do not have work or have the least work at the time. The system displays the customer a list of service providers available along with the approximate cost. The system organizes the list of service providers focusing on customer feedback. Once the customer chooses a service provider, the job is assigned to the service provider and task information is sent to the service provider.

If the service provider refused the work, the customer will have to seek another service provider and the customer is free to proceed if the service provider approved the request.

The location of the service provider is monitored using Google location API and the customer is indicated with the arrival time. After the work, the consumer provides the service provider with reviews as texts. These reviews are analyzed using sentimental analysis which is an NLP technique. Sentiment Analysis is the process of determining whether a piece of writing is positive, negative, or neutral. A sentiment analysis system for text analysis combines natural language

processing (NLP) and machine learning techniques to assign weighted sentiment scores to the entities, topics, themes, and categories within a sentence or phrase [7].

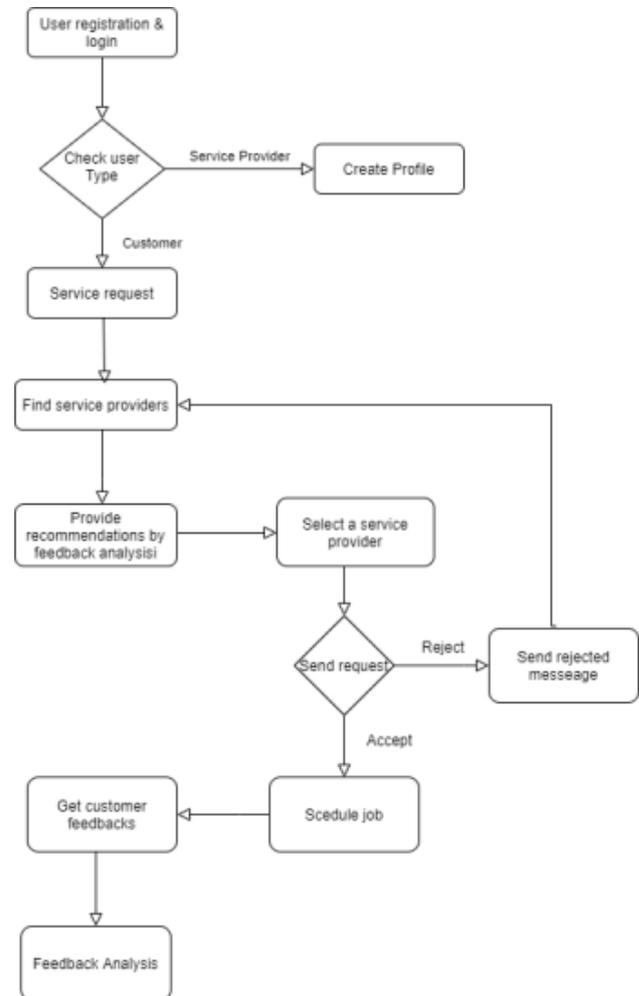


Figure 1: Service provider allocation, job scheduling, and feedback analysis

Overall rating of reviews can vary from 2.5/10 to 10/10. To clarify the problem, they were divided into two categories:

- Bad reviews have overall ratings < 5
- Good reviews have overall ratings >= 5

A ranking system is developed to identify the best service providers using the ratings generated by evaluating those customer reviews.

#### B) Automation of service request management, generation of solutions and suggestions

Smart automation systems are an excellent way to draw substantial insights across large pools of data. Besides, automation of service request management helps in providing better service for the customer. The end-user initiates touch and receives support from the application immediately.

Customers are asked what they need, and the application based on underlying machine learning, profound learning, neural networking, and natural language processing technologies understands what they require and answers it accordingly. It will generate results for the end-user in seconds rather than waiting for an individual to act.

It was designed to generate and train a natural language model using Google Dialogflow. Dialogflow is essentially a Natural Language Processing Engine with a focus on the Natural Language Understanding (NLU) part of the "comprehension" of natural language. While the Dialogflow engine can enhance and learn, the developer / narrative engineer can only progress through active training [8].

The method used in this section is divided into two sections, i.e. knowledge abstraction and response generation. Information processing is subjected to knowledge abstraction. On the other hand, it depends on the characteristics of the data generated in the data abstraction phase as well as the features of the Dialogflow tools and their various integrations.

*a) Knowledge abstraction*

For conversational agents, knowledge engineering is extremely useful. For example, in answering basic questions about general facts. Knowledge abstraction involves three phases: gathering, manipulation, and augmentation [9].

*Data gathering:* This step involves finding and collecting information on key concepts of service requests.

*Data manipulation:* The second step is to store this data in the database. This categorizes questions that have a similar answer and each question & answer pair have a label attached that specifies the name of the target.

*Data augmentation:* The number of training for the natural language processing model available in Dialogflow will be increased. Then attempts to search for correlations between questions and responses to the same purpose. It is very helpful when Dialogflow recognizes entities, and when all entities appear in a single entity, the model learns better. The function of clarifying user intents allows the application to ask the user questions explicitly or at least encourage the user to explain what he or she means [10].

The Bayesian approach consists of using a Bayesian update to infer the correct user intent. It is based on Bayes' rule:

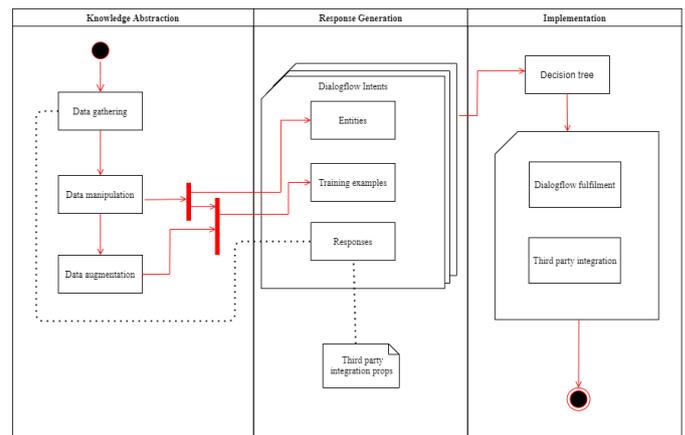
$$P(c|m) = \frac{P(m|c)P(c)}{P(m)} \quad (1)$$

C is the symbol of the user question, and m is the message of the user. Since the update result should be a vector of all class probabilities, P (m), since it is only based on m and only works as a standardization process, should simply be ignored. P(c) is the preceding likelihood and is directly taken from the output of the objective classification. The message is assumed to be first classified, but this restriction is not strict. Lastly, on the user's answer using the intent classifier, the term P (m) is calculated. The user is supposed to use a language in close relation to what other users might have said when clarifying their first post.

*b) Response generation*

The approach to producing responses is recall-based. The responses have a framework that reflects the actual experiences of real customer service providers [11]. A detailed overview is available on how entities and attempting inside Dialogflow operate, but it is appropriate to explain how the approach suggested is already applied in this framework. Training examples include the sentences in two categories: templates and examples. They seem to be plain text in many ways, but Dialogflow permits direct integration with applications that fit content into cards, cards, tables, lists, and other information structures.

Entities are classified as keywords as previously stated depending on their role. Some entities correspond to geographical locations, numbers, or dates. The advantage in analytics because the number of potential attempts that fit the query is reduced every time an object is identified.



**Figure 2: Diagram of the sections in which the methodology is divided and how each other's related**

Consider if the agent will say any written words or if it will only expect the user to read them. We found that a mixture between the two would be better: let the agent tell the user what it shows, but not the actual content. Because otherwise, hearing the agent talked for a long time would be annoying.

An example of this would be the agent who asks for the BFS algorithm: here is the BF's algorithm and then the algorithm is displayed as a list of steps.

c) The flow of conversation and decision trees

Decision trees are often referred to as interaction trees and used to incorporate a virtual assistant framework. They consist of nodes, each containing a response to a particular question. This provides every node with a condition that is activated when the user query matches the node answer (to a certain extent). This last step is achieved with keywords and the recognition of natural language. In Dialogflow, nodes are equivalent to intents [12].

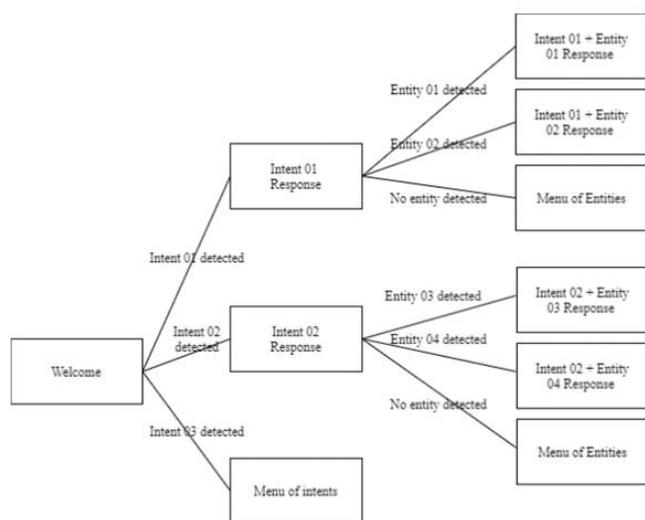


Figure 3: Fundamental structure of the proposed decision-making tree with two intents and four different entities that work with those intents

This structure is designed to react with intent or entity menus to fallback cases from which the user can interactively select one. The existence of jumps between the related nodes, so that one can visit the father and the sibling node directly, is not seen here but has to do with the non-linear communication fluid. A conversational flux is the first step to the implementation of a decision tree. This refers to how the agent handles forks and how it passes through the content during a conversation. We can determine the conversation flows in both linear as well as non-linear.

*Linear flow:* It is a two-phase, question, and answer conversation stream. These are fairly easy to implement because there is only one node in the decision tree. However, they are only useful if there is a manual. This manual will provide you with information on how the wizard should communicate and the user.

*Non-linear flow:* This conversational flow is largely based on feedback and makes it possible to analyze the decision tree

much deeper. The decision tree is not entirely different from the linear flow, but the main difference is that it contains jumps between nodes. Such jumps allow suggestions that can be directly linked in our decision tree to any other node.

C) Online consulting service system

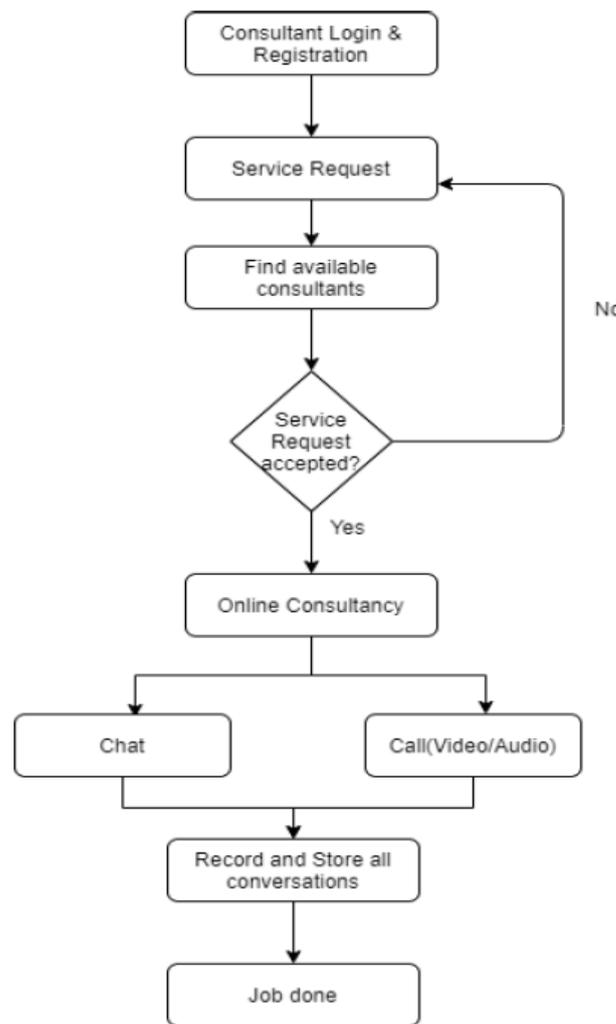


Figure 4: Flowchart of online consulting system

This research describes an online consulting service consisting of several features. If a customer is unable to get a service provider nearby, the customer can get online consultation. An online consultant is provided to the customer according to the customer's needs. The automatic system sends a service request to available consultants where they can accept the service request. All the conversations between customers and consultants are saved for future needs.

The system automatically filters the problem and automatically sends a service request (SR) to all available consultants. They can accept the service request. The first consultant who accepts the SR will relate to the customer. The consultant who accepted the request and the customer will

meet on the same platform where they can chat, video call, and share information regarding the service request.

To know about materials, vendors, and a rough budget, and where the customer just wants details but does not require a service provider to visit the location can online consultation. Online consulting can be done independently or as a company. The concept of the Smart Contract in the Blockchain is used for this function.

The system architecture was designed and implemented to use blockchain for sending messages securely as a software component. Sockets are used and manipulated to create a connection between software in other words a way of connecting two different nodes on a network to communicate with each other. In the implemented application all the communicated messages are stored on a block which is connected to other blocks forming a chain. When a chat conversation happens between two parties, A new block will be created for the instance and the hash value of the message will be generated and get stored in the previous block. This is how the latest block gets added to the blockchain network. These created blocks are linked through a chain of cryptographic hash pointers in which helps to trace back all historical changes made.

**D) System for payment handles and predicts the cost**

The Random Forest (RF) algorithm introduced by Breiman in 2001 is a hybrid algorithm [13]. If the assumptions are discrete, random forest classification, and if a continuous value, random forest regression. Various z empiric studies have demonstrated the probability that the random forest algorithm has high predictability for an odd value and tolerance to noise. Two phases are used for an RF classification algorithm. In the RF algorithm, three steps are also used:

Choose the training set. Using the random sample strategy for the bootstrap to get K training sets from the initial dataset (M properties) with the scale of training set like that of the initial training set.

*Create the RF model:* Through the bootstrap training package, build the regression classification tree for generating K decision trees for the creation of a "forest". These trees are not pruned. When considering the growth of the individual tree, this method selects not the best features as internal branch nodes but instead selects a random set of all features.

Formation of a single majority. Since the process of planning each decision tree is special, the development of random forests will work at the same time, significantly increasing its efficiency. The RF algorithm decides the

samples by creating a sequence of independent and distributed decision trees and sets the final sample group for each decision tree.

Malek et al. combined RF and Autonomous Maps to effectively predict pediatric fracture healing times [14]. Wang applied RF to the monitoring of manufacturing conditions and fault diagnostics and introduced a standardized RF-dependent panoramic crack detection system [15]. Malazis and Davari have used RF and evolving pattern algorithms to classify age-old behaviors at home and to achieve high precision efficiency with the F-Measure Index [16]. Santana et al. quantified soil quality parameters based on RF regression, allowing rapid and automated soil testing [17]. Anitha and Siva have proposed a new computer-aided method for detecting brain tumors using the RF classifier [18].

To solve the problem of identifying new activities, Hu et al. proposed an additional RF class (CIRF) [19]. Abellan et al. suggested an RF (RTRF) Random Confidence, which showed improved noise data and efficiency [20]. Gomes et al. proposed an adaptive RF algorithm (ARF) [21]. For the classification of data streams. Gender et al. have introduced an ideal RF algorithm for Big Data Analysis that solves problems related to parallel computing, on-line shifting, and off-bag error [22].

**IV. RESULTS**

Automation of service request management and generation of solutions and suggestions are core functionalities of "UTILIQUE". In this automation concept, we have been proposed to use the Bayesian approach to clarify user intents during the process of training data models using Dialog flow. When applying the Bayesian update, a comparative examination should be undertaken to make sure that the application helps the consumer assess its intention. For this, a standard application with no modification of Bayesian and a Bayesian modification application has been considered. They are both coupled to a user simulator which is explained by providing an answer per the user's purpose. The sample shall be marked as "No clarification" if the applicant has not previously understood the customer. The dataset used for this comparison is simply the test set from Table 1 containing the distribution of tickets for the two variants.

**Table 1: Distribution of tickets for the two variants**

Variant	Correctly identified w/out clarification	Identified after clarification	Failed to clarify	Incorrectly identified
Standard	16,508	0	0	4,899
Bayesian update	16,508	4,302	37	560

As anticipated, the Bayesian update helps the agent to address the unknown problems correctly initially. As seen in the example, the Bayesian update nearly describes all user issues in the test sample. However, the findings should not be taken as a matter of fact as the clarifications made by the user simulator are very optimistic and represent the ideal environment in which users explain their problems very clearly. This implies, if correct, that the agent could achieve a precise 95% with a Bayesian update. Of course, that is impossible, but it demonstrates that a Bayesian update is helpful to determine the intent of a user.

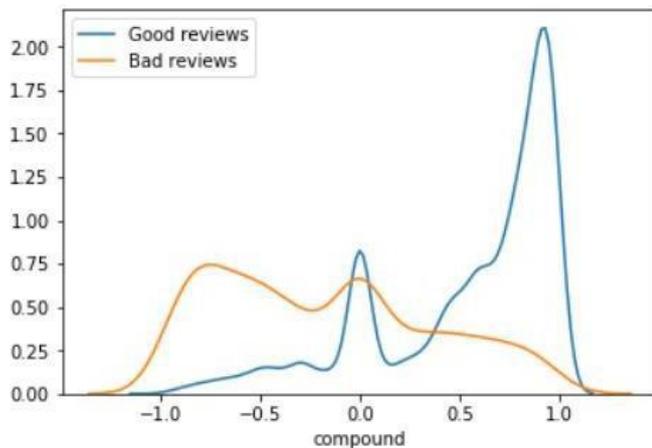


Figure 5: Distribution of the review sentiments

The graph in fig. 5 shows the distribution of the review sentiments between good reviews and bad reviews. We can see that good reviews are considered by Vader to be very positive for most of them. On the contrary, bad reviews tend to have lower compound sentiment scores.

## V. CONCLUSIONS AND FUTURE DIMENSIONS

Since this strategy does not constitute a panacea, a variety of adjustments should be made to broaden the reach of the department. However, since extensive studies have not shown that they are feasible in this situation, the following declaration should be taken carefully. This is intended more like brainstorming than a straightforward roadmap to simplify service request management and to create ideas and suggestions for the application in the future.

To serve a broader user base, additional languages could be trained. The framework may be built for a different dynamic version. This variant will be sensitive to the variant in this document by displaying small talks and providing more immediate and personalized customer experiences. So, this version can be used on Facebook and other instant messaging applications.

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## REFERENCES

- [1] E. A. Portman et al., "Location-based services," 6944447, 13-Sep-2005.
- [2] Scherer, Anne & Wunderlich, Nancy & Wangenheim, Florian. (2015), "The Value of Self-Service: Long-Term Effects of Technology-Based Self-Service Usage on Customer Retention", *MIS Quarterly*, 39, 177-200.10.25300/MISQ/2015/39.1.08.
- [3] B. Maleki Shoja and N. Tabrizi, "Customer reviews analysis with deep neural networks for E-commerce recommender systems," *IEEE Access*, vol. 7, pp. 119121–119130, 2019.
- [4] L. Qiu, S. Gao, W. Cheng, and J. Guo, "Aspect-based latent factor model by integrating ratings and reviews for recommender system," *Knowl. Based Syst.*, vol. 110, pp. 233–243, 2016.
- [5] K. Bauman, B. Liu, and A. Tuzhilin, "Aspect based recommendations: Recommending items with the most valuable aspects based on user reviews," in *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '17*, 2017.
- [6] X. Delman, Z. Shibeshi, and M. Scott, "Development of a Location Based Service for technician allocation," in *2016 IST-Africa Week Conference*, 2016, pp. 1–8.
- [7] "Sentiment Analysis," Lexalytics.com. [Online]. Available: <https://www.lexalytics.com/technology/sentiment-analysis>. [Accessed: 12-Nov-2020]
- [8] M. Vibbert, J.-O. Goussard, R. J. Beaufort, and B. P. Monnahan, "Dialog flow management in hierarchical task dialogs," 9767794, 19-Sep-2017.
- [9] P. Kumar, M. Sharma, S. Rawat and T. Choudhury, "Designing and Developing a Chatbot Using Machine Learning," *2018 International Conference*

on System Modeling & Advancement in Research Trends (SMART), Moradabad, India, 2018, pp. 87-91, doi:10.1109/SYSMART.2018.8746972.

- [10] M. Y. Helmi Setyawan, R. M. Awangga and S. R. Efendi, "Comparison Of Multinomial Naive Bayes Algorithm And Logistic Regression For Intent Classification In Chatbot," *2018 International Conference on Applied Engineering (ICAE), Batam*, 2018, pp. 1-5, doi:10.1109/INCAE.2018.8579372
- [11] Dongkeon Lee, Kyo-Joong Oh and Ho-Jin Choi, "The chatbot feels you - a counseling service using emotional response generation," *2017 IEEE International Conference on Big Data and Smart Computing (BigComp), Jeju*, 2017, pp. 437-440, doi: 10.1109/BIGCOMP.2017.7881752
- [12] J. Li, X. Chen, E. Hovy, and D. Jurafsky, "Visualizing and understanding neural models in NLP," *arXiv [cs.CL]*, 2015.
- [13] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
- [14] S. Malek, R. Gunalan, S. Kedija et al., "Random forest and Self Organizing Maps application for analysis of pediatric fracture healing time of the lower limb," *Neurocomputing*, vol. 272, pp. 55–62, 2018.
- [15] S. Wang, X. Liu, T. Yang, and X. Wu, "Panoramic crack detection for steel beam based on structured random forests," *IEEE Access*, vol. 6, pp. 16432–16444, 2018.
- [16] H. T. Malazi and M. Davari, "Combining emerging patterns with random forest for complex activity recognition in smart homes," *Applied Intelligence*, vol. 48, no. 2, pp. 315–330, 2018.
- [17] F. B. de Santana, A. M. de Souza, and R. J. Poppi, "Visible and near infrared spectroscopy coupled to random forest to quantify some soil quality parameters," *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, vol. 191, pp. 454–462, 2018.
- [18] J. Abellán, C. J. Mantas, J. G. Castellano, and S. MoralGarcía, "Increasing diversity in random forest learning algorithm via imprecise probabilities," *Expert Systems with Applications*, vol. 97, pp. 228–243, 2018.
- [19] C. Hu, Y. Chen, L. Hu, and X. Peng, "A novel random forests based class incremental learning method for activity recognition," *Pattern Recognition*, vol. 78, pp. 277–290, 2018.
- [20] J. Abellán, C. J. Mantas, J. G. Castellano, and S. MoralGarcía, "Increasing diversity in random forest learning algorithm via imprecise probabilities".
- [21] H. M. Gomes, A. Bifet, J. Read et al., "Adaptive random forests for evolving data stream classification," *Machine Learning*, vol. 106, no. 9-10, pp. 1469–1495, 2017.
- [22] R. Genuer, J. Poggi, C. Tuleau-Malot, and N. Villa-Vialaneix, "Random forests for big data," *Big Data Research*, vol. 9, pp. 28–46, 2017.

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