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An Intelligent Shopping Cart Chatbot Using Amazon Lex

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Abstract

The advanced Artificial Intelligence (AI) technology has smart agents to improve the customer satisfaction and efficient operation for e-commerce applications. The chatbots facilitate the communication between the customers that saves the human intervention, increase the speed of response and quality of services automatically. This proposed work explains the development and implementation of an AI-based customer service chatbot with the help of Amazon Lex for online shopping. This work also discusses the improved quality of response. When the data has been received, the system will detect the customer objective and guide them using a series of questions based on products, delivery information, payment methods and general shopping support. The chatbot will evaluate the user input, receive key parameters and provide customized responses with the help of Amazon Lex's Natural Language Understanding (NLU) and the slot-mapping functionalities. This system recognizes the purpose of the response and generates effectively for customers can receive the relevant data about the details of products and their services rapidly. This paper also shows the AI-based conversational interfaces improve the customer experience, automatic communication and support customer service in online shopping. When compared to the rule-based and proposed chatbot model improves the classification accuracy as 92% with accurate response metrics.

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Keywords: Chatbot, Machine Learning, Amazon Web Services (AWS), Amazon Lex, AI, Shopping Cart Chatbot.

1. Introduction

The evolution of chatbot innovation in Artificial Intelligence (AI), Natural Language Processing (NLP) and Machine Learning (ML) has caused extensive research on various domains. The chatbots are identified as a tool to facilitate customer support and improve the efficient operations, user involvement and provide digital services [12,14]. The research [1] explains that NLP-based conversational AI chatbots increase the quality and responsiveness of integration with customers and users in different fields. The analysis of these chatbots are capable of scalable, dependable and rapid responses for their enquiries which are commonly posted for user better experience. Chatbots are one of the important elements for the industries that provide automatic customer services and improve digital shopping experiences. The recent development in natural language processing allows the chatbots to understand user questions and interact with customers in conversational manner to improve user involvement and communication. These technologies provide reliable service delivery rapidly and customized in the e-commerce environment. The new generation of internet users expects to search the products in real-time, receive data rapidly and have a comfortable shopping experience. The traditional ways of customer services using the telephone and email is not effective and serves the customers rapidly. These issues are solved by using chatbots allows constant communication with customers during the shopping experience like product identification, recommendation and proceed for the payment process. It decreases the operational cost, manual involvement for operation of customer service solutions

The implementation of chatbots present challenges include accurate recognition, able to process the complex enquires of customers and the back-end system connections are the major technical risks. The personalized user experiences require collection of customer data and process to deliver the personalized data such as name, address, taste and so on to manage for privacy and data protection policies.

Amazon Lex is one of the possibilities for developing a scalable conversational chatbot system. The service is the cloud-based platform allows user to design conversational bots using advanced natural language processing and speech recognition features. It is able to interface effectively with other AWS services, simple to use, real-time conversational flow management

and the capacity to develop personalized chatbots make it possible platform for advanced e-commerce applications. Developers designed a chatbot can recognize a complicated user inquiry by maintaining the discussion active and dynamic with the customers using the characteristics of multi-purpose support, slot filling and customizable execution method. This paper presents the development of online shopping chatbot based on Amazon Lex improves the experience of e-commerce by automating customer interactions and responses. The chatbot collects the required data about the user, recognizes the user intent, helps with product selection, manages shopping and facilitate delivery process. Furthermore, the system is connected to external discussion platforms like Kommunicate.io to increase and manage the conversations. The work advances the research in the following ways.

- Designing a smart Shopping Support Chatbot: This work proposed a design and implementation of an AI-based shopping which supports chatbot for e-commerce questions of a customer regarding the product description, order tracking, shipping, payment and delivery. The chatbot uses natural language understanding of Amazon Lex and Kommunicate.io to make dynamic interaction.
- Intent-Slot based Conversational Framework: An effective conversational system based on target detection and slot extraction is developed. The system allows multiple objectives and entity slots like product name, location, order ID and payment method to ensure the data is accurately received
- Efficient Customer experience: Due to the customer experiences, when discussing the design of AI-enabled conversation systems that can predict, improve customer contact and provide automatic scaling features for online shopping.

Each section of the paper is presented as follows: Section II analyzes recent literature for significant updates. Section III explains the characteristics and advantages of Amazon Lex's system design. Section IV describes the execution of the proposed chatbot and its findings. Section V provides the final conclusion.

2. Related Work

The technologies of conversational agents and chatbots have been developed at a rapid pace because of artificial intelligence (AI), natural language processing (NLP) and machine learning (ML). The technologies have allowed chatbots to replicate human conversations and provide automated services in various fields of application. The initial advancements in NLP

has an extensive process in enhancing the semantic perception ability of conversational systems. To illustrate, word embeddings in the distributed word representation model were brought forward by [22] and improved the semantic links between words during text processing. Subsequently, the contextual language modeling was greatly advanced due to the transformer-based architecture that was provides and employed the attention mechanisms [25]. Based on these developments, the research introduced the BERT model, which also reached state-of-the-art results in many NLP tasks such as text classification and intent recognition [23]. These innovations formed the basis of the present-day conversational AI systems that are able to comprehend complex user queries. The recent research has investigated the empirical uses of chatbot technologies in customer support and online communication platforms. The research [1] were able to prove that NLP-based conversational AI chatbots are highly effective in enhancing the efficiency of customer service by responding to questions promptly and at scale. Their results suggest that chatbots improve the quality of interaction and decreases the load of human customer service representatives. Likewise, [3] also performed a detailed overview of chatbot products and emphasized the growing popularity of conversational agents in areas like e-commerce, healthcare, and education. Their analysis found out the major challenges associated with natural language comprehension, dialogue management and system integration. Chatbot technologies have also been greatly adopted in the healthcare industry. The research [29] created AI-based healthcare chatbots that can provide medical data and can help patients answer health-related questions. Likewise, the research [34] reviewed conversational agents to support healthcare and revealed that AI-enabled chatbots are capable of responding as quickly as possible and enhancing interactions with a patient.

Table 1. Literature Study

Reference	Year	Method / Model	Dataset / Application	Key Results
[3]	2022	Survey of architectures chatbot	Multiple chatbot platforms	Identified major chatbot architectures and NLP techniques
[6]	2024	Deep learning conversational AI models	Customer service chatbot data	Improved response generation accuracy
[11]	2024	Retrieval-augmented intent classification	Multi-turn dialogue dataset	Improved intent detection accuracy in contextual

				conversations
[8]	2024	Systematic meta-analysis of AI chatbots	Education chatbot systems	AI chatbots enhance engagement and learning outcomes
[16]	2021	Conversational AI model	Customer service request	Studied impact of chatbot on customer experience
[2]	2024	Conversational commerce AI	E-commerce datasets	AI bot to improve customer purchase decisions
[10]	2022	SEM-ANN hybrid model	Brand interaction dataset	Improved brand prediction and engagement using AI chatbots
[18]	2024	Review of technology Chatbot	Multiple AI conversational chatbot	Studied trends in AI chatbot research
[20]	2022	AI chatbot request For service	chatbot for Customer service request	AI for service customization
[19]	2024	Ontology expansion for conversational AI	Dialogue datasets	Enhanced knowledge representation in chatbots
[15]	2021	Universal intent recognition system	Customer support dataset	Achieved high accuracy in intent classification
[13]	2023	AI voice assistant engagement model	Voice assistant interaction data	Increased customer engagement through conversational AI
[7]	2023	AI assistant consumer interaction model	Retail chatbot dataset	Chatbots influence consumer decision-making
[5]	2023	Voice assistant brand loyalty model	Voice assistant dataset	AI voice assistants improve brand loyalty
[4]	2022	AI service analysis delivery	Tourism chatbot data	Improved service efficiency using AI chatbots
[17]	2023	Anthropomorphic AI design	AI product interaction dataset	Human-like design improves user experience

[27]	2023	AI chatbot architecture framework	Multi-domain chatbot systems	Demonstrated improved conversational quality
[21]	2023	Systematic review of intent modeling	Conversational recommender systems	Identified common intent classification approaches
[24]	2022	Cloud chatbot using Amazon Lex	Healthcare chatbot	Studied about scalability and integration
[9]	2022	Intent-based system chatbot	College enquiry chatbot dataset	Improved automated query handling efficiency

The systematic reviews also stressed the opportunity of conversational agents to assist in counseling patients, in primary triage and decrease the load on the conventional healthcare [30]. These articles outline the increased relevance of conversational system in enhancing access and efficiency in healthcare services. Conversational commerce is another critical area of the chatbot application. The work [28] investigated the use of AI-based chatbots will impact consumer perception within the context of e-commerce and recorded that interactions with chatbots will have a positive impact on the purchasing decision-making process and the customer loyalty to the brand. Likewise, the research [33] examined the incorporation of intelligent chatbots in e-commerce sites and showed increased efficiency and operational efficiency in the customer service quality. According to their findings, conversational interfaces can be successfully used to assist complex tasks like product suggestions, shopping cart administration, and payment procedure. The capabilities render chatbots useful in order to improve the online shopping process. The technologies of chatbots were also implemented more within education and the administration of the state. The research [31] designed an education chatbot in the field of radiotherapy and proved its usefulness as an interactive learning one. Similarly, the study [35] studied the place of AI chatbots in education and pointed out that they can be utilized to make students constantly supported, whereas the issues of privacy, contextual sensitivity, and system stability have to be outlined. A survey of chatbot applications in government service delivery [32] study employed in the public sector indicated that conversational interfaces enhanced accessibility, efficiency, and satisfaction of the citizens. Otherwise, these developments have been made, there are still some challenges with the practical implementation of chatbot systems. A significant number of the existing studies are dedicated to the development of algorithms or conceptual framework instead of analyzing

the efficiency of the cloud-based conversational platforms based on real-life data. Correct recognition of intent, processing of the various user queries, and connection with the back-end services are still important technical challenges in the implementation of chatbots. Amazon Lex is a scalable infrastructure and an in-built capability to understand natural language, available on cloud-based platforms like Amazon Lex offered by Amazon to create conversational systems. Nevertheless, a small number of studies have assessed the efficacy of this type of platforms in domain-based applications like e-commerce chatbot systems. The systematic performance assessment based on such measures as classification accuracy, confusion matrices, response time analysis, and statistical significance testing are not typically covered in literature. Consequently, it is necessary to conduct a study aimed at the creation and testing of scalable chatbot systems based on the use of cloud-based chatbots and the inclusion of the strict analysis of quantitative performance. The solution to these issues will help to enhance the reliability, scalability and usability of real-world conversational AI systems.

3. Methodology

3.1 Amazon Web Services

Amazon Web Service provides management, cloud service and integrated data analytics. AWS provide an inbuilt infrastructure. Its services range from business applications, robotics, content distribution and consumer interaction, storage developer tools, databases, game technology and media services. The process of Amazon Lex shown in Figure 1 is a service for building conversational interfaces into any application using voice and text inputs. This helps the developers and businesses that create applications with UIs and conversational interactions, leveraging built-in deep learning capabilities from Amazon Lex. The features like Automatic Speech Recognition (ASR), Natural Language Understanding (NLU) to determine whether a text is an intent. Amazon Lex allows developers to rapidly develop voice and text chatbots in short time. Amazon Lex can be easily connected to many other AWS services such as Amazon Cognito, Amazon Mobile Hub, CloudWatch and DynamoDB with AWS Lambda. To integrate with Lambda, the bots get access to pre-built serverless enterprise connectors for linking data in SaaS platforms.

3.2 Benefits of Amazon Lex

- **Ease of Use:** Amazon Lex allows easily to develop a human-like conversational model with minimal sample phrases, which works in both text and speech to ask questions, provide responses, or perform complex actions.
- **Deep Learning Technologies:** Built on the NLU technology, all the Speech Language Understanding (SLU) systems used by Amazon Lex that powers Alexa. With SLU, Lex takes natural language speech or text and extracts the intentions of a user before seamlessly fulfilling them by calling the corresponding business function. Voice and text chatbot publications on mobile apps, web apps or different chat services facilitated through Amazon Lex.
- **Native Compatibility with AWS Platform:** Amazon Lex natively fits into the third-party services such as Amazon Cognito, AWS Lambda, CloudWatch and Mobile Hub.
- **Cost Efficiency:** No minimum costs or upfront expenditures are required for Amazon Lex. Only charged for the text or speech requests that you make. In terms of pricing, Snips offers pay-as-you-go prices and charges only a fraction for each request sent to the service [36].

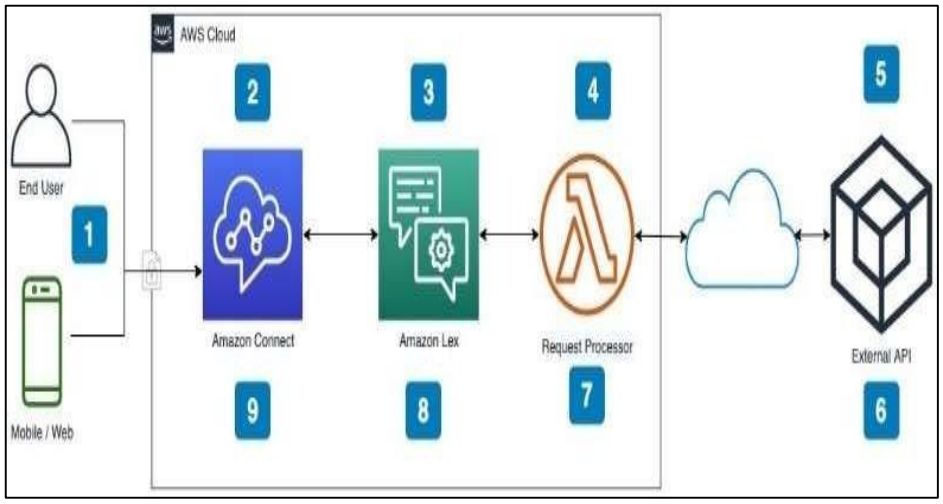


Figure 1. Process Diagram for Amazon Lex [26]

3.3 System Architecture

The proposed system develops an intelligent online shopping chatbot using cloud-based conversational AI technologies. The chatbot is implemented using Amazon Lex provided by AWS, which offers built-in natural language understanding (NLU) and automatic speech recognition (ASR) capabilities. The architecture is divided into five components, which are user interface, natural language processing module, intent classification module, integration of the backend service and response generation module. The chatbot communicates with the user via a web-based chat interface which is incorporated into Kommunicate. Amazon Lex analyzes the input query to determine the intent of the user and isolates the parameters as slots which is referred to as relevant. The system makes connections to the backend services performing product search, cart management and order processing functions after intent recognition. The chat robot subsequently produces a suitable reply and sends it back to the client. Figure 2 represents the system architecture

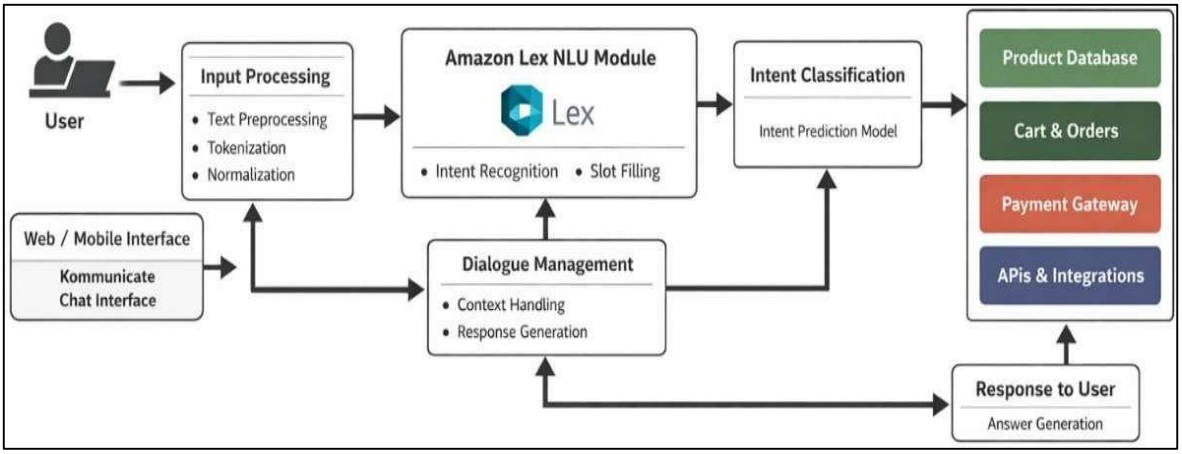


Figure 2. System Architecture

3.4 Components of the System

- **User Interface:** The interaction point between the users and the chatbot system is the user interface. The queries made by the users may be done via web applications, mobile applications or messaging platforms. The input is presented in the form of text or speech. Strict user queries are sent to the conversational engine where preprocessing tasks that include text normalization and tokenization and noise removal are performed. This is done in order to make the input in a format that can detect intentions.

- **Natural Language Understanding Module:** The NLU system maps the query to an intent and compare it with trained words of the model. The NLU module analyzes the user input and executes the tasks:
  - Intent detection
  - Slot extraction
  - Context mapping
- **Intent Classification Engine:** The intent classification determines the relevant intent based on probabilistic and language models. Every intent has many sample utterances for model training.
- **Dialogue Management:** When the intent is found, the dialogue manager finds the next action. In case of any information is missing, the chatbot ask the user to provide details through slot-filling.
- **Backend Integration:** The conversational chatbot interact with other services like databases, APIs, or applications to retrieve the required information. Amazon Web Services enables scalable deployment and response generation. Then the chatbot generates an appropriate response and sends it to the user through the interface.

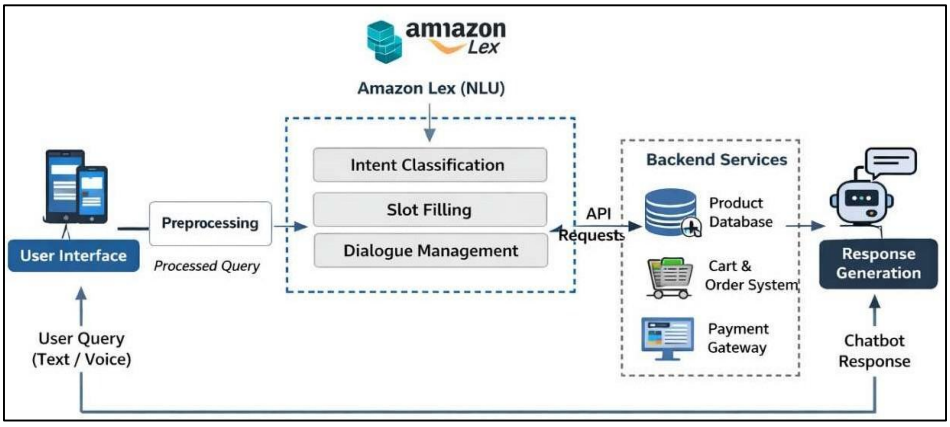


Figure 3. Work Flow Diagram

Figure 3 illustrates the workflow of the proposed conversational AI system and it shows how user queries are handled, interpreted and answered with the help of the cloud-based conversational platform Amazon Lex combined with backend services.

Step 1: User Query Submission

The interaction starts when user ask a query to the chatbot interface. The input is in the form of text and which can represent the user's request.

Step 2: Query Reception

The user query is obtained using the interface, which will be send to the conversational engine. Then, the system verifies the input and ensures the query is send to the processing module.

Step 3: Intent Identification and Slot Extraction

Now the query is sent to the NLU module of Amazon Lex. The NLU performs following tasks:

- Intent recognition, where the system determines the purpose of the user query.
- Slot extraction, where key entities or parameters required to fulfill the request are identified. This step converts natural language input into structured data that can be processed by the chatbot system.

Step 4: Dialogue Management

Now, the dialogue manager verifies the context and finds the appropriate action. And checks all required information to complete the user request. In this step the system collects information before the task is executed.

Step 5: Backend Processing and Data Retrieval

Now, the chatbot communicates with backend services of Amazon Web Services. These services include databases, APIs, and transaction systems. The backend performs the operations like retrieving data, executing the tasks, or transaction processing.

Step 6: Response Generation

After receiving the results from the backend services, the system generates responses to the user’s intent. The dialogue manager converts the response into natural language response to interact with the user. Lastly, the response is sent to the user using the chatbot interface. The user gets the suitable answer, to complete the conversational loop.

This approach enables efficient chatbot interaction while ensuring scalable, flexible and enhanced user satisfaction.

4. Implementation and Results

4.1 Experimental Setup

The online shopping chatbot is implemented in various modules based on the Amazon Lex with Natural Language Processing (NLP) platform include other AWA services provide effective performance and scalability.

4.1.1 ChatBot Design

The chatbot was designed using Amazon Lex application and several objectives were assigned to provide responses to the users regarding the shopping experiences. A variety of specific responses suited for purpose allows the chatbots to understand the users request (e.g., Find Headphones-Add this to my basket). Slots were used to identify essential items (product names, categories, quantities, user information (name, email, phone), and delivery addresses) in the conversation flow. Table 2 represents the experimental setup and the Table 3 represents the sample intent and slot mapping.

Table 2. Experimental Setup

Parameter	Value
Total queries	500–800
Intents	10
Slots	5–6
Queries per intent	50–70

Table 3. Sample Intent and Slot Mapping

Intent	Slots
product_information	product_name
product_availability	product_name
order_status	order_id

shipping_information	Location
return_policy	product_name
cancel_order	order_id
payment_methods	payment_type
delivery_time	Location

4.1.2 Slot Filling and Dialogue Management

Slot filling will collect the required data in a systematic manner. The application Lex's native conversation management helped the users in completing the data collection process by providing missing slots with responses and correcting errors. For example, if a user fails to enter their address for product delivery, the chatbot leads the user to do the work before processing the order. The parameters mentioned below are utilized to compare a normal rule-based chatbot with the proposed NLU-based chatbot include accurate intent recognition and response efficiency.

4.1.3 Intent Recognition Accuracy

Measure the accuracy of the chatbot identifies the user's intent.

Formula (plain text):Intent Accuracy = (Number of correctly identified intents / Total number of queries) × 100

- Higher accuracy indicates better understanding of user queries.
- NLU-based chatbots generally outperform rule-based systems for varied or complex inputs.

4.1.4 Response Accuracy

Measures whether the chatbotprovides the correct response to a user query. Response Accuracy = (Number of correct responses / Total responses generated) × 100

- Rule-based chatbots perform well only when queries match predefined patterns.
- NLU chatbots handle paraphrased or natural queries more effectively.

4.2 Implementation

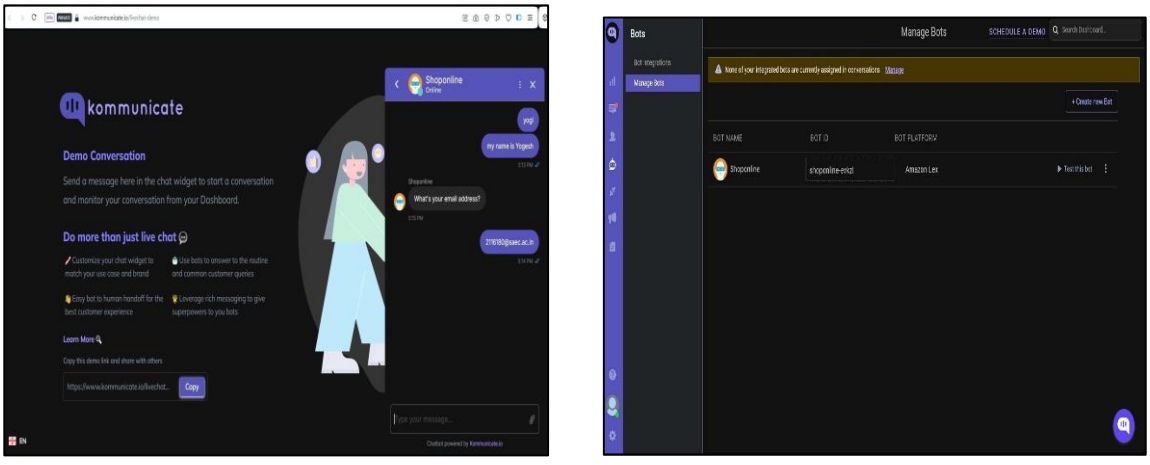
The evaluations were executed on a real-time shopping helps the chatbot dataset consisting of 600 customer inquiries classified into ten intents. Each purpose includes different kinds of 60 queries represents the common customer interactions in an e-commerce. The dataset provides the highlighted slots for product name, order ID, location and payment method that helps with intent identification and entity extraction.

4.2.1 Integration with AWS Lambda

The addition of AWS Lambda function improves the execution of each purpose. When an intent was achieved, the Lex executes appropriate Lambda function provide the slotted values and collects the characterized sessions. The python services will handle the business logic such as assessing the product database, loading the shopping cart, verifying an order and inventory data were encoded as lambdas.

4.2.2 Multi-Platform Deployment through Kommunicate.io

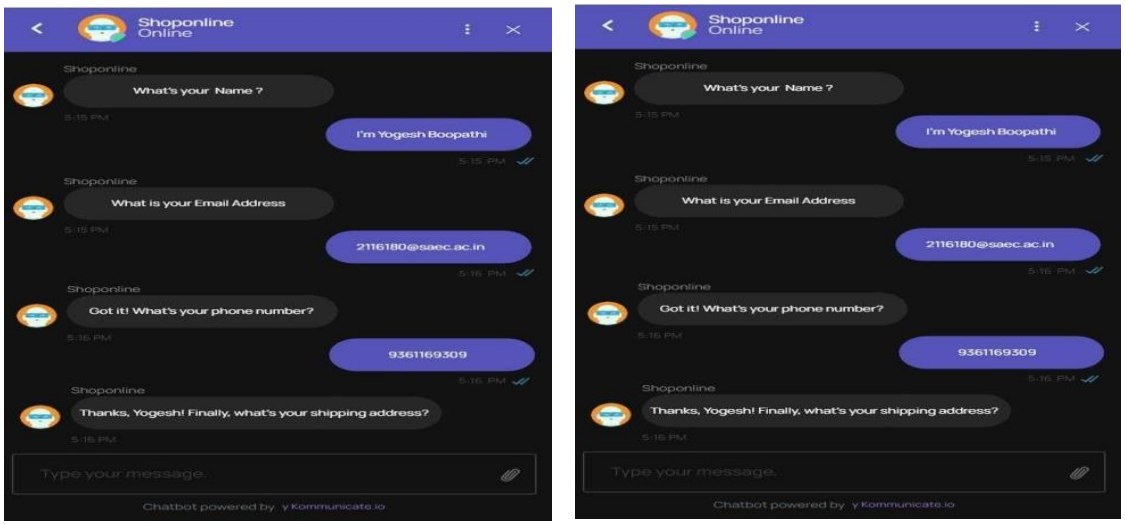
Amazon Lex bot integrated with Kommunicate.io to provide an automatic chatbot implementation on online applications and mobile interfaces provide users with an easily accessible and advanced conversation experience. Kommunicate.io was utilized as the channel layer to format messages, sending real-time alerts and transferring them to human agents when it is required.



(a) **(b)**

Figure 4. a) Kommunicate.io for the Purpose of Deploying My Amazon Lex to Their Website, b) Kommunicate.io Interface

Figure 4(a) and 4(b) shows the Kommunicate.io implementation as interface. Figure 5 (a) and 5(b) provides the results of chatbot implementation and the sample interactions with the chatbots.



(a) **(b)**

Figure 5. (a), (b) Provides the Results of Chatbot Implementation and the Sample Interactions with the Chatbot

Figure 6 shows the confusion matrix illustrates the performance of proposed chatbot intent categorization developed using Amazon Lex. The matrix evaluates the systems' ability to accurately categorize the user queries into ten predefined intent categories includes product name, availability, order status, shipping data, return policy, cancel order, payment methods, delivery time, order modification and customer support. If there is a slight misclassification will increase the issues in overall evaluations. For example, slight misunderstanding occurs between order status and delivery data and also between product details and their availability. Such overlaps are excepted in conversational systems that users frequently phrase their requests with identical wordings. Another small confusion exists in shipping data and delivery time which is closely connected to e-commerce transactions. These examples suggest that a more comprehensive training words or specific conversation handling techniques are helped to improve the intent classification. In general, the data indicate that the chatbot system is highly accurate in intent identification. The large number of diagonal domination in the confusion matrix demonstrates the Amazon Lex Natural Language Understanding tools can accurately determine users' intent. The few instances of misclassification suggest that the model can be applied to different query versions. The result supports the theory that the proposed

conversational chatbot architecture is capable of processing a variety of user inquiries in an e-commerce environment with a suitable accuracy.

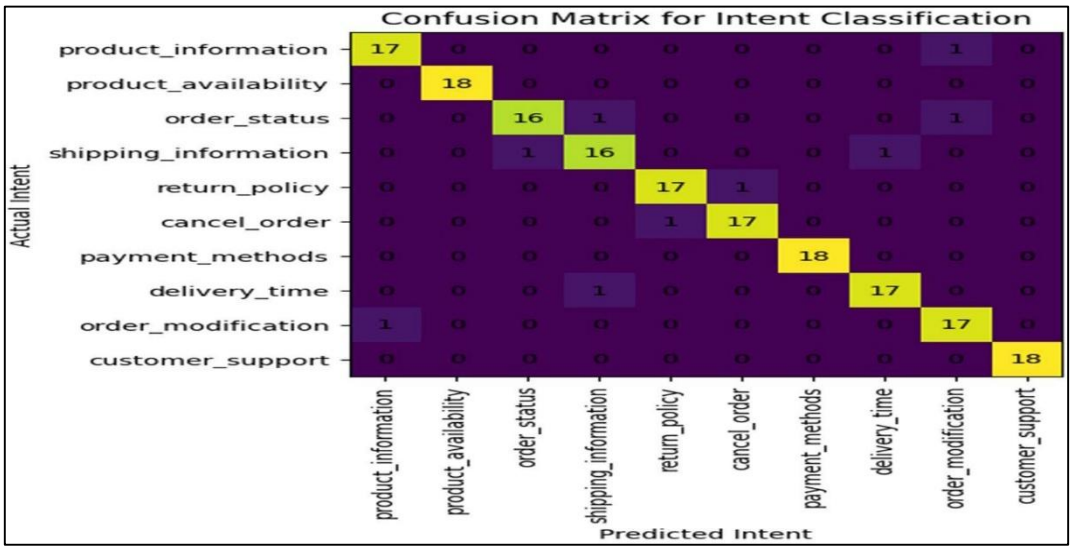


Figure 6. Confusion matrix

Table 4 shows the results of the experiment proves that the NLU-based chatbot is better than the rule-based chatbot with accurate intent recognition and response. The proposed system achieved in understanding the natural language variations when a user makes a query and this allows it to give more relevant and accurate response. The presented NLU-based chatbot that is operated by Amazon Lex takes advantage of the ability of natural language understanding and slot extraction to make stronger interpretations of user input and provide more valuable responses. In turn, it gets a better overall performance in customer support communications in an e-commerce setting.

Table 4. Comparison of Rule-Based and NLU-Based Methods

Metric	**Rule-Based Chatbot**	**NLU-Based Chatbot**
Accuracy	0.70	0.92
Precision	0.68	0.90
Recall	0.66	0.89
F1-score	0.67	0.895

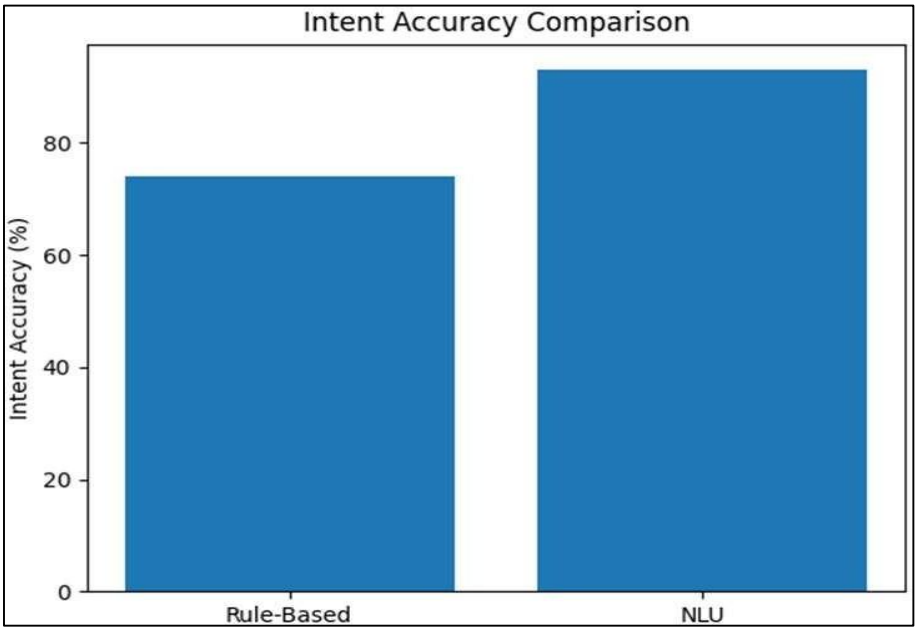


Figure 7. Intent Accuracy

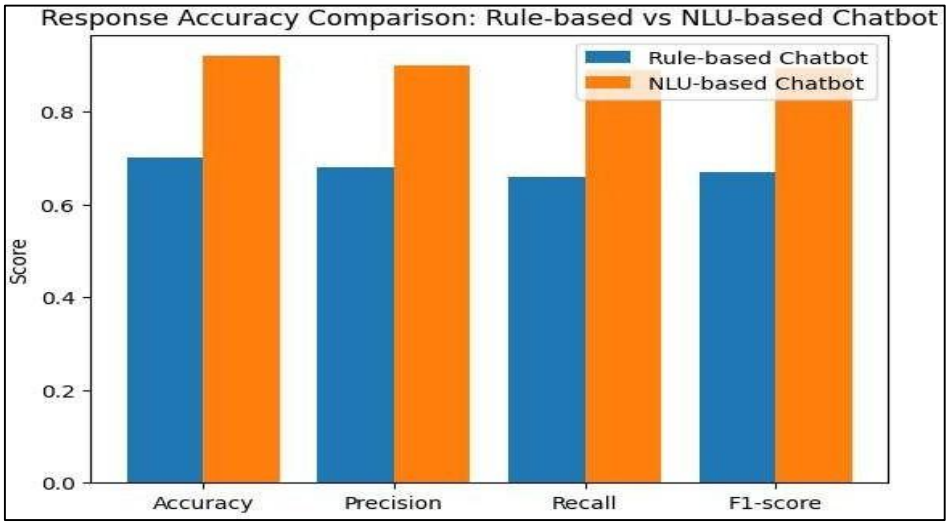


Figure 8. Response Accuracy

Based on Figure 7, it can be seen that the Intent Recognition Accuracy is considerably 92% in the NLU-based chatbot respectively, due to its ability to comprehend variations of natural language. The results of the comparison show that the NLU-based chatbot developed with the help of Amazon Lex is far better than the rule-based chatbot in all the evaluation metrics. The proposed system, developed on the basis of NLU, had an accuracy of 92% which is lower than that of the rule-based system which was 70%. As shown in Figure 8, the values of precision, recall and F1-score of the NLU-based approach were always higher which means that the approach has better capabilities to recognize the intent and generate responses. These

findings demonstrate the benefit of machine-learning-based natural language understanding in processing dissimilar user queries to the inflexible keyword- based rule systems.

5. Conclusion

Using AWS Lex, a efficient e-commerce chatbot platform has been developed and tested with natural language processing (NLP) and Amazon Lex technologies to enable customers to interact with automated conversational agents to retrieve products and order data, track orders, obtain payment information, and receive assistance with other customer service. The new system can provide customers with real-time responses to questions and the scalability of AWS support numerous concurrent requests from multiple customers. The experimental evaluations shown that the intent classification accuracy of the chatbots was high for a variety of intent classifications based on the evaluation of their confusion matrices. It indicates that the majority of predicted classifications have been accurate for the chatbot systems; thus, the NLU Engine functioned according to expectations in correctly determining user intent based on textual inputs. The few instances of incorrect identification of very similar intents (e.g., shipment or order status) provide data to improve the chatbot systems through increasing training data and background knowledge. This study has showed the proposed chatbot architecture can successfully implemented and used as an automated Customer Interaction Solution for e-Commerce. The proposed system enhances the customer experience using reduced workloads of representative-based customer service assistance and provides customers with a continuously available Customer Service Operation. Future studies focus on exploring new deep-learning architectures with increase in the number of images used during training, the introduction of multilingual capabilities and improvements in the overall accuracy and capacity of conversational interactions with humans effectively determine the customer's intended message. In addition, improvements may be made by adding additional datasets, expanding the context of the previous conversational history and using complex language models to classify multiple intents where confusion exists.

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