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An Analysis of Natural Language Processing-Based Chatbot Development

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Abstract—The increasing integration of artificial intelligence into several facets of the business environment is causing society to shift toward increased human-machine interaction. In this transition, chatbots and other technologies that use Natural Language Processing (NLP) make it easier for people and computers to communicate. By examining important recent research, this study examines the evolution of chatbots that use natural language processing. It looks at how computational linguistics and artificial intelligence help robots understand natural languages, parse text, plan texts and sentences, and interpret human language.

Keywords: text analysis, machine linguistics, chatbots, artificial intelligence, and natural language processing

I. INTRODUCTION

Humanity is getting closer to a future in which machines will be essential in resolving complicated issues thanks to notable developments in artificial intelligence. The creation and application of chatbots to improve communication has expanded quickly in recent years. A chatbot is a piece of software that uses Natural Language Processing (NLP) to speak and engage with people in order to fulfill their requirements [1]. A branch of artificial intelligence called natural language processing (NLP) helps computers comprehend and interpret natural human language input. It facilitates text analysis, which makes it possible for machines to understand human language. The hierarchical structure of human language—words make phrases, phrases form sentences, and sentences carry meaning—is exploited by natural language processing (NLP) [2]. Even though there are many benefits to communicating with computers using human language, AI researchers frequently undervalue how difficult it is to create and comprehend language. knowing the arrangement of words is just as difficult as knowing their meanings and phrases. Institutions use chatbots (robotic virtual agents) to provide support via desktop interfaces [3,4]. Because chatbots are available 24/7 and facilitate human-machine connection, many businesses use them. In the near future, chatbots are expected to eventually take the place of conversational applications on a variety of devices [5]. Furthermore, chatbots are becoming more and more popular on mobile devices due to their intelligence and ease of use. A perfect chatbot should be able to comprehend the context of discussions, learn from interactions, and get better over time.

II. CHATBOT EVOLUTION

A computer program created to mimic human communication via the internet is known as a chatbot, or talk-bot. Michael Mauldin developed Verbot, the first chatterbot, in 1994 [6]. Developing a tool that communicates so well that consumers are unable to tell it apart from human interaction is the main objective of conversational applications. An experiment with three participants—a man, a woman, and an interrogator—was first presented by Alan Turing in 1950 [7]. The purpose of the questions was to improve the guessing process and test the interrogator's ability to identify the man and lady based on their answers. Ten years later, ELIZA—the first public chatbot—was introduced, simulating discussions with limited knowledge through the use of specialized scripts [8]. Later, another bot called PARRY was created to act as a paranoid patient during therapy sessions. The conversation-forwarding strategies used by PARRY and ELIZA were comparable [8]. While PARRY employed a narrative model to incorporate stories into its conversations with therapists, ELIZA used inquiries and human replies to steer the topic away from itself [9]. In order to increase the knowledge base for dialogue patterns, Wallace created ALICE, an open source bot that built on the capabilities of ELIZA [10]. The 21st century's commercial bots were made possible by these early inventions. The Smarter Child bot was first released in 2001 and can respond to inquiries regarding country populations, movie showtimes, and other topics [11]. The groundwork for contemporary commercial bots that allow both speech and text-based inputs, such as Google Assistant, Microsoft's Cortana, Apple's Siri, and Amazon's Alexa, was established by Smarter Child [12].

III. DISCUSSION

Pattern matching is a commonly used strategy in chatbot systems, according to Sarkania, V. K., and Bhalla, V. K. [13]. By using this method, chatbots can classify text and provide users with relevant responses. The chatbot is very useful for question-answering systems since it uses pattern matching to produce a response that matches the user's input.

Paluszy, W., Faculty, R., and Wroc, E. [14] talked about another natural language processing method that's utilized to create chatbots. They emphasized how crucial it is to have a vocabulary that is adaptable and globally understood in order to create successful chatbots. Knowledge representation in chatbots is made possible by AIML (Artificial Intelligence Markup Language), which helps create XML-based structures that satisfy this requirement. This method enables the definition of data items and facilitates the description of the programs that handle them.

Shrestha, A. and Mahmood, A. [15] showed in their work that deep learning, a subfield of machine learning, is the driving force behind the majority of natural language processing technology. To mimic and learn human decision-making skills, machines employ sophisticated algorithms and enormous volumes of data.

Y. Shrikhande, A. Gyani, N. Rathod, and A. Vichare [16] described how NLP allows chatbots to behave intelligently. They pointed out that chatbots employ natural language processing to interact with human users, just as people use language for conversation. Three chatbots were analyzed in their study: Siri, Alice, and Eliza. ELIZA, which was developed in 1966, used key word substitution and parsing to construct rephrased responses. ELIZA served as the inspiration for ALICE, an NLP-based chatbot that successfully answered user questions by matching patterns. Siri is a knowledge navigator and virtual assistant created by Apple Inc.

In their study, N. Dandekar and S. Ghodey [17] talked about using natural language processing (NLP) to construct chatbots. They covered methods including deep learning, AIML, parsing, and pattern matching, with pattern matching being the most commonly utilized in chatbots. The original text is divided into word sets by textual parsing, which aids in identifying grammatical structure. Lexical structures are then confirmed through the use of expressions. One popular tool that facilitates the development of a versatile, globally intelligible language is AIML. Lastly, an area of machine learning called deep learning replicates decision-making processes using sophisticated algorithms and big datasets.

Kulkarni Chaitrali, B. Amruta, P. Savita, and Prof. Satish K. [18] included more basic NLP techniques utilized in chatbot building in their study. Entity recognition is a crucial technique that entails locating and classifying named entities into predetermined groupings. Dependency parsing is another crucial method that helps identify sentence boundaries and iterate over base noun phrases.

S. Bhalotia and S. Bisen [19] investigated the creation of a chatbot system that makes use of AI and NLP in their study. Context identification, a personalized query response system, an AIML response mechanism, query analysis, and context resetting are some of the crucial steps in the comprehensive implementation process they described. Pre-processing is first carried out to standardize the input in order to satisfy system criteria during context identification. After receiving a question, the system confirms the user's identity during the personal query response phase. An suitable answer is produced if the user details are invalid; if not, the system extracts keywords from the input text. The AIML response phase comes next, during which the user's input is mapped and an appropriate response is given based on the context of the conversation. Ultimately, after the

Gokaran and Ayush [20] looked into the process of creating chatbots with Python and deep NLP techniques. They also discussed a number of issues that chatbots face. The dependence on fixed rule-based systems, which employ simple processes with predetermined rules, is one difficulty. Because it can only respond to queries within specific, predetermined domains, the chatbot's limited capacity to identify grammatical problems is another problem. Additionally, because every language has its own set of norms, chatbots may have trouble with sentence construction. It might also be difficult to discern emotions like grief, happiness, and anger. NLP and deep analysis are two examples of artificial intelligence techniques that can be used to overcome these obstacles.

S. Raj [21] noted in his study that although natural language processing (NLP) can be used to construct chatbots, scaling these systems while keeping clean code is still difficult. Important NLP approaches utilized in chatbot building were also covered in the paper. Part-of-speech (POS) tagging is one of these; it helps identify entities by allocating textual segments to particular word kinds, such as verbs or adjectives. The paper also discussed lemmatization, which is an algorithmic technique that determines a word's base form (lemma) based on its intended meaning, and stemming, which reduces inflected words to their root form.

According to a study by F. Promoteur and L. Facult [22], chatbots are mainly used for customer service these days, particularly in the banking industry. Banks can provide clever ways to improve services and grow their clientele by deploying chatbots. By reducing human interaction, chatbots can make 24/7 customer service possible, increasing efficiency. The primary objective is for the chatbot to provide precise and pertinent responses to consumer questions in natural language.

A. Tiha [23] investigated the creation of chatbots by deep learning in this paper, emphasizing how they are made to resemble human-to-human communication. Numerous industries, including NGOs, commercial businesses, and governmental organizations, make extensive use of these chatbots. They perform a variety of tasks, including personal help, product suggestions based on questions, and customer service. The development mostly uses machine learning algorithms, retrieval strategies, and rule-based approaches. The retrieval approach uses a keyword scan to find pertinent answers to the user's query.

G. V. Padma Raju, G. N. V. G. Sirisha, and K. Jwala [24] investigated the popularity of chatbots and the replacement of traditional chatbots with conversational ones. Conversational and domain-based chatbots are the two primary categories into which the study divided them. Conversational chatbots can be made for informal "chit-chat" or to carry out particular duties. While task-oriented chatbots concentrate on tasks like placing orders or organizing events, conversational chatbots frequently lack a target outcome. There are two types of domain-based chatbots: open-domain and closed-domain. While closed-domain bots are focused on particular topics or domains, open-domain bots are made to respond to a wide range of queries.

S. Ayanouz, B. A. Abdelhakim, and M. Benhmed [25] examined chatbot designs based on natural language processing (NLP) and machine learning. The study focused on parsing, an NLP approach in which different NLP functions are used to examine and interpret the input text. The original text is divided into word groups through parsing, which aids in interpreting the input's meaning and grammatical structure.

Web Empathy, an emotion detection tool for chatbots that analyzes vocal characteristics including tone, pitch, volume, and speed to identify emotions, was studied by Spring, T. et al. [26] in their study. One of the main benefits of this method is that it works in any language. Web Empathy is able to identify emotions such as rage, joy, sadness, tranquility, and energy since it is based on tens of thousands of speech samples.

According to Pratt, E. [27], a human face image is mapped into a 128-dimensional vector space by the Dlib face recognition tool. With the use of this technique, chatbots may detect faces by mapping comparable photographs of the same person together while maintaining a distance between them.

Masi, I. et al. [28] talked about the four essential elements of the Deep Face Recognition method utilized in chatbots: detection, alignment, representation, and classification. Because it creates a frontal depiction of the face from input photographs that may show the face from different perspectives, the alignment stage is particularly crucial.

A tool called Watson Tone Analyzer was used by Sharp, R. D. et al. [29] to help in speech and emotion identification. This tool uses linguistic analysis to distinguish between three different communication tone types: verbal, social, and emotional. This system's simple interaction with chatbots, which enables it to recognize client tone and modify dialogue tactics appropriately, is one of its main advantages. It also helps with customer service by keeping an eye on interactions to guarantee precise, scalable answers to consumer questions.

Solase, M., Pedgaonkar, S., and Pathade, M. [30] talked about face-api.js, a method for detecting faces and emotions in chatbots that is based on tensorflow.js. This method's capacity to identify emotions in real-time chat discussions is a noteworthy benefit. This method can also be used to help spot depression symptoms.

D. R. Kalbande, R. Dsouza, R. Patil, and S. Sahu [31] found a number of methods to improve neural networks in the areas of emotion, speech, and facial recognition. These consist of depth-wise separable convolutions, quantization, transfer learning, and knowledge distillation. Two networks of varying sizes are used in knowledge distillation; the bigger network teaches the smaller network, increasing its efficiency after training. By using specialized datasets for speech, emotion, and face identification to train the entire network or individual layers, transfer learning improves accuracy. By minimizing computations, quantization maximizes processing speed by optimizing the neural

Table 1

network. Because depth-wise separable convolutions enable CNNs to be constructed with fewer parameters, chatbots are better suited for applications using mobile vision.

Table 1 provides a summary and comparison of various NLP techniques used in chatbots, while Table 2 compares methods for face and voice detection, detailing their advantages and disadvantages.

Techniques	Advantages	Disadvantages
Pattern matching	• Learns natural variation in data automatically. • Can be widely applied across various neural-based programs. • Supports large-scale parallel computations and is scalable for high data volumes.	• Responses are repetitive, predictable, and lack a human touch. • Lacks memory for previous responses, which can lead to conversation loops.
Parsing	• Allows semantic objects within each grammar rule. • Supports systematic, grammar-independent error handling.	• Common issues include backtracking, left factoring, and ambiguity.
A.I.M.L	• Easy to implement. • Provides better access to external resources. • Facilitates knowledge acquisition.	Not suitable for addressing all issues. • Vulnerable to misuse by non-knowledgeable users.
DEEP Learning	• Automatically deduces features and optimally tunes them for expected outputs. • Avoids time-consuming feature extraction processes. • Adaptable to new problems in the future.	• Requires large datasets for optimal performance. • Can be costly. • No standard criteria for selecting tools, making it challenging for less skilled users. • Output can be difficult to interpret.

Table 2

Techniques	Advantages	Disadvantages
Web empathy	• Quick and easy to use. • Visualization helps broaden understanding and align with the user's ideal vision.	• Validating emotional datasets is challenging. • Difficulty in expressing emotions across different
Dlib	• Operates in real-time. • Simple architecture. • Can detect faces at various scales.	• Potential for false predictions. • Limited to frontal images. • Does not perform well with occluded faces.
Deep face	• Collects both physical and behavioral samples. • Matches facial features to samples. • Supports data extraction..	• Vulnerable to recognition issues. • Requires significant data storage.
Watson tone analyzer	• Enables social listening. • Enhances customer service. • Integrates efficiently with chatbots.	• May lack accuracy. • Risk of misinterpretation. • Struggles with accents and speech recognition.
Face-api.js	• Easily scalable. • Simple programming features.	• Stability issues with the interface. • Lacks comprehensive library support

IV. MODERN CHATBOTS REVIEW

Since their inception, chatbots have made great progress. Based on a number of criteria, this article looks at some of the most recent advancements in chatbots [32].

A variety of datasets used from different sources in chatbot generation are also described in the literature. Additionally, a variety of approaches, including intent classification, AIML, LSTMs, and natural language processing with NLTK, were used in the development of the chatbot. Additionally, Wit.AI frameworks are included. Below is a review of research papers and studies referenced in the evaluation strategy.

In their study, Prashik Sahare, Amber Nigam, and Kushagra Pandya [33] used the Stanford CoreNLP dataset and a methodology that included entity recognition at several stages using Named Entity Taggers and classification of objectives into subcategories and categories using RNNs. An intent label was the result of preprocessing searches using entity inputs.

For their study, Ashly Ann Mathew, Belfin R. V., Shobana A. J., Megha Manilal, and Blessy Babu [34] used data that had been scraped from cancer forums. Neo4j graph modeling and NLTK preprocessing were part of their methodology. A human-like response in the form of a sentence was the output, and the input was an unidentified information source. Nevertheless, this method's drawback was its inability to classify intents into distinct labels, which prevented any quantitative assessment.

NoSQL was used in the study by A. Sheth, D. Kadariya, H. Y. Yip, K. Thirunarayanan, M. Kalra, and R. Venkataramanan [35] for processing in Dialog Flow and Contextualization Knowledge Base techniques. The inputs were the symptoms of the patient, and the outputs were certain trigger alerts. One drawback, though, was that the approach did not account for the existence of severe symptoms. The quality, usefulness, and acceptance of the technology were used to assess the chatbot's performance.

In their study, Raut A, Rai S, Shankarmani R. Darwin, and Savaliya A [36] applied Convolutional Neural Networks and a Disease Symptom Knowledge Dataset to a Message Intent Classification approach. The user message served as the input, and an intent label served as the output. The percentage of intents that were correctly classified served as the primary metric for assessing the chatbot's accuracy.

To satisfy domain needs, S. Pérez-Soler, J. de Lara, and E. Guerra [37] used a session participation methodology. They used a scaled vote stimulus as input and a continual consensus process with predetermined values. Telegram chats served as the basis for the collection. A five-point Likert scale survey that used a consensus procedure was used for the evaluation. Their method's inability to support domain specialists in making later judgments was a drawback, though.

An intent classification methodology was employed in the work by E. Handoyo, E. W. Sinuraya, M. Arfan, Y. A. A. Soetrisno, A. Sofwan, and M. Somantri [38]. It involved using entity recognition to extract structured information, creating user replies to choose the best one, and using the DBpedia dataset. A valid response or an invalid response with an explanation would be the output, while the user's message and action served as the input. The inability of the system to react to every instance in the request was one of its limitations.

In their publication, S. Wu, L. Chen, P. Yang, and T. Ku [39] used a multi-step process. They started by identifying important nouns in a narrative. Second, in order to identify crucial acts, they used significant verbs. Third, they recognized the major characters' sentences. The Simplified CKIP POS tag set was utilized in their dataset. A tale conversation script served as the input, while an AIML dialogue script served as the output. The evaluation metrics were centered on the relevance and correctness of the responses. The method's drawback was that it was difficult to identify the story's characters' emotional states.

In their research, M. Su, K. Huang, C. Wu, H. Wang, and Q. Hong [40] employed the Multilayer LSTM approach. While the second layer finds connections between sentences, the first layer pulls semantic information between words in a sentence. They made advantage of the Chinese MHMC Chitchat dataset. The output was a response taken from the dataset, while the input was domain-specific, easily spoken Chinese. Nevertheless, no metrics were employed to evaluate the accuracy and importance of the answers. The discussion was the primary constraint.

Kulkarni, Chaitrali S., et al. [41] used information from bank websites and frequently asked questions to implement an approach that included NLTK pre-processing, tokenization, and lemmatization. The input consisted of messages and questions from bank customers, and the output consisted of pre-written responses. Each classification algorithm's precision, recall, and cross-validation scores were used to assess their system. The drawback was the absence of more complex responses obtained by combining more than just the existing list of frequently asked questions.

V. CHATBOTS INTERACTIONS

The chatbot starts by delving further into the subject and examining the main elements. The chatbot attempts to determine the primary topic of the conversation when the user asks a question. It narrows the topic by taking behavioral, social, and psychological aspects into account using the funnel principle. Lastly, a summary of the chatbot-user communication results is provided. When chatbots are seen as team participants rather than merely technical tools, people are more likely to trust them. The information provided by chatbots is frequently regarded as more reliable when they speak in a manner similar to that of their users [42].

The design of chatbots is also influenced by gender stereotypes, which are examined in psychology and sociology. For example, when it comes to technical questions, people are more likely to trust male chatbots than female ones [42]. Nonetheless, consumers frequently favor female chatbots for customer service-related inquiries. In sectors like transportation, tourism, and beauty, chatbots are usually made to look and behave like women. More study should concentrate on comprehending user expectations and the impact of gender features in order to develop more successful gender-specific chatbots.

Users will quit using chatbots if they consistently ask the same questions and give inaccurate or insufficient responses, as this will damage their credibility. Chatbots ought to learn from previous exchanges and refrain from posing the same queries over and over again [43]. When chatbots express a variety of emotions, they gain credibility. Positive emotions like kindness, love, and happiness can be expressed to strengthen bonds and increase user eng0061gement. An effective chatbot should act with compassion and in a way that is appropriate for the situation. Chatbots can also entertain users and strike up conversations to improve the user experience. When chatbots use pauses to mimic human communication rather than constantly responding right away, it is more desired [42].

VI. FINDINGS

The current study emphasizes the significance of natural language processing (NLP) in enabling chatbots to identify voice and translate it into text. It focuses on the development of chatbots using NLP. In order to process spoken instructions and human language, this method primarily uses two components: natural language production and interpretation. Pattern matching, parsing, AIML, and deep learning are some of the methods used in NLP. When creating chatbots for customer support, product recommendations, personal help, or virtual help like Apple's Siri, pattern matching is frequently utilized. The paper also discusses basic natural language processing (NLP) ideas that are utilized in chatbot development, like part-of-speech (POS) tagging, which aids in entity identification by allocating words or tokens, such as verbs, adjectives, and nouns, to various textual segments. Furthermore, lemmatization focuses on identifying the appropriate lemma based on context, while stemming reduces inflected words to their basic form. Entity identification and dependency parsing, which aid in identifying sentence boundaries and enable restating information over base chunks or noun phrases, are two more crucial strategies covered.

VII. CONCLUSION

The global development of artificial intelligence has given rise to a new school of thought that has the potential to revolutionize customer service and offer premium services that satisfy the demands of contemporary customers. This study highlights the evolution of chatbots that use natural language processing (NLP) techniques. The suggested system might be the first step in developing a remarkable query-handling program that helps users at any level. In addition to improving their own performance and providing excellent customer service, NLP-based conversational agents have been developing steadily to lessen the workload for humans and increase system productivity. By providing all required information on a single interface and eliminating the need to browse numerous platforms, it streamlines the process from the customer's point of view. To sum up, a well-designed chatbot can be an intuitive user interface that can successfully respond to customer inquiries.

VIII. FUTURE PROSPECTS

Chatbots that use natural language processing (NLP) are an important part of contemporary operational systems, particularly in large enterprises. It drives fully functional, semi-autonomous systems that improve user experience and customer service response times. Its future is uncertain, though, as chatbots continue to struggle to keep up with the rapid advancements in technology and gain broad acceptance in both private and professional contexts. With the growing use of chatbots, developers need to handle any possible problems. Given that chatbots are now expanding at a rate of 24% and are expected to reach a market value of $1.25 billion by 2025, developers are focusing heavily on lowering barriers to entry. But the future of the sector mostly rests on the technology being used more widely, going beyond simply to become a universal instrument in the fields of technology, finance, and healthcare.

Eliminating the obstacles preventing wider chatbot use is a crucial first step towards achieving broad adoption. Because of their robotic language, lack of flexibility, and inability to comprehend the meaning of human input, chatbots currently struggle with conversational flow and frequently fall short. Although it is difficult to improve this procedure, it is crucial to give users a worthwhile and relevant chat experience. Chatbots need to be more adaptable and have great natural language processing abilities in order to serve as efficient customer support assistants because today's users want interactions to be smooth and comfortable.

As previously said, the development of artificial intelligence has significantly changed chatbots, making them more skilled at comprehending human wants and needs. The gap formerly created by chatbot discussions' lack of emotional depth has been significantly closed with the advent of emotional artificial intelligence. This development is essential for improving the customer experience and may even help people with illnesses like dementia by providing them with the emotional support they require.

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framework for creating AI systems that can have conversations.

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