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A Survey on Various Chatbots

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***Abstract*— In today's fast-paced world, people constantly seek new information and more efficient learning methods. Traditional approaches, such as books, search engines, and online encyclopedias, can be both time-consuming and challenging. Chatbots offer a solution by providing instant answers across various sectors, including banking, retail, travel, healthcare, and education. These computer applications are designed to mimic real-world conversations, powered by artificial intelligence (AI) and natural language processing (NLP) technologies, allowing them to comprehend and respond to human language. Chatbots can perform tasks, provide information, and address queries with ease.**

This paper surveys several methodologies for chatbot implementation, including cutting-edge techniques like Long Short-Term Memory (LSTM), Natural Language Generation (NLG), Supervised Machine Learning (SVM), Model Driven Engineering (MDE), Dialogue Management, Human-in-the-Loop (HITL), Audio-Frame Mean Expression (AFME), Random Forest, Support Vector Machine (SVM), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN). These methodologies enable the development of chatbots with advanced natural language understanding and response capabilities. The objective of this paper is to review and compare various chatbot development approaches to identify the most suitable for specific applications. The study concludes that while multiple methodologies and algorithms can be used to implement a chatbot, each method has its strengths depending on the task requirements. The paper also presents evaluations of the methodologies' accuracies and provides suggestions for their application.

Keywords — CHATBOT, ARTIFICIAL INTELLIGENCE, NATURAL LANGUAGE PROCESSING.

I. INTRODUCTION

Chatbots are computer programs that use conversational AI technology to mimic human user chats. They are widely used in customer service and healthcare settings, where they can answer inquiries, provide assistance, and solve problems. Beyond these areas, chatbots are also utilized in marketing, sales, and education. They offer numerous benefits, such as making our lives easier, more convenient, and enjoyable. Chatbots can respond to questions 24/7, deliver personalized recommendations, automate various customer service tasks, engage with customers across multiple channels, and tailor the customer experience by learning individual preferences. While still evolving, chatbots have the potential to revolutionize how we interact with machines. They are a powerful tool for improving customer service, reducing costs, and boosting efficiency. In education, chatbots can support students struggling with specific concepts or those needing more personalized attention. By making learning more engaging and interactive, chatbots can enhance the overall educational experience and increase students' interest in the subject matter.

This paper explores the key technologies available for building educational chatbots. It addresses the vanishing gradient problem by using memory cells to store long-term information. It also discusses Natural Language Generation (NLG), which creates natural language text from structured data. Supervised Machine Learning (SVM) is highlighted for its ability to learn from labeled data, where each data point is associated with a known outcome or label. Model Driven Engineering (MDE) is presented as a powerful chatbot development platform that helps businesses create high-quality chatbots more efficiently. Dialogue management, which combines statistical models and rule-based systems, ensures smooth conversations and accurate recognition of user intent. The paper also covers Human-in-the-Loop (HITL) tasks, such as fraud detection, object detection, image classification, and medical diagnosis. AFME (Audio-Frame Mean Expression), a feature extraction technique used in speech processing and music information retrieval, is discussed as well. Random Forest, which constructs multiple decision trees and bases predictions on their consensus, and Support Vector Machine (SVM), which classifies data points by finding a hyperplane, are also examined. Convolutional Neural Networks (CNNs), known for learning spatial hierarchies in data, are particularly well-suited for tasks like image classification, object detection, and semantic segmentation. The paper concludes that there is no one-size-fits-all solution; the best approach depends on the specific context and requirements.

Developers have access to numerous methodologies, but the primary challenge lies in selecting the most suitable one for their specific application. This survey paper aims to assist researchers in identifying the appropriate methodology for their needs. It provides an analysis of various chatbot methodologies, with evaluation results summarized in a comparison table to guide decision-making.

II. RELATED WORK

S. Venus Jin & Seounmi Youn. (2022). Analyzed the elements that affect customers' decision to keep using AI chatbots. Chatbot continuance intention is positively connected with social presence, imagery processing, and psychological ownership. To gather and process data, they employed a variety of techniques and tools. The authors employed statistical analysis software to examine the survey data, the correlations between social presence, imagery processing, and chatbot continuance intention using Pearson's correlation coefficient, and a sample of 372 participants who had interacted with a chatbot in the previous six months. They discovered the important chatbot continuation intention factors by using multiple regression analysis.

The links between social presence, imagery processing, psychological ownership, and chatbot continuing intention were investigated using route analysis in the study. The study provides useful information about the elements that affect users' intentions to keep using chatbots powered by AI. The results of this study can be used to create chatbots by programmers and designers that are more engaging and effective.[4]

Sanjay Chakraborty, Hrithik Paul et al.(2022). have developed a chatbot named Kiwi that can be used to promote infectious disease prevention and cure. The chatbot uses a variety of technologies and methods, including Recurrent Neural Networks (RNNs), decision trees, machine learning (ML), Python and a deep feedforward multilayer perceptron (MLP) model for infectious disease prediction which is trained on a dataset of infectious disease cases and learns to identify patterns in the data that are associated with different infectious diseases. It can provide doctor contact details, hospital addresses, oxygen cylinder contact details, disease symptoms, prevalence, diagnosis, and treatment procedures and concluded that It uses TensorFlow to build an NLP model that can make accurate predictions for user queries even when they are not contained in the training dataset. [5]

Vorada Socatiyanurak, Nittayapa Klangpornkun et al.(2021).describe the development and evaluation of a chatbot that counsels people who have experienced sexual assault on legal matters. The chatbot, called LAW-U, was developed using a combination of NLP, ML, and text summarization to train LAW-U. Initially, NLP was utilized to extract keywords from Supreme Court cases. Then, they used ML to train the chatbot to identify the most relevant Supreme Court cases for each user's input, and also uses NLU to understand the user's query and identify the relevant legal issues, Information retrieval (IR) to retrieve the Supreme Court rulings that are most relevant to the user's query. Finally, they used text summarization to provide the user with a summary of Supreme Court cases. The chatbot can answer questions about a variety of legal topics related to sexual violence, such as the rights of victims, the available legal remedies, and the process of filing a lawsuit. The authors concluded that LAW-U has the potential to be a valuable resource for sexual violence victims.[6]

Silvia García-Méndez et al.(2021).describes the development and evaluation of an entertainment chatbot for elderly people with limited abstraction capabilities. In order to provide customers a personalized and interesting experience, the chatbot, named EBER, was created utilizing a variety of artificial intelligence techniques, including sentiment analysis, natural language generation (NLG), and a spatially represented word space. The purpose of EBER is to entertain senior citizens. It is able to play games, tell jokes, and read news. A user's emotional state can also be used by EBER to modify its responses. The authors used a sample of elderly people with limited capacity for abstract thought to assess EBER.

The results showed that EBER was able to provide entertainment and companionship to the participants. The authors concluded that EBER has the potential to be a valuable tool for the digital inclusion of elderly people.[7]

Antonello Meloni, Simone Angioni et al.(2023). suggested AIDA-Bot, a conversational bot with SKG interaction capabilities. It is predicated on parsing, constructing queries, and producing responses. AIDA-Bot has been implemented in four different ways: as an Alexa skill, a web application, a Telegram bot, and an NAO humanoid robot. The algorithm proposed in the paper is called the Natural Language Query Processing (NLQP) algorithm. This is a novel approach to interacting with knowledge graphs, as it allows users to communicate with it using natural language way. This gives output by using user entities like telegram, browser etc.. There is need to develop more advanced techniques to enable chatbots to react to more sophisticated queries. [8]

Lenin Medeiros and Tibor Bosse et al.(2022). proposed a chatbot to reduce stress levels by mapping stress features and providing strategies to provide emotional support to the user input. Here, text mining and NLP are used to combine

the stress features with the strategies. Three groups participate in the experiment, and neither human nor chatbot support is provided. Interacting with chatbot can decrease stress levels and the chatbot gives equal support to human interaction.[9]

The authors of the paper Silvia T. Acuna and Oscar Dieste,(2022). have suggested using chatbots for educational purposes. An extensive mapping analysis on chatbot usability evaluation is presented in this paper. After more than 700 sources are analyzed, 28 primary studies are found. ANOVA, MANOVA, t-tests, Wilcoxon tests, and Mann-Whitney tests are examples of statistical tests used in data analysis. By using these tests, we can enhance the user experience with the chatbot. The paper provides insights into the benefits of conducting experiments to evaluate chatbot usability and suggests future directions for study in this discipline. Based on the findings, the paper outlines future research directions in chatbot usability evaluation guiding researchers towards areas that require further investigation.[10]

Addi Ait-Mlouk and Lili Jiang,(2020). proposes a knowledge graph-based chatbot that can generate SPARQL queries to obtain information from knowledge bases. The KBot architecture consists of three main components: a user interface, a natural language understanding (NLU) module, and a knowledge base access module. The paper also describes the implementation of KBot which was implemented using Jena and evaluated on a dataset of natural language queries. It was able to understand and answer the majority of the queries correctly. The paper concludes by discussing the limitations of KBot and the future work that could be done to improve it.[11]

Daniel Carlander-Reuterfelt et al.(2020). proposes a chatbot that can answer questions about data science and machine learning. The chatbot is called JAICOB.The paper begins by discussing the challenges of building a chatbot for data science then propose an architecture in support of JAICOB that solves these issues. To comprehend natural language queries, produce code, and keep up user discussions, JAICOB leverages dialogue management, code generation, and natural language understanding (NLU). The paper concludes by Despite these challenges, the use of cognitive assistants in education has the ability to transform how we teach and learn.[12]

This study, written by Liang Zhang, Yan Yang, Jie Zhou, Chengcai Chen, and Liang He (2020), presents a two-step retrieval-polished response generating approach for chatbots. The method first retrieves a set of candidate responses from a large dataset of text and code. The candidate responses are then polished by a language model to improve their fluency and informativeness by using Keyword Matching, Natural Language Processing (NLP)techniques The suggested approach can provide more intelligent and fluid responses than conventional chatbots, according to the authors' evaluation of it across a range of tasks. The conclusion of the paper is that the proposed method is a promising approach for generating fluent and informative responses for chatbots.[13]

Gwendal Daniel,Jordi Cabot,Laurent Deruelle and Mustapha Derras.(2020). introduce Xatkit, a low-code chatbot development framework that supports multimodal interaction. Xatkit is designed to make it easy to develop chatbots without requiring a lot of code or knowledge of natural language processing. Xatkit is a modular, low-code, multimodal chatbot development framework which uses Natural Language Processing (NLP) approaches are used to determine the user's purpose and create responses that are relevant and coherent, Deep Learning (DL) algorithms are used to train language models that can interpret and generate human language more accurately, On the other hand, the chatbot's performance is gradually improved through the application of Machine Learning (ML) algorithms, which learn from user interactions. This means that it is made up of smaller, independent components that are easy to customize and extend. They came to the conclusion that Xatkit is an effective and user-friendly chatbot development framework. The authors suggest that future work on Xatkit could focus on improving its natural language processing capabilities, user interface, and integration with other systems.[14]

Paula Maddigan And Teo Susnjak.(2023). focuses on using Large Language Models (LLMs) to convert natural language queries into data visualizations (NL2VIS). It confirms that LLMs are effective in this NL2VIS task when backed by well-engineered prompts. It gives a summary of the arrangement and structure of the paper. These LLMs are pre-trained deep-learning models based on transformer architectures. Future research could focus on conducting user studies and obtaining feedback from end-users to evaluate the real-world usability and user-friendliness of NL2VIS systems like Chat2VIS.[15]

Yang Ye, Hengxu You and Jing Du.(2023).proposed "Improved Trust in Human-Robot Collaboration With ChatGPT". The study explores the use of ChatGPT, an AI language model, in human-robot collaboration (HRC) to enhance trust and performance. A 15-participant human-subject experiment was conducted, comparing fixed verbal commands and ChatGPT-controlled robot assistance in an assembly task. It uses a "dual-stage impedance control" algorithm for understanding the robot arm's movement. Future studies could examine efficient HRC workflows, and

improved AI model training could alleviate problems with erroneous judgments and miscommunication. The Reduced cognitive load was observed when working with ChatGPT. Finally, The research indicates ChatGPT's potential for enhancing trust and performance in HRC. [16]

Angelo Salatino and Francesco Osborn.(2023) proposed the response given by the chatbot by integrating knowledge graphs and Conversational Agents. Here, the Conversation Agent is a computer program that understands natural language and gives responses. Knowledge graphs are the databases that store the graphs related to text, images, and videos. The authors developed a chatbot named AIDA -Bot to give responses. They used methods for processing natural language include entity recognition, entity linking, and semantic parsing are examples of approaches, to retrieve relevant information from the user's queries and map them to the knowledge graph. The project's output is a response to inquiries about scholarly publications, scholars, and organizations.[17]

In this paper, the authors, Tzu-Yu et al.(2023) propose a multimodal chatbot for intelligent manufacturing. The chatbot is designed to help workers with tasks such as assembly, maintenance, and troubleshooting. It can understand natural language queries and provide answers or instructions in a variety of ways, including text, speech, and images. The YMC model is a basic yet effective method for capturing video information for the purpose of user intent categorization. The results of the studies revealed that the YMC model functions somewhat superior to the YOLOv3 model. This is because YOLOv4 is a more accurate object detection model. They think that the chatbot can boost manufacturing processes' productivity and efficiency.[18]

Giovanni Almeida et al.(2023).proposes a Computational Meaning Processing(CMP) methodology for managing and evolving the content of chatbot systems. Which is separated into three sections according to the experiences gained during development Evatalk, the chatbot for the Brazilian Virtual School of Government. The paper evaluated the proposed methodology by applying it to the development of the Evatalk chatbot. The results revealed that the methodology was successful in improving the chatbot's performance, reducing its human hands-off rate, increasing its knowledge base, and keeping the user satisfaction stable.[19]

Shahid, M. A. Hossain, S. S. I. Ahad, M. B. M. Al-Mamun, and N. K. Alam. (2022) proposed Survey on Detecting Fake News Spreaders". In the digital age, online social networks (OSNs) like Facebook and Twitter are central to modern life, serving as platforms for communication, self-expression, and news consumption. It emphasizes the significance of detecting and categorizing fake news spreaders on social media platforms. This outlines the primary categories used to classify spreaders based on source, propagation, and target features. Researchers may use machine learning algorithms like Random Forest, Support Vector Machine (SVM), or deep learning models such as RGA, based on the requirements of their experiments and the type of features they are analyzing. Future work should focus on developing platform-independent classifiers for detecting fake news spreaders across various social media platforms.[20]

Kulothunkan Palasundram ,et al.(2023) suggested "Enhancements to the Sequence-to-Sequence-Based Natural Answer Generation Models". The NLP algorithm for answer generation uses the Seq2Seq Model with Attention Mechanism, and Seq2Seq Model Prediction (Beam Search) used for this paper. The future work includes enhancement of data and use of advanced algorithms, Fine-tune model parameters to maximize performance Conducting real-world testing, and considering scalability for practical deployment. Finally, Artificial intelligence (AI) has made significant strides, enabling machines to perform tasks once exclusive to human intelligence.[21]

Martha T. Teye 1, et al. (2022) suggested that context, culture, and environment be understood while detecting emotions. Since feelings are essential to human social life, understanding them is vital in interactions between humans and AI. They describe the preprocessing methods for the data and present the idea of the AFME algorithm for emotional validation. This research investigates the use of Convolutional Neural Networks (CNN) for facial expression and speech recognition of emotions. Emphasizing the significance of both speech (audio) and image frames associated with speech, the paper highlights the role of context, rate of speech, and non-verbal communication cues. Future research should focus on differentiating features in emotion recognition among diverse demographic groups.[22]

Soufia Kausar, Bilal Tahir, And Muhammad Amir Mehmood (2022) introduce the Push-To-Trend framework for identifying trend promoters in Twitter hashtags. And highlights the language-independent nature of the framework, making it applicable to various languages.It talks about sentiment analysis and demography using the framework. It makes use of classifiers like Logistic Regression (LR), Decision Tree (DT), and Random Forest (RF) for performance evaluation. It needs to extend the framework to analyze trends and trend promoters across multiple social media platforms, such as Facebook, Instagram, or YouTube. This expansion would provide a more comprehensive view of online trend dynamics.[23]

Chen Li 1,(Member, Ieee), et al. (2022) suggested "ToD4IR: A Humanised Task-Oriented Dialogue System for Industrial Robots" .A humanized task-oriented dialogue system for industrial robots called ToD4IR is presented. The system's goals are to improve user experience and help with production operations. It integrates the principles of conversational tactics with small chat for easy and interesting exchanges. The first industrial-oriented discourse corpus, the IRWoZ dataset, is presented in this publication. The core algorithm for the dialogue system is likely based on pre-trained language models and transformer architectures, as is common in many modern natural language processing (NLP) applications. Future work includes expanding the IRWoZ dataset to cover more industrial domains and tasks and coherence of dialogues generated by ToD4IR.Finally,the system holds promise for improving human-robot interactions in manufacturing settings through natural and task-oriented dialogue.[24]

This project's authors are Angel Antonio Martinez-Garate ,et al. (2020) are propose the use of Model-Driven Development (MDD) approaches for the creation of conversational agents or chatbot. The project was conducted using a systematic mapping study (SMS) approach which is organized into five stages. The authors applied MDD to conversational agent development by formulating a set of research questions and extracting the data of interest from the articles. The final result of this project is a systematic mapping study (SMS) that provides an overview of the state of the art in the field of conversational agent development process automation using Model-Driven Engineering methodologies. Model-Driven Approaches refer to a software development paradigm that emphasizes the use of models to represent the system being developed.[25]

R. Rajkumar and V. Ganapathy (2022) are proposed to employ Brain Computing Interface to develop a Bio-Inspiring Learning Style Chatbot Inventory, which would improve the efficiency of learning conducted online. E-learning is the online Learning through the internet. The authors classify the learning styles by conducting two experiments using EEG signals and machine learning. They also implemented VARK questionnaires to classify the learners as introverts or extroverts based on their learning performance. EEG signals are used to analyze the learning styles of individuals and classify them into visual or audio learners. VARK is a learning style inventory that categorizes learners into four different types based on their preferences for visual, auditory, reading or writing and kinesthetic learning. The algorithms used are Naive bayes and J48.Naive bayes is used to classify learners as visual or audio.J48 is a decision tree used for classification and regression. The future work of chatbot is working with AR and VR technologies. This chatbot helps learners to study easy.[26]

The authors of this paper are E.H.-K. Wu et al. (2020) a hybrid model K–12 E-Learning Assistant Chatbot is suggested, and its benefits and limitations in relation to e-learning platforms are explored. The authors propose a chatbot model that combines retrieval-based and generative-based approaches to provide assistance to K-12 students in E-Learning platforms. The chatbot is designed to comprehend and resolve learning-related issues in online education. The retrievalbased model uses a keyword matching algorithm to identify relevant responses from a pre-defined set of responses while the generative-based model uses a neural network to produce replies based on the input query. Additionally, the authors employ the SQuAD Evaluation performance for evaluation and the QANet model for question answering. The acronym SQuAD refers to the Stanford Question Answering Dataset, a substantial dataset created by Stanford University that provides question-answer pairings for reading comprehension. By using this chatbot there will be easy way for education at anytime anywhere.[27]

The author of the paper is John Levi Martin(2023) and the paper explain about ethico-political universe of ChatGPT, an AI tool and the challenges of creating ethical and unbiased AI tools. The paper discusses the attempts to make AI tools "ethical" and "unbiased", and how these attempts can have unintended consequences. The author also examines the underlying model and corpus on which ChatGPT was trained, and analyzes the responses generated by the tool. The paper includes detailed appendices that provide additional information on the methodology used in the investigation. The author also discusses the need for ethical considerations in the development of AI tools and raises important questions about the role of AI in society.[28]

The authors of this project are Kulothunkan Palasundram, et al. (2021) They suggested a multitasking-based Sequence-to-Sequence model to produce pertinent and significant responses to the user's questions. Thus, the authors use eight alternative models to provide the answers. SEQ2SEQ++ was shown to have the lowest errors and the most pertinent answers across these eight models. In this project, different techniques and methods are used by the different models such as global attention mechanism, ternary answer classification to improve the accuracy and relevant answers. The final result is that SEQ2SEQ++ can produce with lower errors and higher errors on the datasets compared to other models. The advantage of this project is SEQ2SEQ++ model gives more accuracy to questions asked by the users[29]

III. Model Analysis and Discussion

Table 3.1: Comparing Method Accuracy Results

S No	Authors	Methods	Accuracy
1.	Sanjay Chakraborty, Hrithik Paul et al.(2022).	Long-Short Term Memory	94.32%
2.	Vorada Socatiyanurak, Nittayapa Klangpornkun et al.(2021).	Rule-based reasoning, Human supervision	88.89%,
3.	Silvia García-Méndez et al.(2021).	Artificial Intelligence Markup Language, Natural Language Generation	79.99%
4.	Daniel Carlander-Reuterfelt et al.(2020).	SVM is a supervised machine learning	85.37%
5.	Gwendal Daniel,Jordi Cabot,Laurent Deruelle and Mustapha Derras.(2020).	Model Driven Engineering (MDE) techniques,machine learning	90%
6.	Henry Boateng Essel, Anastasios A. Economides et al.(2022).	Quasi-Experimental Design	70%
7.	Antonello Meloni, Simone Angioni et al.(2023).	Quasi-Experimental Design	71.7%
8.	Paula Maddigan And Teo Susnjak.(2023).	Large Language Model(LLM)	71.7%
9.	Kulothunkan Palasundram ,et al.(2023)	Recurrent Neural Network(Rnn),Convolution Neural Network(Cnn)	81%
10.	Martha T. Teye 1, et al. (2022).	Audio-Frame Mean Expression(Afme)	82.59%
11.	E.H.-K. Wu et al. (2020	Retrieval-Based Model,Generative-Based Model	-
12.	John Levi Martin(2023)	Ethical And Political Considerations Surrounding AI	-
13.	Silvia T. Acuna and Oscar Dieste,(2022).	Usability questionnaries,Eye tracking	67.9%
14.	Lenin Medeiros and Tibor Bosse et al.(2022).	Mapping Of Stressors To Support Strategies Used	

The table 3.1 shows the outcomes of a study on the preciseness of different methods. The majority of the studies in the table were conducted in 2020-2023, suggesting that this is an active area of research. There is a wide range of accuracies reported in the table, indicating that there is no single "best" method. The best method for a particular task may depend on the specific data and requirements

Table 3.2: Chatbot Research Paper Insights

S No	Authors	Methodologies And Algorithms	Problems Discussed	Challenges	Future Research Direction
1.	Sanjay Chakraborty, Hrithik Paul Et Al.(2022).	Long-Short Term Memory	1.Lack Of Healthcare 2.Access,Unaffordable Cost	Data Scarcity And Quality, Algorithm Complexity, Security And Privacy	1.Developing Models For More Diseases 2.Improving The Accuracy Of Models 3.Deploy The Model In Real-World Settings
2.	Vorada Socatiyanurak, Nittayapa Klangpornkun Et Al.2021	Rule-Based Reasoning, Human Supervision	1.Access ToJustice, Sensitive Nature Of TheTopic,Accurate 2.Access To Legal Information,Cultural Barrier	1.Acceptance And Adoption, 2.Security And Privacy	1.Developing Chatbots For Different Languages Culture, 2.To Promote Healing
3.	Silvia García-Méndez Et	Artificial Intelligence	Personalized And Socialized	1.Familiarity In Digital Technologies,Privac	1.More Transparency, Improve Over Time

	Al.2021	Markup Language, Natural Language Generation		2.Security Concerns	2.Better User Interfaces
4.	Daniel Carlander-Reuterfelt Et Al.(2020).	Supervised Machine Learning (SVM)	1.Social Presence 2.Imagery Processing	1.Small Sample Size 2.Lack Of Control Over Chatbots	1.Consider The Cultural Context 2.Explore The Role Of Other Factors
5.	GwendaDaniel, Jordi Cabot,Laurent Deruelle And Mustapha Derras.2020	Model Driven Engineering (MDE) Techniques,Machine Learning	Flexibility,Complexity	Deployment,Time And Cost	1,Improvment In Accuracy Of NLU 2.Evaluation Of Xatkit In More Domains
6.	Chen Li 1,(Member, Ieee), et al. (2022)	1. Dialogue Management 2. Human-in-the-loop (HITL)	1.Interaction With Industrial Robot 2.Productivity And Safety In The Workplace	1.To Assist With Manufacturing Tasks 2.Incorporates Conversation Strategies	More Industrial Domains And Tasks
7.	Martha T. Teye 1, et al. (2022).	Audio-Frame Mean Expression(Afme)	1.Ability to detect emotions 2.Actors of culture, context 3.Environment for evaluating	1,Cultural bias 2.Environmental factors 3.Lack of data	More factors of culture, context, environment
8.	Shahid, M. A. Hossainet al. (2022)	Random Forest, Support Vector Machine (Svm),	Comprehensive survey for detecting fake news spreaders.	Fake news spreaders can be human or cyborg that are constantly evolving to avoid detection	New detection methods for adversarial attacks
9.	Yang Ye, Hengxu You And Jing Du.(2023).Proposed	Regular Expression Search Algorithm	1.Trust In Human-Robot Collaboration 2.Miscommunication Between Humans And Robots	1.Robustness 2.Transparency	1.Enabled HRC Systems 2.Developing New Ways
10	Kulothunkan Palasundram ,Et Al.(2023)	Recurrent Neural Network(Rnn) Convolutional Neural Network (CNN)	1. Generic, Meaningless, And Inconsistent Answers.	1.Inability To Deal With Rare Words 2.Language Model Influence	New Training Methods And Datasets
11	Lenin Medeiros And Tibor Bosse Et Al.(2022).	Stressor Mapping to Support Strategies Used by the Proposed Chatbot	Providing Emotional Chatbot To Humans	Whether The Response Is Given Computer Generated Or Human Generated	Including More Stress Features And Giving More Realistic Response To Humans
12	R. Rajkumar And V. Ganapathy (2022)	Naïve Bayes And J Tree Classifier Algorithm(J48)	Chatbot Is Take Long Time To Respond To User Queries Due To Complexity Of Nlp	Less No Of Learners Is Used In The Study,Classification Algarithm Is Depend On The Eeg Signals	Use The Other Psychological Signals,Increase The No Of Learners In The Study,Use Different Machine Learning Algarithms For Better Experience
13	Kulothunkan Palasundram, Et Al. (2021)	Comprehensive Attention Mechanism (CAM),Diverse Loss (DL)	Difficulty In Identifying Input Sequence Such As Parts Of Speech,Generating Repeated Answers	Difficulty In Handling Long Inputs,Generated Answers Which Are Irrelevant To Question	Taking Differnt Datasets In Different Languages To Enhance Chatbot Response

14	Angelo Salatino And Francesco Osborn.(2023) .	Support Vector Machine (Svm),	Given Data Have Errors And This Effects The Accuracy And Knowledge Graphs	Ntegrating Data Into Knowledge Graph Require Many Data Formats,Understanding Human Language Queries Is A Big Challenge	Adding The Different Queries Types,Integrating More Data Sources To Develop The Accurate Knowledge Graphs

The table 3.2 provides a snapshot of the current state of research, highlighting the key challenges that need to be addressed and the promising directions for future work.

IV. CONCLUSION

In this paper, we have conducted a survey on the current advancements in chatbot technology. We looked at several kinds of chatbots, the methods used to design them, and the results of their assessments. Additionally, we highlighted key findings from the survey, discussed the challenges and limitations of existing chatbots, and outlined future research directions in this field. Chatbots represent a promising technology with the potential to revolutionize our interactions with computers. However, it is crucial to recognize the challenges associated with chatbots and to implement them responsibly. Educational chatbots, powered by NLP, can provide 24/7 availability, personalized learning experiences, proactive support, cost reduction, and improved student satisfaction. By integrating chatbots into education, we can create a more tailored and efficient learning environment for students, allowing teachers and tutors to focus on more complex tasks.

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