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Review Paper

Conversational Health Bots for Telemedicine Services: Survey

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ABSTRACT

An increasing number of individuals take refuge in telemedicine systems for medical diagnosis and treatment due to their numerous benefits, including reduced healthcare costs, enhanced efficiency, and the ability to treat and prevent a wide range of physical and mental health problems. To improve the health status and clinical findings of older and underserved individuals, healthcare institutions have expanded telemedicine services, integrating them with advanced assisted living systems and environments. Conversational chatbots, or dialogue systems, are software tools designed to emulate human interaction via the Internet. These conversational bots can engage in natural conversations and can be merged into websites, mobile apps, and messaging platforms.

Moreover, they can be used across various fields, such as healthcare, to support and enhance health services. An essential key feature of conversational chatbots is their ability to deliver swift and automated responses. In healthcare, these bots serve multiple purposes, including setting appointments, answering questions, and providing recommendations.

Modern-day conversational chatbots leverage artificial intelligence techniques, such as machine learning and natural language processing, to understand and respond to user inquiries effectively. This study will discuss the objectives of developing chatbot systems, the fundamental methodologies and datasets used, the primary challenges and limitations of existing works, and insights into future trends in chatbot development.

Index Terms: Natural Language Processing (NLP), Chatbot, Argumentation, Machine Learning (ML), Recommendations.

1. INTRODUCTION

Healthcare refers to the organized delivery of medical services aimed at maintaining or improving health by preventing, diagnosing, treating, and managing diseases, injuries, and other physical and mental conditions in individuals and communities. To address the diverse health demands of populations, healthcare endeavours to promote overall well-being and quality of life [1]. Telemedicine techniques have become integral to voguish healthcare because of their revolutionary nature. They connect individuals in underserved or rural regions to healthcare providers, minimizing or eliminating the need for long-distance travel. For those who face difficulty reaching healthcare facilities due to distance or other factors, telemedicine marks a crucial advancement in enhancing access to healthcare [2].

A chatbot is a web-based interface or software application designed to emulate human conversations via text or voice inputs. Modern chatbots, usually connected to the Internet, use obstetric AI systems to engage in natural conversations, mimicking human interaction as a conversational partner [3]. Chatbots are beginning to incorporate conversational AI, such as natural language processing (NLP), to understand and respond to user queries, even when grammatically incorrect, offering answers based on their collected data. These chatbots may request clarifications and provide explanations or summaries. Chatbots are either simple, addressing straightforward questions, or sophisticated, learning from user interactions and enhancing their assistance over time [4].

One essential NLP subfield is argument mining, also referred to as argumentation mining. This approach involves the use of computer systems to extract and recognize argumentation patterns from natural language texts

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automatically. These frameworks include premises, conclusions, argument schemes, and the relationships between major and subsidiary arguments, also known as primary and counter-arguments [5]. Chatbots proficient in argumentation can construct, evaluate, and interact naturally and compellingly. Arguments involve claims supported by evidence and reasoning that seek to persuade the other side, altering their perspective or clarifying a point of view. Argumentative chatbots can be effective in healthcare because they assist users in making educated and responsible health decisions while providing emotional and social support [6]. Chatbots use machine/deep learning methods to store and manipulate training models, allowing them to respond more accurately and appropriately to domain-specific inquiries from users [7].

Healthcare plays a vital role in our daily lives; thus, several firms and institutions have partnered with hospitals in recent years to assist doctors and medical staff in dealing with patients more effectively and reducing their workload through technology. Chatbots have the potential to significantly transform healthcare by enabling predictive diagnoses and providing assistance, such as appointment scheduling [7].
This study offers three contributions, as follows: (i) a comprehensive literature review on health bots and the current state of chatbot implementation in healthcare; (ii) an overview of the challenges associated with implementing and using health bots; (iii) recommendations for future research on health bots.

This paper is organized as follows: **Section 2** provides background information on health bots. **Section 3** clarifies the challenges associated with health bots. **Section 4** reviews related works, and **Sections 5 and 6** illustrate the discussion, recommendations, and future research directions. The conclusions are presented in **Section 7**.

2. AI HEALTH BOT

An intriguing category of chatbots, health bots are medical virtual agents that use natural language to communicate with patients. They enable patients to send in their symptoms from anywhere, receive important information, assess the likelihood of certain diseases based on their symptoms, monitor and record their health, and easily schedule doctor appointments [2]. One of the advantages of health bots is that they provide access to health information and services anytime and anywhere. They can also assist individuals who face barriers such as language, stigma, or limited literacy. Health bots can reduce healthcare costs by decreasing the demand for human health experts and offering free or low-cost information and services.

Moreover, by providing coordinated and reliable information and services, health bots can enhance the quality of healthcare while reducing the likelihood of errors or bias from human health providers. Depending on user profiles, preferences, and behaviour, the bot can tailor health information and services accordingly. The primary goal of this bot is to offer recommendations and counsel based on its evaluation and health-related arguments. The process of gathering health information and generating arguments, evaluations, responses, and suggestions is carried out through a hybrid-based approach known as a conversational health bot [8]. The general structure of the health bot is displayed in Figure 1, which illustrates its main components as follows:

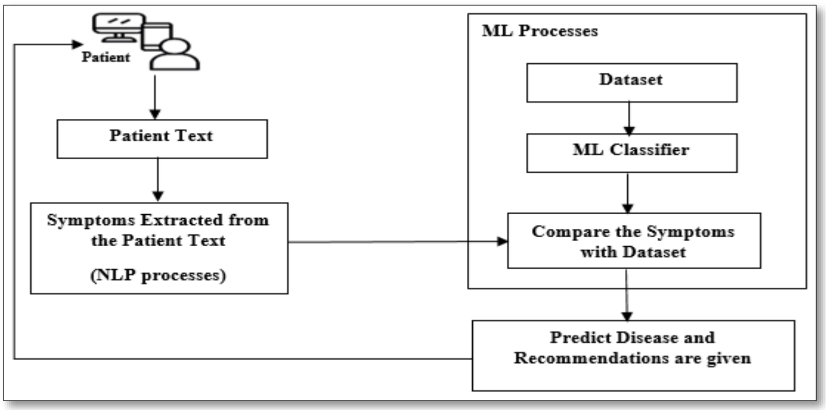

Figure 1: General Structure of the Health Bot [3]

2.1 Health Bot Using NLP

NLP enables machines to learn, analyze, and comprehend context by parsing and semantically interpreting of human-generated text [9].

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NLP extensively uses several methods, including grammar induction, which generates a formal grammar without relying on existing context; lemmatization, which identifies a word's lemma based on its context-dependent meaning; morphological segmentation, which involves decomposing words into their components and determining their categories; the word embedding algorithm, which uses semantic similarity and vector space distances to extract features from words with the same meanings; "parts of speech (POS)" tagging, which assigns specific parts of speech; the "bag of words" method, which converts words into unique symbols after splitting them from sentences [10, 11, 12]. NLP systems have demonstrated their value and innovation in retrieving and analyzing large volumes of unstructured clinical records, transforming them into structured data through defined user queries. The primary objective of any NLP system is to provide a representation of the knowledge conveyed in written text [13]. Coreferences and other linguistic patterns pose challenges in medical text interpretation; medical acronyms and other distinctive language entities further complicate knowledge extraction from such texts. In addition, medical records mostly contain various issues, including misspellings, medical jargon, inconsistent formatting, incomplete sentences, missing expected words and punctuation, and atypical POS. NLP can effectively address these challenges to extract a clear representation of knowledge from such records [14].

a. NLP-based Argue

Argumentation is a method of reasoning that involves presenting arguments to justify claims and provide reasons for accepting them. It allows individuals to introduce their ideas, rebut opposing opinions, and defend their positions using logical reasoning and supporting evidence. An argumentation-based model typically follows five steps: first, presenting arguments in support of the claims; second, defining the relationships (such as attack or support) among the arguments; third, assessing whether the arguments are sufficiently strong to support or challenge the claims; fourth, identifying the model's output, which may include a collection of formulas inferred from a knowledge base; finally, evaluating the arguments [15].

Arguments are structured within a framework consisting of a pair of graphs and semantics. Argument graphs can be represented as node-link diagrams or trees appropriate for hierarchical structures. The nodes represent complete, grammatical, declarative sentences and fall into four categories: reasons/premises (evidence supporting claims), claims (asserted ideas considered correct), conclusions (final claims supported by reasons), and objections (evidence countering the findings). The reasoning relationships (such as attacks and supports) between arguments are represented by lines and arrows connecting the nodes. The semantics evaluate the strength of the arguments in the graph and can identify whether an argument is accepted or defeated [16, 17]. Figure 2 illustrates the argument graph, which is flat when no initial weights are assigned; otherwise, it is referred to as a weighted graph. The credibility of the argument's origin, the confidence in the argument's reasoning, the number of votes from users, the likelihood of accepting the argument, and the relevance of the value it promotes can influence an argument's initial weight. Decisions are made based on the strength of the arguments in the final step of the argumentation process [15]. Semantics involves various evaluation methods, such as extension, labeling, gradual, and ranking. Extension semantics aims to identify jointly admissible arguments, whereas labeling semantics classifies them as in, out, or uncertain. Gradual semantics assigns numerical or qualitative values to arguments, whereas ranking semantics orders them by strength without assigning values. The selected semantics are determined based on the specific problem being solved [18].

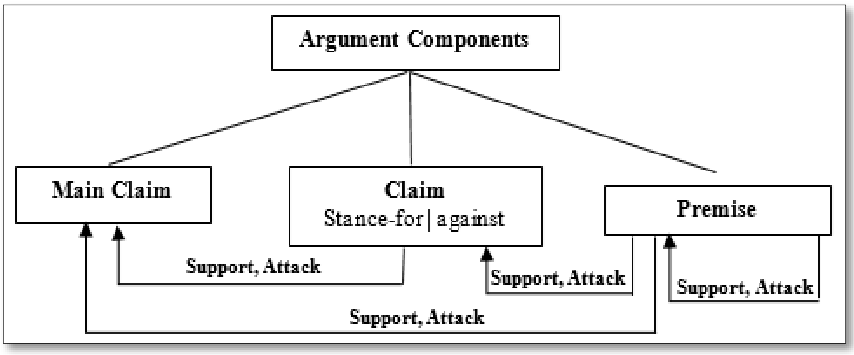

Figure 2: Argument Components and their Relationships [17]

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b. Justification via Argumentation

Justification (explanation) offers reasoning or evidence to support a claim or stance. It involves constructing logical arguments and presenting them cohesively and compellingly to persuade others of the validity or truthfulness of a specific viewpoint [19, 20]. The primary purpose of justification through argumentation is to build a rational and persuasive case for a particular claim or proposition. This approach often entails detecting relevant facts, examples, or expert views that support the argument, anticipating and resolving any counter-arguments or objections, and using logical reasoning to prove the soundness of the position being advocated [21, 22]. Justification via argumentation does not involve influencing or winning discussions through rhetorical tricks or fallacies. Instead, it emphasizes the use of sound reasoning, logical consistency, and evidence-based support to present a well-structured and convincing argument [23].

Chatbot-based argumentation systems can engage in argumentative discourse with users on specific issues. Argumentative discourse is a communication process in which two or more individuals exchange arguments about a particular problem. Arguments are claims supported by evidence and reasoning that seek to persuade the other side, alter their perspectives, or clarify a point of view. Argumentative discussions can be diverse, encompassing pro, con, neutral, and mixed arguments. They can also be multidimensional, involving major, subsidiary, and counter-arguments [24].

Health bot-based argumentation systems can assist users in improving their health by encouraging positive behavioural changes, such as quitting smoking, increasing physical activity, and adopting healthier eating habits. These bots generate and assess health-related arguments, presenting users with relevant information and opinions. They create health arguments using a generative approach, evaluate them using a neural approach, and respond using a transformer-based method [22].

2.2 ML-based Health Bots

ML is a method of processing and extracting implicit, known, unknown, and potentially useful information from data. ML is a vast and complex field, with its scope and applications expanding daily. It comprises several classifiers for supervised, unsupervised, and ensemble learning that are used to forecast and define the accuracy of a determined dataset [25]. Ensemble learning, which are used to predict and evaluate the accuracy of a given dataset [25].

ML and AI are now well-known for their substantial impact on medical issues. Numerous ML and deep learning (DL) models can be applied to diagnose diseases and categorize or predict outcomes. These models facilitate extensive data analysis, allowing for the training of systems to forecast epidemics and transform medical records into large-scale datasets, enhancing prediction accuracy [26]. Health bots employ machine learning methods to learn from data, improve efficiency, and increase complexity without requiring explicit programming [25]. These bots use a variety of machine learning or deep learning methods, or a hybrid of both, including support vector machine (SVM), support vector regression (SVR), random forest (RF), decision tree (DT), gradient boosting (GBoost), extreme gradient boosting (XGBoost), AdaBoost, logistic regression (LR), Naïve-Bayes (NB), Gaussian Naive-Bayes (GNB), multi-layer perceptron (MLP), stochastic gradient descent (SGD), convolutional neural network (CNN), recurrent NN (RNN), NN, K-nearest neighbours (KNN), long short-term memory (LSTM), gated recurrent unit (GRU) [27—38] to implement the following:

- ***Natural Language Understanding NLU:*** is a subgroup of NLP that can interpret and comprehend natural language. It processes raw, unstructured data and translates them into structured and intent-specific data by explaining the concept of the input string. Approaches, such as sentiment and content analysis, are used to detect meaning, categorize data, and define appropriate actions. Health bots powered by artificial intelligence rely heavily on NLP [39]. Understanding and interpreting user input is crucial for health bots, as inputs may include vagueness, vernacular, mockery, or typographical errors. In addition, health bots must provide accurate and rational responses that adhere to the principles of argumentation and reasoning [40].
- **Creating a Knowledge Base:** Health bots must uphold their arguments through authoritative and pertinent sources to enhance their credibility. In addition, they must be capable of defining whether the information they provide is exact and veritable to avoid bias and logical faults [41].
- **User Adaptation:** Health bots adjust their arguments and approaches based on the user's preferences, goals, arguments, and emotions. They must also maintain politeness and helpfulness when handling customer complaints, conflicts, and feedback [42].

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- **Socially and Ethically Accountable:** Health bots must adhere to established standards and values when engaging in arguments. They should protect the user's privacy, freedom, and dignity by avoiding harmful or deceitful information [43].

Many challenges and restrictions hinder the effectiveness of ML-based health bots, such as:

- ***Ensure the "why" is evident and easy to understand:*** health bots that rely on machine learning must justify their findings and processes, ensuring that users can comprehend their reasoning. This transparency increases user trust and accountability. However, the inner workings of some ML models, such as deep neural networks, can be difficult to comprehend due to their intricacy and vagueness [44].

- ***Vagueness and suspicion transaction:*** Health bots powered by machine learning must be able to handle data, user entries, and findings that may contain vagueness and uncertainty. These factors may also influence the health bots' reliability, accuracy, and performance. For example, the data may be incomplete, noisy, or incompatible, and users may use unclear or misleading language. Health bots must address these problems and present their findings to the user clearly and understandably [45].

- ***Reverence of the user's dignity, independence, and privacy***: Machine learning-based health bots must be designed to prevent unauthorized access or manipulation of the user's private data and preferences. They must interact with users in a respectful and dignified manner, ensuring their independence in making decisions. They must not collect or use personal information without explicit permission and must not expose the user to undesirable or harmful findings. Health bots must prioritize the user's privacy with dignity and respect [44, 46].

2.3 Recommendation Approach in Health Bot

Healthcare recommendation systems improve users' comprehension of their medical cases by providing accurate information about their health while ensuring information accuracy, security, and privacy [47]. These systems are designed to enhance decision-making regarding health risks and the severity of different diseases by offering personalized recommendations based on individual health issues. These recommendations may include treatment options, preventative measures, explanations of factors contributing to the disease, or additional courses of psychotherapy [48].

3. CHALLENGES OF HEALTH BOTS

Many challenges must be considered when constructing a health bot, as shown in Figure 3 and explained in detail as follows:

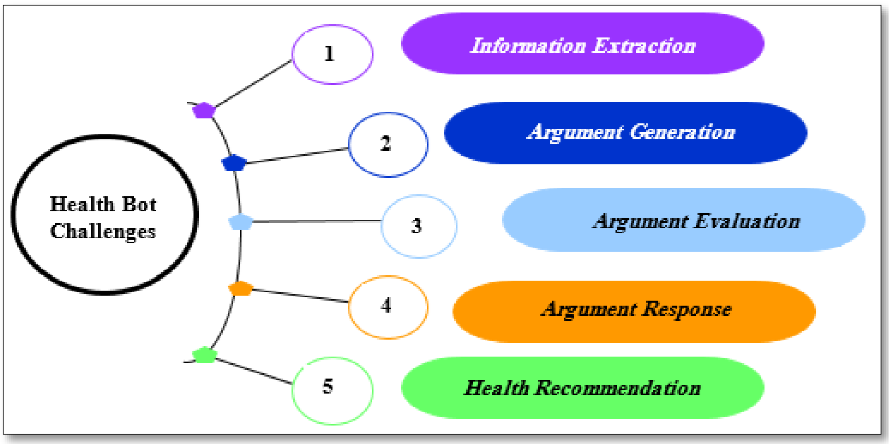

Figure 3: Main Challenges of the Health Bot

Information Extraction: is the automated process of extracting and recognizing health-related information from natural language documents, such as symptoms, diseases, treatments, and preventative strategies. It involves understanding, processing, and reasoning over the data. Various strategies are used for this task, including rule-based, statistical, and neural-based methods, to retrieve health information [49].

Argument Generation is the process of autonomously generating new or existing arguments concerning health-related subjects using accessible health data. It requires creativity, rationality, and knowledge. Approaches used

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for generating health arguments include template-based, retrieval-based, and generative-based approaches, producing relevant arguments in health-related discussions [50].

Argument Evaluation is the automated assessment of the quality and strength of health arguments using criteria such as validity, soundness, relevance, and coherence. It necessitates inference, logic, and judgment. Rule-based, probabilistic, and neural-based strategies are used to evaluate health arguments [51].

Argument Response is the process of automatically selecting or generating optimal responses to health arguments based on a dialogue's purposes and circumstances. It involves comprehension, persuasion, and naturalness. Ranking-based, reinforcement-based, and transformer-based strategies are used for health argument response [52].

Health Recommendation is the process of automatically recommending the most relevant or effective health information or services to a user based on their profile, interests, and behaviour. This process requires personalization, modification, and feedback. Some health recommendation strategies include collaborative filtering, content-based approaches, and hybrid models [53].

4. RELATED RESEARCH

Researchers and app developers have made great strides in improving healthcare through cutting-edge technology, such as AI, ML, and DL. These innovations have enhanced the lives of patients and doctors, potentially transforming the practice of medicine. Alongside these technological advancements, healthcare providers have improved their performance and delivered exceptional healthcare. This section focuses on modern and relevant studies leveraging advanced technologies to assist in the early detection of symptoms that could result in serious diseases or even death. In addition, these studies aim to motivate individuals to maintain a healthy lifestyle. Table I shows a synopsis of modern and relevant studies on health bots and associated technologies conducted over the past five years.

Table I. Related Research on Health Bots and their Technologies.

Authors	Methodology	Dataset	Pros	Cons/ Challenges
Kamalapurkar & Gunjal 2020 [54]	Web-based system. It uses the K-nearest neighbour algorithm to prophesy heart disease.	Data was collected from 300 patients while examined and categorized into objective, subjective, and test attributes.	- The findings displayed that the system works more effectively when it merges with other techniques, such as ant colony optimization.	- Some misclassifications. - There is a need for careful selection of the 'k' value. - It has a limited dataset size.
Sharma, Aujla, & Bajaj 2020 [55]	A recommendation system for healthcare. It was designed using a deep neuro-fuzzy technique incorporating convolutional neural networks (CNN) to categorize diseases depending on the patient's vitals and a fuzzy inference engine to prophesy risk.	Data was gathered from 1032 individuals with heart, liver, and kidney disorders from the University of California (UC), Irvine Library.	- It forecasts risk levels using a type-2 fuzzy engine.	- There is no considerable emphasis on accuracy, risk assessment, or severity evaluation for unsupervised ML algorithms and real-world evaluation with IoT sensors.
Mayer, Cabrio & Villata 2020 [56]	An argument-mining pipeline for randomized controlled trials (RCTs) based on deep bidirectional transformers integrated with various NNs, including LSTM, GRU, and CRFs NNs.	500 RCT abstracts from the MEDLINE database.	- It solves the limited availability of comprehensive annotated datasets in healthcare argument mining.	Limitations in: - Mislabeling. - Defining. - Component. - Boundaries. - Relation classification errors.
Naveenkumar et al. 2021 [57]	A web application forum. It forecasts illness manifestations based on user-inputted symptoms and conditions using the Naïve Bayes algorithm.	Data was collected from numerous health-related websites.	- User-friendly web system.	- Possible limitations in accuracy and cost-effectiveness.

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Stylianou & Vlahavas 2021 [58]	A multi-model system known as TransforMED. Which integrates two models (Evidence-based Medicine (EBM) and Medical Argument Mining (MAM).) It also includes (TreeLSTM, attention-based networks, and BiGRU with a conditional random fields (CRF) layer).	The EBM-NLP corpus contains 5,000 medical abstracts, and the AMCT corpus has 919 components from 159 abstracts.	- It achieves a high rate of precision, recall, and F1 score.	Challenges in: - Recall for outcomes. - Precision for populations. - Conflicting annotations in the dataset.
Dhavan 2021 [59]	An intelligent Medicare Chatbot. It uses Dialog flow and SVM algorithms for health services and heart disease prediction.	Heart disease dataset from the UCI machine learning repository.	- Dialogflow integrates with platforms like Google Assistant and Facebook Messenger, providing a text chat interface for ongoing heart disease consultation.	- Risk of misclassification. - Effectiveness depends on the accuracy of symptoms and the quality of the training dataset.
Sanchez-Graillet et al. 2022 [60]	A web-based application called Dynamic Interactive Argument Trees (DIAeT). It integrates evidence from clinical trials into a hierarchical argument that suggests one therapy is better than another based on several major dimensions related to the clinical endpoints.	Not specified.	- It is considered beneficial for clinical decision-making and supplements existing medical recommendations.	- It supplies a knowledge base manually. - It lacks dynamic updating.
Vasileiou & Maglogiannis 2022 [2]	Health bot platform. The platform includes a Health Bot User Interface (UI) that enables voice and text-based conversational interactions. DialogFlow NLP, the platform's main module, analyzes the input data (text and voice) utilizing NLP techniques to specify and categorize requests, triggering the appropriate response management component. It also involves intent classifiers to gather demographic and symptom data. Both the COVID-19 model and the heart disease model trained using (LR)	Cleveland heart dataset from UCI machine learning repository.	- It utilizes Google Cloud services for scalability and availability, such as Firebase functionalities, database and hosting, BigQuery ML, and AI cloud.	- Demographic entity questions are required. - These questions pertain to specific body anatomy types and are grouped under the symptom intent. - Requires precise replies before proceeding to the next question.
Alamoodi et al. 2022 [61]	Mobile health framework. It uses wearable medical sensors and IoT technologies to choose hospitals for patients residing in remote areas who suffer from several chronic conditions. MCDM (multi-criteria decision-making) methods are used to rank hospitals and give weights to criteria. These methods include (fuzzy-weighted zero-inconsistency and fuzzy decision-by-opinion score in a Q-rung ortho-pair fuzzy environment).	Patient data was sourced from many studies, including a survey on hospital choice, datasets on healthcare services, another study of MCD (multiple-chronic diseases) patient datasets, and a decision matrix.	- It addresses uncertainty in hospital selection. - It utilizes systematic ranking and sensitivity analysis to validate the framework.	- A static selection technique was used for outside patients. - The hospitals were chosen based only on the risk level of MCD patients.
Mazhar et al. 2022 [62]	An online expert system. It uses fuzzy logic to diagnose and cure cardiac disease accurately. Online symptoms are submitted via the patients, and then the system compares them with the database.	Data from THQ Tehsil-Based Hospital Yazman.	- It aims to reduce time and increase efficiency while diagnosing cardiac patients. - It can identify depressed levels of the disease and recommend suitable treatments.	- It relies on online symptom submission. - Accuracy depends on dataset quality. - Misclassification may be possible.

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Pati et al. 2023 [63]	Fog-empowered framework. It uses Ensemble Deep learning (FRIEND) for real-time cardiac patient analysis.	Heart disease data from Long Beach, Cleveland, Switzerland, and Hungary.	- Real-time remote diagnostics. - Low latency. - Low energy usage. - Better performance is achieved when the bagging and hard-voting classifiers are integrated with the deep neural network.	- High cost. - It has a limited dataset (920 cases). - Reliance on a single-platform-based approach.
Himi et al. 2023 [64]	'MedAi' framework. It uses eight ML algorithms. (SVM, SVR, KNN, RF, XGBoost, LSTM) to predict a variety of diseases. - The framework has three primary components. First, a prototype wristwatch called 'Sense O'clock' has 11 sensors to gather biological statistics. Second, an ML model for data analyses and prophesy. Third, a mobile app will be used to show the outcome of the foretelling.	A dataset was acquired from a local hospital, which contained patient body statistics.	- It records the user's physical condition round-the-clock to offer prompt assistance and recommend suitable treatments. - It predicts disease vulnerabilities early.	Challenges in: - Data collection due to a lack of open-source datasets and limited smartwatch sensor data - Emphasizes the importance of effective data storage.
Nancy et al. 2023 [65]	Fog-assisted smart healthcare system. It integrates fuzzy inference with the gated recurrent unit to aid in diagnosing cardiovascular and heart-related issues.	Heart disease dataset from UCI machine learning repository.	- It enhances cloud-based systems by improving jitter, delay time, and response duration.	- Confronts challenges in the environment of fog-based healthcare, such as: • Device heterogeneity. • Wide geographic dispersion. • Interoperability. • Maintainability. • Operational costs. • Privacy and security concerns.
Baghdadi et al. 2023 [66]	Catboost model	Heart condition data synthesized from the UCI machine learning repository.	- It automatically identifies critical features. - It detects and diagnoses cardiovascular disorders early.	- It uses secondary data. - Missing variables. - Cross-sectional design.
Ogunpola et al. 2024 [38]	Seven ML/DL classifiers were examined for prematurely detecting heart diseases, especially myocardial infarction; these classifiers include (KNN, SVM, LR, CNN, GB, XGBoost, and RF).	Data was collected from the Cardiovascular and heart disease Cleveland datasets.	- Careful XGBoost model tuning for cardiovascular diseases is effective. - The XGBoost model has solved the problem of unbalanced datasets that can cause biased prophecies, especially when the datasets have junior categories.	- More searching for ensemble and gradient-boosting models is needed for the accuracy optimization of heart disease prediction.
Hauptmann et al. 2024 [23]	German-language Chatbot. It is used to debate virtual future scenarios involving independent AI systems in the medical, legal, and self-driving car industries and their ethical consequences.	Data was collected from 178 student participants.	- Its ability to effectively introduce users to new viewpoints makes their views more moderate. - Its ability to add diversity to the conversation.	- The results may not apply to the general public because the study's sample size is too tiny (college students). - The lack of data that have long-term impacts makes it impossible to conclude the Chatbot's constant influence on users' viewpoints. - Currently, the Chatbot is unable to distinguish argumentative and non-argumentative user input.

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Unnithan & Jeba 2024 [67]	A modern-day model for prophesying various diseases in telemedicine consists of long short-term memory (LSTM) modules.	The "Multiple Disease Prediction" dataset is from the repository of the YBI Foundation. This dataset comprises 4920 rows with 133 columns, where the columns from 1 to 132 represent various symptoms from numerous diseases. Column 133 represents the diagnosis kind.	- It's a real-time interactive system for efficient patient-provider connection. - The patient gets high-quality services. - It provides time, costs, and annoyance related to the conveyance.	The system requires: - High-quality data. - Scalability challenges. - Managing huge datasets. - Privacy and standards issues. - Synchronization hurdles.
Babu & Boddu 2024 [68]	A healthcare Chatbot. It uses the BERT (bidirectional encoder representations from transformers) NLP paradigm to facilitate communication between patients and healthcare professionals.	Datasets including MIMIC-III, BioASQ, PubMed, and COVID-19.	- It showed efficacy in medical query processing and disease prediction.	Challenges in: - Computing demands of BERT-based models. - Bias in training data can have an impact on performance. - Interpretability. - Data privacy and continuous learning.

The related research provides a detailed overview of various methodologies and techniques used in the healthcare domain, notably focusing on disease prediction, diagnosis, and therapy.

Table II summarizes the key results and future directions for each work. By contrast, Table III compares the various evaluation metrics for the methodologies used in each related work.

Table II. Results and Future Directions for the Related Research of Health bots and their Technologies

Authors	Results	Future Works
Kamalapurkar & Gunjal 2020 [54]	- Develop a web-based system using the KNN algorithm for heart disease prediction. - It identifies fundamental risk factors involving cholesterol levels, high blood pressure, and family history. - Emphasize the importance of choosing the correct 'k' value for the KNN algorithm. - The system is tested on 50 patient records, leading to 40 correct identifications of heart disease. - When it trained on all attributes, it achieved a 97% accuracy rate, a high rate for precision, recall, and F1 score.	- Integrate KNN with other accurate algorithms. - Extend the system to predict other illnesses. - Validate the model on various real datasets. - Develop a more user-friendly interface. - Automate the selection of the best 'k' value. - Benchmark against existing prediction methods. - Perform external validation and clinical trials.
Sharma, Aujla, & Bajaj 2020 [55]	- Introduce a healthcare recommendation system using a deep neuro-fuzzy technique. - It uses CNN for categorization and a type-2 fuzzy engine for risk prediction integrated inside the system. - It analyzes data for 1032 individuals with heart, liver, and kidney disorders. - It achieved accuracy between 90% and 99% and fairness in illness prediction.	- A real testbed with IoT sensors will assess the suggested system, and real-time data will be gathered.
Mayer, Cabrio & Villata 2020 [56]	- Create an argument-mining pipeline for RCTs using deep bidirectional transformers. - It achieves an F1-score of 0.87 for component recognition and 0.68 for relationship forecast. - It widens the dataset with 500 RCT abstracts and a thorough pipeline for analyzing clinical trials, yielding 4198 argument components and 2601 relations on five diseases (neoplasm, glaucoma, hepatitis, diabetes, and hypertension).	- Aim to annotate relations across RCTs to reason and cluster arguments regarding the same disease. - Hand medical acronyms effectively. - Merge a distance parameter to get around the problems of connecting components in general. - Merge outside expert knowledge to understand medical domain nuances. - Explore the boundaries of multiple-choice structure in articles with their entire text. - Use comprehensive study reports to analyze individual parts.
Naveenkumar et al. 2021 [57]	- Construct a web application using the Naïve Bayes algorithm for disease prediction. - It achieved high accuracy and fairness in illness prediction. - It emphasizes acquiring clinical symptom-related information for accurate prediction.	- Address limitations in accuracy and cost-effectiveness. - Improve system response mechanisms. - Compare datasets with queries. - Create Association Rule Mining Reports based on historical data for accurate, prompt diagnosis.

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Stylianou & Vlahavas 2021 [58]	- Present TransforMED, a sophisticated EBM and MAM system. - It is trained on EBM-NLP and AMCT datasets. - It includes advanced methods like TreeLSTM and attention-based networks, BiGRU with CRF layer. - It outperformed existing models (EBM-NLP, BERT, EBM+, and QA-PICO) in precision, recall, and F1-score.	- Solve challenges with recall for outcomes, precision for populations, and conflicting PICO annotations. - Fine-tune model performance. - Integrate with clinical practice. - Expand training data.
Dhavan 2021 [59]	- Develop an intelligent Medicare Chatbot that uses Dialogflow and SVM algorithm for heart disease prediction. - The Chatbot's SVM model predicts cardiac disease with an accuracy rate of 82.4%. However, this indicates a risk of misclassification.	- Improve accuracy through better symptom detection and quality training data. - Predict and assess the risk of other diseases. - Improve user interaction and conversational capabilities. - Integrate with Electronic Health Record (HER) systems. - Focus on continuous model improvement. - Ensure regulatory compliance and security. - Increase multilingual support.
Sanchez-Graillet et al. 2022 [60]	- Create a web-based application called a DIAeT to aid clinical decision-making. - It is rated using use cases and medical specialists' surveys.	- Address the limitation of the manually collected knowledge base. - Develop a methodology to support "living" systematic reviews. - Develop information extraction methods for automatic evidence extraction.
Vasileiou & Maglogiannis 2022 [2]	- Present a Health Bot platform using LR for COVID-19 and heart disease prediction. - The COVID-19 model achieved 98.3% accuracy, and the heart disease model achieved 82% accuracy. - The COVID-19 model precisely predicts whether the patient should be quarantined, while the heart disease model accurately predicts the existence of heart disease.	- Train NLP algorithms in more languages and vocabularies. - Integrating accessible health data sources through application programming interfaces and Internet of Things data streams can enrich patients' past data and improve algorithm accuracy and outcomes.
Alamoodi et al. 2022 [61]	- Introduce a mobile health framework. - Use MCDM methods for hospital selection to overcome uncertainty. - During the development phase, hospitals are ranked, and criteria are weighted using q-ROFWZIC and q-ROFDOSM. - The access time is identified as a primary criterion, with its importance increasing with the q value in the sequence (0.1837, 0.183, 0.230, 0.276, 0.335) for (q = 1, 3, 5, 7, 10), respectively. - Hospital H-4 consistently ranks as the best across all tested scenarios.	- Address the limitations of high-risk MCD patients for hospital selection. - The dynamic nature of indoor patient arrivals is not considered.
Mazhar et al. 2022 [62]	- Develop an online expert system. - It could diagnose and treat cardiac problems with an average accuracy of 95.5%.	- Increase improvements in accuracy and efficiency. - Develop real-time interactive systems. - Expand the disease prediction model. - Integrate with IoT and electronic health records. - Conduct further research on remote patient monitoring.
Pati et al. 2023 [63]	- Introduce a Fog-empowered framework. - The model was tested using eight essential ML approaches (XGBoost, KNN, SVM, DT, LR, RF, NB, and AdaBoost), as well as ensemble techniques (weighted averaging, soft and hard voting, and bagging classifiers), which resulted in improved results. The models were evaluated based on 16 performance and nine network factors. - It achieved 94.27% accuracy, 97.59% precision, 96.09% recall, 75.44% specificity, and 96.83% F1 scores.	Address limitations such as: - High cost and reliance on a single-platform approach. - Explore cost-effective implementation methodologies. - Expand datasets. - Utilize edge computing concepts.
Himi et al. 2023 [64]	- Create 'MedAI,' a smartwatch application framework for early disease forecasting employing various ML algorithms to keep track of the physical status of the user all day long. - The Random Forest algorithm obtained the best results compared with existing ML methods: 99.4% accuracy, 99.6% precision, 99.4% recall, and 99.1% F1 score.	- Growing the dataset will enhance the model. - Develop real-time systems for better patients. - Utilize deep learning for disease prediction and monitoring. - Integrate with IoT and electronic health records. - The system will include significant diseases by adding other seasonal ailments to the forecasting list. - The smartwatch will be manufactured in the future, where an entire "Sense O'clock" design is presently accessible. - The mobile app will be launched on Google Play Store.

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Nancy et al. 2023 [65]	- Create a smart healthcare system that uses fog to diagnose cardiovascular and heart-related issues. - It achieved 99.13% accuracy, 99.13% precision, 99.12% sensitivity, 99.13% specificity, 99.13% F1 score, and a misclassification rate of 0.0087.	- Address device heterogeneity and interoperability challenges. - Develop authentication and privacy-preserving mechanisms.
Baghdadi et al. 2023 [66]	- Introduce a Catboost model for automated identification of essential attributes and early detection of heart illnesses. - It achieved a 92.3% F1 score and 90.94% average accuracy. - It outperformed other modern classification approaches, including AdaBoost, Gradient Boost, RF, KNN, SVM, and Decision Tree classifiers.	- Address limitations such as missing variables and cross-sectional design. - Improve prediction techniques by combining various ML techniques. - Evaluate datasets with more risk factors. - Investigate different population datasets.
Ogunpola et al. 2024 [38]	- Examine several ML/DL classifiers for early diagnosis of heart diseases, focusing on myocardial infarction. - The XGBoost optimization method achieved impressive outcomes: 98.50% accuracy, 99.14% precision, 98.29% recall, and 98.71% F1 score. - This optimization considerably improves the accuracy of the diagnosis model for heart disease.	- Broaden the scope through the merging of more comprehensive medical imaging datasets. - Improve the heart disease prediction accuracy by discovering ensemble models.
Hauptmann et al. 2024 [23]	- Build and test a German-language Chatbot to debate virtual future scenarios involving autonomous AI systems. - The Chatbot Got moderate to high scores because of a positive impression from the users. - Users were valued for arguments and the system's general design.	- Incorporate studies with varied and representative demographics to ensure the replication of results. - Improve technological capacities for argument recognition. - Use recent progressions in big language models to identify better user input that isn't arguing. - The Chatbot will become a more robust instrument for public enlightenment and debate with these enhancements.
Unnithan & Jeba 2024 [67]	- Present a telemedicine framework for predicting multiple diseases using LSTM modules. - It achieved 98.51% accuracy with a loss of 0.0842. .	- Address limitations such as data quality, scalability, privacy issues, and synchronization. - Develop real-time systems for better communication. - Utilize deep learning for disease prediction and monitoring. - Integrate with IoT and electronic health records. - Leverage data mining for healthcare insights.
Babu & Boddu 2024 [68]	- Develop a healthcare Chatbot based on the BERT NLP paradigm. - It achieved 98% accuracy, 97% precision, 96% recall, 97% AUC-ROC Score, and 98% F1 Score. These outcomes proved that the Chatbot is trustworthy when answering medical questions and making disease forecasts.	- Address challenges such as computational needs and biases in training data. - Enhance multilingual support. - Implement continuous learning mechanisms. - Strengthen data privacy measures. - Integrate multimodal data. - Address operational considerations.

Table III. Methods Type and Metrics Used in Related Research

Authors	Year	ML Method	DL Method	Accuracy	Precision	Recall	F1 score	Another Metrics
Kamalapurkar & Gunjal	2020	✓	✗	✓	✓	✓	✓	✗
Sharma, Aujla, & Bajaj	2020	✗	✓	✓	✗	✗	✗	✗
Mayer, Cabrio & Villata	2020	✗	✓	✗	✗	✗	✓	✗
Naveenkumar et al.	2021	✓	✗	✓	✗	✗	✗	✗
Stylianou & Vlahavas	2021	✗	✓	✗	✓	✓	✓	✗
Dhavan	2021	✓	✗	✓	✗	✗	✗	✗
Sanchez-Graillet et al.	2022	✓	✗	✗	✗	✗	✗	✓
Vasileiou & Maglogiannis	2022	✓	✗	✗	✗	✗	✗	✗
Alamoodi et al.	2022	✓	✗	✗	✗	✗	✗	✓
Mazhar et al.	2022	✗	✗	✓	✗	✗	✗	✗
Pati et al.	2023	✗	✓	✓	✓	✓	✓	✗
Himi et al.	2023	✓	✗	✓	✓	✓	✓	✓
Nancy et al.	2023	✗	✓	✓	✓	✓	✓	✗
Baghdadi et al.	2023	✓	✗	✓	✗	✗	✓	✗
Ogunpola et al.	2024	✓	✓	✓	✓	✓	✓	✗
Hauptmann et al.	2024	✗	✗	✗	✗	✗	✗	✓
Unnithan & Jeba	2024	✗	✓	✓	✗	✗	✗	✗
Babu & Boddu	2024	✗	✓	✓	✓	✓	✓	✗

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5. DISCUSSION

Various techniques for constructing chatbots are grounded in NLP and ML. Maher et al. [39] explored methods such as RNN, LSTM, and GRU. Hauptmann et al. [23] developed a German-language chatbot to discuss future AI scenarios in the medical, legal, and self-driving car industries. The study aimed to test the argumentation effect hypothesis, suggesting that a conversational system with diverse arguments can provide a broader understanding. On the contrary, Babu et al. [68] executed the BERT NLP paradigm in their chatbot system to enhance healthcare service quality. This study describes the evolution of a medical chatbot powered by BERT, a cutting-edge NLP software that demonstrates considerable innovation in healthcare information deployment and patient involvement. Vasileiou et al. [2] also used NLP as a DialogFlow NLP module for analyzing the input data (text and voice), adopting NLP techniques to specify and categorize requests that trigger the appropriate response management component.

Furthermore, the system involves intent classifiers to gather demographic and symptom data. Based on their findings, the Chatbot emerges as an optimal tool for performing sentiment analysis, capturing insights from users' experiences. Another application of NLP within this context involves decomposing input (strings) into system-handling chunks or tokens.

Several studies employed machine learning techniques to enhance healthcare services. For example, [54] used KNN to design a web-based system to improve healthcare services by forecasting cardiac issues at an early stage. Similarly, [57] implemented the Naïve Bayes algorithm to predict diseases based on user-provided symptoms. Another study [59] applied the SVM approach to classify data into two groups, determining the hyperplane that effectively separates them while minimizing errors associated with unseen patterns. Furthermore, [66] introduced the CatBoost model to automate the identification of critical features and enable the early diagnosis of cardiovascular diseases. In addition, [64] developed a smartwatch application framework, "MedAI," which leverages the RF algorithm. Lastly, [38] examined seven ML/DL classifiers for early diagnosis of heart diseases, especially myocardial infarction. The study addressed the problem of imbalanced datasets that can reason biased prophecies, especially those with junior categories. The XGBoost was superior in its performance to other classifiers.

Ensemble learning is valuable for various reasons; each model uses multiple fractions of the data to produce predictions, capturing some but not all of reality. For example, [63] introduced a fog-empowered framework based on ensemble deep learning (FRIEND) for real-time cardiac patient diagnostics.

In [67], deep learning was used to present a framework for predicting multiple diseases in telemedicine using LSTM. In [55, 61, and 65], fuzzy inference engines were integrated with machine/deep learning methods to define the disease's risk level. In [62], an online expert system using a rule-based inference engine and fuzzy logic was proposed to offer techniques of forward-chain for cardiac disease diagnosis. In [56, 58, and 60], argument mining, which frequently aims to describe argumentative components (claim and evidence) in text and forecast the relationships (support or attack), was employed. With evidence-based decision-making in the healthcare domain, doctors evaluate and determine the most appropriate course of action when assessing a medical situation.

6. RECOMMENDATIONS

ML and NLP are the most effective techniques for a health bot because they complement each other. Several ML techniques are used, including supervised and unsupervised learning, ensemble learning, neural networks, regression, and classification. NLP processes user input (raw data) into tokens that machine learning can comprehend. Important considerations for developing a health bot include:

1- Merging various types of data (multimodal data), such as text, speech, images, videos, and gestures, can improve health information and services, providing more thorough evidence and a customized experience.

2- Current language models fail to precisely simulate human dialogue because they use a next-step prediction technique that ignores context and shared knowledge. Dialogue models may improve interactions' relevance and naturalness, provide better context, and promote effective communication and feedback. Using knowledge graphs can improve the precision and depth of health information and services by providing logical structure and enabling advanced inference.

3- A flexible AI model is required for information retrieval chatbots that can adapt to different datasets, as the present models rely extensively on training data.

4- Chatbots require significant computational power and massive training datasets to deliver qualitative and accurate responses to users' requests.

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7. CONCLUSION

This survey introduces the fundamental concepts of a health bot, which engages in argumentative conversations with users on health-related topics. It provides accurate health information and convincing answers to users' questions, helping them make informed and responsible decisions regarding their health. Health bots offer several advantages, including cost efficiency, accuracy, flexibility, and the ability to access, adapt, and persuade users. However, they face challenges in creating, evaluating, and responding to arguments naturally.

This survey discussed the architecture of health bots and suitable algorithms to build them, such as NLP, ML/DL, keyword matching, and data mining, as well as the datasets collected through various methods to train health bots effectively.

This survey also reviewed research related to health bots, examining the algorithms used in each study and the results achieved. It compared these results and provided recommendations for improving health bots. In addition, the drawbacks, challenges, and directions for future research were determined for each of the studies reviewed.

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