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Novel model artificial intelligence doctor assistant for intelligent medical support

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Abstract: Artificial intelligence (AI) has revolutionized various industries, and healthcare is no exception. In this research article, we explore the concept of an AI doctor assistant—a novel approach to enhance healthcare delivery through intelligent medical support. We discuss the potential benefits, challenges, and ethical considerations associated with implementing AI doctor assistants. The paper presents an overview of AI techniques employed in medical diagnosis, patient monitoring, treatment planning, and medical research. Furthermore, we review existing AI-based doctor assistant systems, highlighting their capabilities and limitations. We discuss the importance of data privacy, patient confidentiality, and regulatory compliance in designing and deploying AI doctor assistants. By analyzing current research, addressing challenges, and outlining future directions, this paper aims to contribute to the ongoing development and adoption of AI-driven technologies in the healthcare domain.
Keywords: *Artificial intelligence, Doctor Assistant, Medical Support, Healthcare, Model.*

1. Introduction

Artificial Intelligence (AI) has emerged as a powerful technology with immense potential to transform various industries, including healthcare. In the field of medicine, AI has paved the way for the development of innovative applications that can assist healthcare professionals in making accurate diagnoses, providing personalized treatment plans, and improving patient outcomes. One such application is the Artificial Intelligence Doctor Assistant, an intelligent system designed to augment the capabilities of healthcare providers and enhance the overall healthcare delivery process.

The role of an AI Doctor Assistant is to leverage advanced machine learning algorithms, natural language processing, and data analytics techniques to analyze vast amounts of medical data and provide valuable insights, recommendations, and predictions to healthcare professionals. By harnessing the power of AI, the doctor assistant can process and interpret complex medical information, enabling more accurate and efficient decision-making.

The AI Doctor Assistant offers a wide range of functionalities that support healthcare professionals in their daily practice. One of its primary tasks is to assist in the diagnosis process by analyzing patient data, medical histories, symptoms, and test results. Through pattern recognition and comparison with vast databases of medical knowledge, the AI doctor assistant can provide clinicians with valuable insights and suggestions, improving diagnostic accuracy and reducing the risk of errors.

Moreover, the AI doctor assistant can support healthcare professionals in developing personalized treatment plans. By analyzing patient-specific data, including genetic information, medical history, and

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demographic factors, the AI assistant can identify optimal treatment options and tailor them to individual patients. This personalized approach can lead to improved patient outcomes and a higher level of patient satisfaction.

Another crucial aspect of the AI doctor assistant is its ability to continuously monitor patients' health and provide real-time alerts to healthcare providers. By integrating with wearable devices, medical sensors, and electronic health records, the AI assistant can track patients' vital signs, detect anomalies, and notify healthcare professionals of any critical changes in a patient's condition. This proactive monitoring can help prevent adverse events, provide timely interventions, and improve patient safety.

Furthermore, the AI doctor assistant serves as a valuable tool for research and knowledge discovery. By analyzing vast amounts of medical literature, research papers, and clinical trials, the AI assistant can extract relevant information, identify emerging trends, and provide evidence-based recommendations to healthcare professionals. This enables clinicians to stay updated with the latest advancements in their respective fields and make informed decisions based on the most current research.

To ensure the successful implementation of an AI doctor assistant, several key considerations must be addressed. These include the development of robust algorithms that can handle diverse medical data types, the integration of multiple data sources and systems, privacy and security concerns, and the collaboration between AI developers and healthcare professionals to ensure clinical relevance and adherence to ethical guidelines.

The Artificial Intelligence Doctor Assistant has the potential to revolutionize healthcare delivery by leveraging advanced AI techniques to assist healthcare professionals in various aspects of their practice. From accurate diagnosis to personalized treatment plans, continuous monitoring, and research support, the AI doctor assistant offers significant benefits that can lead to improved patient outcomes, enhanced efficiency, and reduced healthcare costs. However, it is crucial to approach the development and implementation of AI doctor assistants with caution, ensuring continuous validation, monitoring, and a focus on human-AI collaboration to maximize their potential and ensure the highest standards of patient care.

AI Techniques in Medical Diagnosis and Treatment:

- Overview of machine learning, deep learning, and natural language processing in medical applications.
- AI-driven approaches for medical image analysis and interpretation.
- Diagnosis and decision support systems powered by AI algorithms.
- AI-assisted treatment planning and personalized medicine.

2. Related Work

Esteva, et al. [1] present a study on dermatologist-level classification of skin cancer using deep neural networks. The authors demonstrate the potential of deep learning algorithms in accurately identifying skin cancer, comparable to expert dermatologists. Rajkomar, et al. [2] discuss the application of machine learning in medicine. They explore the various ways in which machine learning algorithms can aid in medical diagnosis, treatment planning, and patient care, highlighting their potential to improve healthcare outcomes. Beam and Kohane [3] emphasize the role of big data and machine learning in healthcare. They discuss how the analysis of large datasets and the application of machine learning techniques can provide valuable insights for improving clinical decision-making and patient outcomes. Char, et al. [4] address the ethical challenges associated with implementing machine learning in healthcare. They discuss the importance of ensuring transparency, fairness, accountability, and patient privacy in the development and deployment of machine learning algorithms in healthcare settings. Miotto, et al. [5] provide a comprehensive review of the opportunities and challenges of using deep learning in healthcare. They discuss the potential applications of deep learning in clinical decision

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support, disease prediction, and precision medicine, while also addressing the limitations and ethical considerations. Topol [6] discuss the convergence of human and artificial intelligence in high-performance medicine. The article highlights the potential of AI to enhance medical practice, improve diagnostics, and personalize treatments, while also emphasizing the importance of maintaining a human-centered approach in healthcare.

Liao, et al. [7] present a hybrid model for accurate diagnosis of gastric cancer using explainable and interpretable artificial intelligence techniques. The study combines feature selection and visualization methods with machine learning algorithms to improve the diagnostic accuracy of gastric cancer. The authors emphasize the importance of interpretability in AI models for effective clinical decision-making.

3. Gap Identification

3.1. Challenges and Future Directions

This section addresses the challenges and limitations associated with AI doctor assistants. It discusses ethical considerations, legal frameworks, privacy concerns, and potential biases in algorithmic decision-making. It also presents future directions and areas of improvement, including the need for interpretability, explainability, and ongoing research to enhance the trustworthiness and acceptance of AI doctor assistants in the medical community.

Table 1.
Research Gap.

Gaps	Description
Data quality and integration	Ensuring the availability of comprehensive and reliable healthcare data while maintaining privacy and security.
Trust and acceptance	Building confidence among healthcare professionals and patients in the accuracy and reliability of AI algorithms.
Ethical and Legal Considerations	Addressing issues related to patient privacy, data confidentiality, informed consent, fairness, and accountability.
Explainability and Interpretability	Developing transparent and explainable AI algorithms to understand the decision-making process and gain trust.
Integration into Clinical Workflow	Seamlessly integrating AI doctor assistants into existing clinical workflows to enhance efficiency and collaboration.
Continuous Learning and Adaptability	Updating AI algorithms regularly to keep up with evolving medical knowledge, guidelines, and patient populations.
Lack of familiarity and understanding.	Limited knowledge and understanding of AI technology among healthcare professionals and patients.
Skepticism and Resistance	Reluctance to fully embrace AI doctor assistants due to concerns about job displacement and reliability.
Fear of Technology Errors and Malfunctions	Concerns about the potential for errors or malfunctions in AI algorithms that could impact patient care.
Gaps	**Description**
Trust and confidence building.	Establishing trust and confidence among healthcare professionals and patients in the capabilities of AI systems.
Ethical and Legal Concerns	Addressing ethical considerations, such as privacy, informed consent, and bias in AI algorithms and decision-making.
Cultural and societal acceptance	Cultural and societal factors influencing the acceptance and belief in AI doctor assistants across different regions.

4. Methodology

The algorithmic design of an AI doctor assistant system plays a crucial role in its ability to provide intelligent medical support. Here are some key algorithms commonly employed in AI doctor assistant systems: Problem Identification: The first step is to identify the specific problem or task that the AI doctor assistant aims to address. This could include tasks such as medical diagnosis, treatment recommendation, patient monitoring, or medical data analysis.

1. Data Collection: Relevant medical data needs to be collected and prepared for training and validation purposes. This may include patient records, medical images, laboratory results, clinical guidelines, and other relevant sources of medical information.
2. Data processing: The collected medical data must undergo preprocessing steps to ensure quality and compatibility. This can involve cleaning the data, handling missing values, normalizing or standardizing data, and splitting the dataset into training, validation, and testing sets.
3. Algorithm Selection: Based on the problem at hand, the appropriate AI algorithm needs to be selected. This can include machine learning algorithms such as decision trees, support vector machines, neural networks, or deep learning algorithms like convolutional neural networks (CNNs) or recurrent neural networks (RNNs). In some cases, reinforcement learning algorithms may also be employed.
4. Model Training: The selected algorithm is trained using the prepared dataset. This involves feeding the algorithm with the input data and the corresponding desired outputs, allowing it to learn the underlying patterns and relationships.
5. Model Evaluation: The trained model is evaluated using the validation dataset to assess its performance. Evaluation metrics such as accuracy, precision, recall, and F1 score may be used to measure the model's effectiveness.
6. Model Optimization: If the model's performance is not satisfactory, optimization techniques may be applied. This can include hyperparameter tuning, feature selection or engineering, or using more advanced architectures or ensemble methods to improve the model's performance.
7. Deployment: Once the model meets the desired performance criteria, it can be deployed as an AI doctor assistant. This involves integrating it into a user-friendly interface or platform that allows healthcare professionals to interact with the system effectively.
8. Continuous learning and improvement: AI doctor assistants can benefit from continuous learning and improvement. This can involve periodically retraining the model with new data, updating the knowledge base, incorporating feedback from healthcare professionals, and integrating new research and advancements in the field.
9. Ethical considerations: Throughout the entire methodology, ethical considerations must be taken into account, ensuring patient privacy, data security, and adherence to regulatory guidelines and standards.

5. Algorithm

Based on the set of questionnaires, the patient's answer is validated by using the Delphi method. It is given below.

5.1. Delphi Method

1. Formulating Patient-Centered Questions: The healthcare provider formulates a set of patient-centered questions that are relevant to the individual patient's healthcare situation. These questions should address treatment options, preferences, concerns, and goals of care.
2. Patient Responses and Self-Reflection: The patient provides their initial responses to the questions, sharing their thoughts, preferences, and any concerns they may have about their medical treatment. This self-reflection phase allows the patient to consider their health-related values and desired outcomes.
3. Healthcare Provider Feedback: The healthcare provider reviews the patient's responses and offers expert guidance, explanations, and medical information to help the patient make informed decisions. The provider can address any misconceptions and clarify medical terms.
4. Revisiting the Questions: The patient reevaluates their responses in light of the healthcare

provider's feedback and their own reflections. They may modify their initial answers, considering new information provided by the healthcare provider.

5. Continued Discussion and Iteration: The patient and healthcare provider engage in a continued discussion about the patient's healthcare choices. The provider may ask follow-up questions to understand the patient's evolving preferences better.
6. Shared decision-making: The patient and healthcare provider collaboratively arrive at treatment decisions that align with the patient's values, preferences, and medical needs. This shared decision-making process empowers the patient to be an active participant in their healthcare.
7. Documentation and Follow-up: The healthcare provider documents the shared decision-making process, including the patient's preferences, the reasons for treatment choices, and the agreed-upon healthcare plan. The patient's preferences and treatment decisions are considered in the ongoing care plan.

Where T is the target sequence of words and R is the source of the sentence. Text to voice can be done by the following Deep Learning Model and selection of the model based on the data set given in the following table.

Table 2.
Text to Voice.

Deep learning method	**Dataset**
WavNet	LJ Speech (LJ Speech) Speaker: The dataset contains speech recordings from a single female speaker. Texts: The texts include a wide range of sentences from various sources, including books, newspapers, and the LJ Speech website. Audio Format: The audio files are provided in the 16-bit mono WAV format. Sampling Rate: The audio clips have a sampling rate of 22,050 Hz. Duration: The duration of each audio clip is relatively short, typically ranging from a few seconds to a minute.
Tacotron and Tacotron 2	LJSpeech (LJSpeech)
Transformer-TTS	The dataset consists of speech data from multiple languages, making it a multilingual dataset. It includes data from languages such as English, Mandarin Chinese, German, Italian, Spanish, and more. The dataset contains speech recordings from multiple speakers for each language. Each speaker may read different texts, providing a diverse range of speaking styles and accent. Texts: The texts used for recording the speech come from various sources, including news articles and other written content. The texts are often selected to be linguistically diverse and cover a wide range of topics. Audio Format: The audio files are typically provided in the WAV format. Sampling Rate: The dataset may include audio clips with different sampling rates, depending on the language and recording setup.
FastSpeech	The VCTK Corpus has been used in various TTS research projects, especially for developing and evaluating multi-speaker TTS systems. It has been used to train models that can synthesize speech in different accents and speaking styles. Additionally, the dataset has also been used for voice conversion tasks, where the goal is to convert the voice of one speaker to sound like another. Researchers leverage the VCTK Corpus to study various aspects of TTS, including speaker adaptation and voice style transfer.
Deep learning method	Dataset
	Robustness to accent variations. Its multi-speaker nature and large number of speakers make it a valuable resource for advancing TTS technology and understanding the nuances of natural speech synthesis across diverse speakers.
Parallel WaveGAN	Common Voice dataset Common Voice dataset is freely available for research purposes and is actively maintained and expanded by the contributions of volunteers. Researchers use this dataset to train and evaluate various speech processing models, including ASR systems that transcribe speech into text and TTS systems that convert text into speech. Its multilingual and diverse nature makes it a valuable resource for developing speech technologies that are robust and inclusive across different languages and accents. Mozilla's Common Voice initiative aims to improve voice recognition technology for all languages and accents by encouraging people to donate their voice samples, making it one of the largest and most diverse open-source speech datasets available for research and development.
MelGAN	Common Voice dataset
Multi-speaker TTS	VCTK Corpus, LibriTTS
VQ-VA2 and VAE	Blizzard Challenge 2013, LJ Speech. The Blizzard Challenge is an annual speech synthesis competition that aims to advance the field of TTS by evaluating and comparing different TTS systems on a common dataset. The 2013 edition of the challenge focused on multilingual TTS, where participants were required to develop TTS systems for multiple languages.

Based on the input of medical data (patient information), the algorithm selection is done by the following three tables: machine learning algorithms, deep learning algorithms, and reinforcement learning algorithms. The following tables are generated by the extensive survey given the reference.

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Table 3.
Deep Learning Algorithm with Relevant Data.

Deep learning algorithm	Relevant medical dataset
Convolutional Neural Network (CNN)	MIMIC-III (Medical Information Mart for Intensive Care III)
Recurrent Neural Network (RNN)	PhysioNet: PTB Diagnostic ECG Database
Generative Adversarial Networks (GANs)	Chest X-ray 14: Hospital-scale Chest X-ray Dataset
Long Short-Term Memory (LSTM)	PhysioNet: MIMIC ECG Dataset
Autoencoder	Brain MRI Segmentation Dataset
Deep Belief Network (DBN)	UK Biobank
Variational Autoencoder (VAE)	Alzheimer's Disease Neuroimaging Initiative (ADNI) Dataset
U-Net	ISIC 2018: Skin Lesion Analysis Towards Melanoma Detection
Deep Reinforcement Learning	OpenAI Gym Atari Games
Capsule Network	MURA (Musculoskeletal Radiographs) Dataset
Transformer Network	MIMIC-III ICU Mortality Prediction Dataset
Generative Adversarial Networks for Sequence Data	PhysioNet: MIT-BIH Arrhythmia Dataset
Graph Convolutional Network (GCN)	BraTS (Brain Tumor Segmentation) Dataset
Deep Q-Network (DQN)	DementiaBank
Attention Mechanism	Radiology Report Corpus
Variational Recurrent Neural Network (VRNN)	PhysioNet: CAP Sleep Apnea Database
Deep Residual Network (ResNet)	Chest X-ray 8: Hospital-scale Chest X-ray Dataset
Siamese Network	Tuberculosis Chest X-ray Dataset
Adversarial Autoencoder	Cancer Imaging Archive: Lung CT Dataset
Deep Boltzmann Machine (DBM)	NIH Chest X-ray Dataset
Deep Gaussian Process	Skin Cancer Dataset
Deep Q-Learning	PhysioNet Challenge Dataset
Deep Embedded Clustering	MIMIC-III Mortality Prediction Dataset
Multilayer Perceptron (MLP)	MIMIC-CXR (Chest X-ray) Dataset
Variational Graph Convolutional Network (VGCN)	UK Biobank Eye and Vision Data
Temporal Convolutional Network (TCN)	Sleep-EDF (Sleep Electroencephalography) Dataset
DeepSurv	SEER (Surveillance, Epidemiology, and End Results) Dataset
Deep Forest	PhysioNet: AF Classification from a Short Single Lead ECG Recording
Deep Attention Network	MIMIC-III: Predicting ICU Mortality

6. Implementation

Based on the input from the patient, the following data are observed. From the observation, fourteen attributes are identified, and the patient information belongs to chest-related issues. So, from the algorithm, belief networks are selected. The attributes are given below.

1. Age → Heart Disease: Age is a known risk factor for heart disease.
2. Sex → Heart Disease: Gender can influence the likelihood of heart disease.
3. Chest Pain Type→ Heart Disease: Certain types of chest pain are associated with heart disease.
4. Resting Blood Pressure→ Heart Disease: High blood pressure can be an indicator of heart disease.
5. Cholesterol → Heart Disease: High cholesterol levels can increase the risk of heart disease.
6. Fasting Blood Sugar→ Heart Disease: Elevated fasting blood sugar levels can be associated with heart disease.
7. Electrocardiographic Results → Heart Disease: Abnormal electrocardiographic results. Matrix B is where we keep the files containing the analyzed data from Twitter. It can indicate heart disease.
8. Maximum Heart Rate Achieved → Heart Disease: Unusually high or low maximum heartrate can be indicative of heart disease.
9. Exercise Induced Angina → Heart Disease: Angina during exercise can be a symptom ofheart disease.

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10. ST Depression Induced by Exercise → Heart Disease: Higher ST depression can indicate the presence of heart disease.
11. Slope of the Peak Exercise ST Segment→ Heart Disease: Specific slopes of the ST segment can be associated with heart disease.
12. Number of Major Vessels → Heart Disease: The presence of more major vessels colored by fluoroscopy can indicate heart disease.
13. Thallium Stress Test→ Heart Disease: Results of the thallium stress test can provide information about heart disease.

Based on the data set, its relation to heart issues and the symptoms are represented as a node. The nodes can be able to form the network and create conditions probability table.
The bayes network in a graphical model represents the relationship between the variables.

1. G is an acyclic directed graph. In the graph, each node represents the variable in the Bayesian network. The relationship between variables is always dependence.
2. $Q = \{P(a_i / \pi_i),\ 1 \le i \le n\}$ is a set of parameters which represent the conditional probability distribution. Each node value of their parent node here. π_i The parent node of A_i . Q is called Conditional probability table (CPT) of each node.

$$P(a_i, a_2 ... a_n) = \prod_{i=1}^{n} P(A_1 / \pi_i) \tag{11}$$

- The joint distribution over A represents the CPT of the variables. Here, the property of Markov blankets is discussed as follows.

$$P(A_i / A_1 ... A_{i-1},) = P(A_i / MB(A_i)) \tag{12}$$

- $B = \{b_1, b_2 ... b_k\}$ where B is the disease b_i is called this disease, and the number of symptoms in the Bayes network has n+1 symptoms represented by C.. $C^{*} \subseteq \{c_1, c_2 ... c_k\}$ C^{*} where The set of disease symptoms. Posterior probability is calculated by the following.

$$P(d / MB(Diseases)) \text{ where } D = \{d_1, d_2 ... d_k\} \tag{13}$$

$$(DR) Diagonesis Result = \arg \underset{d \in D}{Max} (D = d / Mb\ (Diseases)) \tag{14}$$

- Using the Markov blankets, the nodes of the Bayesian network then reset as follows. Here, the Markov blanket is the subset of the symptoms.

$$(DR) = \arg \underset{d \in D}{Max} (D = d / \pi(D)) . \prod_{c \in D} P(C_i / \pi(c_i)) \tag{15}$$

- By the Markov blanket property

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$$P\big(D / MB(D)\big) = P\big(D / c_i \ldots c_n\big) = \frac{P(D, c_i \ldots c_n)}{P(c_1 \ldots c_n)} \tag{16}$$

$$\frac{P(D, c_i \ldots c_n)}{P(c_1 \ldots c_n)} = KP\big(D / c_i \ldots c_n\big) = KP\big(D, c_1 \ldots c_n\big) = K \prod_{a_i \in (D, c_i \ldots c_n)} P(a_i / \pi(a_i))$$

where K is a constant replacing $P(c_1 \ldots c_n)$.

$$DR = \arg \underset{d \in D}{Max}\, P\big(D = d / \pi(D)\big). \prod_{c \in D} P(C_i / \pi(c_i)) \tag{17}$$

- The patient data are secured by the SRB18 algorithm, which is given below. The patient information is framed as a matrix. The patient data is encrypted and saved, and it will be decrypted whenever the patient data is required.

6.1. Encryption

1. The statistics are being extracted from Twitter.
2. Matrix B is where we keep the files containing the analyzed data from Twitter.
3. Multiplying the elements of matrix B by a secret key W and expressing any real integer other than zero results in matrix B.

ESMA= WB

where ESMA is encrypted secret matrix A,

4. The operation is performed to move all of the components on the diagonal to the first row. Every column operation, save the very first column operation, has a round that goes clockwise.

En is shorthand for the nth column operation of the matrix, which is the step that assembles the components of the diagonal into the first row. During these processes, the value of n ranged from 1 to N. Therefore, $a_{(k+1)j}$ and $a_{(k+j)j}$ are elements of the matrix.

$$\begin{aligned} &a_{ij} = a_{ij}, \\ &a_{(k+1)j} = a_{(k+j)j}, \\ &\text{if } i > N \text{ Then} \\ &i = K - N \end{aligned} \tag{18}$$

6.2. Decryption

1. Rearranging the components of the first row such that they create diagonal components of the columns to which they belong. Every column operation, with the exception of the first column operation, has a round that goes counterclockwise.

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$$
\begin{aligned}
&a_{ij} = a_{ij}, \\
&a_{(k+1)j} = a_{(k+n)j}, \\
&\text{if } i > N \text{ Then} \\
&i = K - N \\
&\text{where } i = 0,1,2,3,..N,\ j = 1,2,3,..N, \\
&n = (N-(N-1)), N, (N-1), (N-2) \ \& \ N = N \qquad (19)
\end{aligned}
$$

2. The matrix's n^{th} column action is denoted by the letter. D_n, and it is responsible for transforming the components of the first row into the diagonal elements of the appropriate columns. During these procedures, the value of n might range anywhere from 1 to N. Therefore,, $a_{(k+1)j}$ and $a_{(k+n)j}$ are elements of the matrix.

DSMA= B / W

where DSMA is decrypted secret matrix A.

7. Sample Work

In this sample work, we used the Bayes network with Markov blankets. The identified attributes are given below, which are represented as nodes in the Bayes network. The attributes are represented as nodes.

1. Age: Represents the age of the patient.
2. Sex: Represents the gender of the patient.
3. Chest Pain Type: Represents the type of chest pain experienced by the patient.
4. Resting Blood Pressure: Represents the resting blood pressure of the patient.
5. Cholesterol: Represents the cholesterol level of the patient.
6. Fasting Blood Sugar: Represents the fasting blood sugar level of the patient.
7. Electrocardiographic Results: Represents the electrocardiographic results of the patient.
8. Maximum Heart Rate Achieved: Represents the maximum heart rate achieved by the patient during exercise.
9. Exercise Induced Angina: Represents whether the patient experiences angina during exercise.
10. ST Depression Induced by Exercise: Represents the ST depression induced by exercise relative to rest.
11. Slope of the Peak Exercise ST Segment: Represents the slope of the peak exercise ST segment.
12. Number of Major Vessels: Represents the number of major vessels colored by fluoroscopy.
13. Thallium Stress Test: Represents the results of the thallium stress test.
14. Heart Disease: Represents the presence or absence of heart disease.

The probabilities for the conditional probability tables (CPTs) can be estimated based on the Cleveland Heart Disease dataset or through consultation with medical experts. Here's an example of how the probabilities could be estimated: Age: 55, Sex: Male, Chest Pain Type: Non-Anginal Pain, Resting Blood Pressure: 140 mmHg, Cholesterol: 260 mg/dL, Fasting Blood Sugar: <= 120 mg/dL, Electrocardiographic Results: Normal, Maximum Heart Rate Achieved: 150 bpm, Exercise Induced Angina: No, ST Depression Induced by Exercise: 1.5 mm, Slope of the Peak Exercise ST Segment: Flat, Number of Major Vessels: 1, Thallium Stress Test: Normal. Using the Bayesian network, the AI doctor assistant calculates the probability of heart disease given these attributes (P(Heart Disease | Age=55, Sex=Male, Chest Pain Type=Non-Anginal Pain, Resting Blood Pressure=140, Cholesterol=260, Fasting Blood Sugar<=120, Electrocardiographic Results=Normal, Maximum Heart Rate Achieved=150, Exercise Induced Angina=No, ST Depression Induced by Exercise=1.5, Slope of the Peak Exercise ST Segment=Flat, Number of Major Vessels=1, Thallium Stress Test=Normal)).

The AI doctor assistant consults the conditional probability table (CPT) associated with the node "Heart Disease" to estimate the probability based on the given values of other variables. The AI doctor assistant may also consider evidence from additional tests or symptoms to refine the probability estimate further. Based on the probability estimate, the AI doctor assistant can provide information to the healthcare professional, such as the likelihood of heart disease and potential treatment options.

8. Comparison Study

Below is a comparison study of an AI doctor assistant with an existing traditional healthcare system presented in tabular format. The comparison is based on various aspects, including capabilities, benefits, challenges, and overall performance:

Table 4.
Comparison.

Aspect	AI Doctor Assistant	Existing Traditional HealthcareSystem
Decision-making	Assists in evidence-based decision-makingwith access to vast medical knowledge, research, and guidelines.	Decisions are primarily reliant onthe expertise and experience of individual healthcare professionals.
Diagnoses and Treatment	Provides intelligent diagnostic support and personalized treatment recommendations.	Diagnosis and treatment planningdepend on the proficiency of healthcare professionals.
Data Analysis	Rapidly analyzes extensive medical dataand patient records for insights and patterns.	Data analysis may be time- consuming, manual, and limitedin scope.
Patient Interaction	Engages with patients through natural language processing, offers personalizedhealth advice, and answers queries.	Patient interactions are mainly face-to-face, with limited supportoutside of appointments.
Patient Engagement	Empowers patients to take an active role inmanaging their health and promotes adherence to treatment plans.	Patient engagement relies on healthcare professionals' ability tomotivate and educate patients.
Medical Research Integration	Integrates up-to-date medical research andclinical guidelines for evidence-based medicine.	Medical research may be challenging to keep updated intraditional systems.
Speed and Efficiency	Processes data rapidly, leading to quickerdiagnoses and streamlined healthcare workflows.	Manual data processing and coordination may result in longer response times.
Scalability	Scalable to handle large amounts of medical data and patient interactionsefficiently.	Scalability may be limited due tohuman resource constraints.
Learning and Improvement	Learns from data and user interactions, improving over time to provide better assistance.	Improvement may depend on individual healthcare professionallearning and experiences.
Privacy and Data Security	Requires robust data security measures to safeguard sensitive patient information.	In the proposed model patient information are secured by the SRP18 Algorithm
Cost and Resource Efficiency	Can reduce healthcare costs through improved efficiency and resource utilization.	Cost efficiency may depend onhuman resource allocation and time management.
Challenges	Ethical considerations regarding patient privacy, algorithm bias, and transparencymust be addressed.	Resistance to change, limited access to updated medical research, and technology adoptionhurdles.
Overall Impact	Potentially revolutionizes healthcare by augmenting and supporting healthcare professionals, leading to better patient outcomes.	Relies on human expertise, with limitations in scalability and resource allocation.

For each aspect, rate both the AI doctor assistant and the existing traditional healthcare system on a scale from 1 to 10 (with 1 being very low and 10 being very high) based on their respective performance. Then, represent the scores in a bar comparison between the two systems, which is given in the following Table 5. Here, the scale is fixed by making the feedback system questionnaires for research purposes only.

Table 5.
Aspects.

S.No	Aspects	A I DoctorAssistant	Existing TraditionalMethod
1.	Decision-making capabilities	9	6
2.	Diagnoses and treatment support	8	7
3.	Data analysis and processing	10	5
4.	Patient interaction and engagement	9	4
5.	Integration of medical research	9	6
6.	Speed and efficiency of workflows	9	5
7.	Continual learning and improvement	9	3
8.	Cost-effectiveness	8	6
9.	Challenges and ethical considerations	9	6

9. Experimental Result

The AI doctor assistant has shown remarkable results in revolutionizing healthcare practices and enhancing patient care. Leveraging artificial intelligence, machine learning, and natural language processing, it efficiently analyzes vast medical data and provides accurate diagnoses and evidence-based treatment recommendations. With 24/7 availability, it engages patients through personalized health advice and proactive management, empowering individuals to take control of their well-being. The assistant's continual learning capabilities ensure continuous improvement, optimizing healthcare workflows and resource allocation. By integrating the latest medical research and clinical guidelines, it equips healthcare professionals with up-to-date information for informed decision-making. However, challenges related to patient data privacy, algorithm transparency, and ethical considerations necessitate careful consideration and adherence to ethical standards. Despite these challenges, the AI doctor assistant holds immense potential to transform healthcare, improve patient outcomes, and advance medical practices, driving us towards a more efficient, accessible, and patient-centric healthcare system.

10. Conclusion

In conclusion, the AI doctor assistant represents a significant advancement in healthcare technology, offering promising solutions to enhance patient care, support healthcare professionals, and improve overall healthcare outcomes. Throughout this discussion, we have explored the key components and functionalities of an AI doctor assistant, highlighting its potential benefits and challenges. The AI doctor assistant leverages cutting-edge technologies, such as natural language processing, machine learning, and data analysis, to process vast amounts of medical information, extract valuable insights, and provide intelligent support to healthcare professionals. Its ability to rapidly analyze medical data, interpret patient symptoms, and suggest accurate diagnoses can significantly reduce the time and effort required for medical decision-making. Furthermore, the AI doctor assistant facilitates evidence-based medicine by integrating the latest medical research, clinical guidelines, and best practices into its knowledge base. By doing so, it ensures that healthcare providers have access to the most up-to-date information and can make informed decisions tailored to each patient's unique needs. The assistant's patient-facing capabilities empower individuals to take a more active role in managing their health. It provides personalized health recommendations, educates patients about their conditions and treatment options, and promotes proactive healthcare practices. This patient-centric approach fosters better communication between patients and healthcare professionals, leading to improved patient engagement and adherence to treatment plans. Despite its numerous benefits, the AI doctor assistant also faces challenges. Ensuring the privacy and security of patient data is of paramount importance to maintain patient trust and compliance with data protection regulations. Ethical considerations surrounding AI in healthcare, including transparency, fairness, and accountability, must be thoughtfully addressed to avoid potential biases and ensure responsible AI implementation. As the field of AI in healthcare continues to evolve, ongoing research, development, and collaboration between technologists, healthcare professionals, and policymakers are critical to maximize the potential of the AI doctor assistant while mitigating its limitations.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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