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Artificial Intelligence Doctor Assistant using Bayesian Networks

S. Selvaraj[1], S. Rajaprakash[2], R. Mariappan[3]

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Abstract: This study proposes the development and implementation of an Artificial Intelligence (AI) Doctor Assistant utilizing Bayesian Networks for enhanced medical decision-making. Bayesian Networks, known for their ability to model complex relationships among variables and handle uncertainty, are employed to create a dynamic and adaptable system for medical diagnosis and treatment recommendation. The AI Doctor Assistant integrates patient data, medical history, and diagnostic information to construct a probabilistic graphical model using Bayesian Networks. This model captures the interdependencies among various medical factors and symptoms, allowing for accurate and personalized assessments. The system employs machine learning techniques to continuously update and refine the Bayesian Network based on new patient data and emerging medical knowledge. By analyzing large datasets, the AI Doctor Assistant enhances its predictive capabilities, enabling more precise and timely diagnosis.

Keywords: *AI doctor Assistant, conditional probability, Bayes network*

1. Introduction

This template, modified in MS Word 2007 and saved as a “Word 97-2003 Document” for the PC, provides authors with most of the formatting specifications. Artificial Intelligence (AI) has emerged as a transformative force in the healthcare sector, offering innovative solutions to complex challenges in medical diagnosis and treatment planning. This study introduces an advanced AI Doctor Assistant that leverages Bayesian Networks, a probabilistic graphical model, to enhance the efficiency and accuracy of medical decision-making. In contemporary healthcare, the volume and complexity of patient data pose significant challenges for clinicians. The integration of AI technologies, particularly Bayesian Networks, presents a promising approach to navigate this complexity and extract meaningful insights. Bayesian Networks excel in modeling uncertain and interdependent relationships among variables, making them well-suited for medical scenarios characterized by intricate diagnostic patterns.

Rationale for AI Integration: The motivation behind integrating AI into medical practice lies in its ability to process vast amounts of data, discern intricate patterns, and provide timely, data-driven insights. The proposed AI Doctor Assistant, centered around Bayesian Networks, is designed to empower healthcare professionals by augmenting their decision-making capabilities.

Key Components: The AI system employs Bayesian Networks to construct a probabilistic model based on patient data, symptoms, and medical history. This model enables the calculation of probabilities associated with various medical conditions, offering a comprehensive and nuanced understanding of potential diagnoses. The use of Bayesian Networks aligns with the need for explainable AI in healthcare, ensuring that clinicians can comprehend and trust the system's recommendations.

Adaptability and Learning: A distinguishing feature of the AI Doctor Assistant is its capacity for continuous learning. Through real-time updates based on new patient cases and evolving medical literature, the system refines its Bayesian Network, enhancing its diagnostic accuracy over time. This adaptability addresses the dynamic nature of medical knowledge, ensuring that the AI system remains at the forefront of evidence-based practices.

Integration with Electronic Health Records (EHR): To maximize its effectiveness, the AI Doctor Assistant seamlessly integrates with Electronic Health Records (EHR). This integration facilitates the extraction of relevant patient information, creating a holistic view for the Bayesian Network to analyze. The synergy between AI and EHR streamlines the diagnostic process and ensures that the AI system operates within the established healthcare infrastructure.

Anticipated Impact: This AI-driven approach is anticipated to revolutionize medical decision-making. By providing probabilistic diagnoses, personalized treatment recommendations, and transparent reasoning, the AI Doctor Assistant has the potential to enhance the overall quality of healthcare delivery. Its real-time learning capabilities ensure that it remains adaptive to the ever-evolving landscape of medical knowledge.

the integration of an AI Doctor Assistant utilizing Bayesian

[1] Research Scholar
[2]Aarupadai Veedu Institute of Technology, Vinyka Mission’s Research Foundation, Tamilnadu , India
[3]Mailam Engineering College, Mailam, Tamilnadu , India
[1]sha.selvaraj@gmail.com[2].srajaprakash_04@yahoo.com
[3] rmmca965@gmail.com

Networks represents a significant stride toward more informed, efficient, and personalized healthcare. This study explores the foundations, capabilities, and potential impact of this innovative AI system in contributing to the advancement of medical practice.

The deployment of an Artificial Intelligence (AI) Doctor Assistant powered by Bayesian Networks is poised to revolutionize healthcare. By providing probabilistic diagnoses based on comprehensive patient data, the AI system significantly enhances diagnostic accuracy, aiding physicians in making informed decisions. Personalized treatment recommendations cater to individual patient profiles, optimizing healthcare interventions. The system's real-time learning ensures adaptability to evolving medical knowledge, maintaining its relevance in dynamic healthcare landscapes. Transparent decision-making, facilitated by Bayesian Networks, builds trust among clinicians by elucidating the rationale behind recommendations. Seamless integration with Electronic Health Records (EHR) streamlines information access, contributing to efficient and holistic patient care. This AI-driven approach not only improves resource allocation and reduces diagnostic errors but also empowers patients through informed engagement. Beyond individual care, the AI system's data analysis holds promise for research insights, potentially shaping preventive healthcare strategies and informing population health management. Challenges like ethical considerations and ongoing algorithm refinement necessitate collaborative efforts for responsible AI integration in healthcare.

2. Past Work

Esteva et al.[1] (2017) 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. In 2019, 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.In (2018) ,Beam and Kohane et al.[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. In 2018, 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. In 2017, 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 support, disease prediction, and precision medicine, while also addressing the limitations and ethical considerations. In 2019, Topol et al [6] discusses 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. In 2017, Chen et al.[7] examine the role of machine learning and prediction in medicine beyond the peak of inflated expectations. The authors discuss the challenges and opportunities associated with implementing machine learning algorithms in clinical practice, emphasizing the need for rigorous evaluation, interpretability, and integration with existing healthcare systems. In the year 2016, Gulshan et al [8] present the development and validation of a deep learning algorithm for the detection of diabetic retinopathy. The study demonstrates the effectiveness of deep learning in analyzing retinal fundus photographs to identify signs of diabetic retinopathy, offering a potential screening tool for early detection of the disease. Jiang et al.[9] provide an overview of artificial intelligence in healthcare in the year 2017, discussing its historical development, current applications, and future prospects. The article highlights the potential of AI to revolutionize healthcare delivery, including disease diagnosis, treatment optimization, and population health management. Rajkomar et al.[10] (2018) present a study on scalable and accurate deep learning with electronic health records (EHRs). The authors demonstrate the feasibility of utilizing EHR data for training deep learning models, showcasing the potential for leveraging large-scale healthcare data to improve clinical decision-making and patient outcomes. In 2017, Ravi et al. [11] provide an overview of deep learning for health informatics. The article explores the application of deep learning techniques in various areas of healthcare, including disease diagnosis, medical imaging analysis, electronic health records, and personalized medicine. It discusses the challenges and opportunities of using deep learning in health informatics and highlights its potential to revolutionize healthcare delivery. Litjens et al.[12] conduct a survey on the use of deep learning in medical image analysis. The authors review the literature and present an overview of the different deep learning architectures and algorithms applied to various medical imaging modalities. They discuss the advancements, challenges, and future directions of deep learning in medical image analysis in 2017. In 2018. Van der Schaar et al.[13] discuss the challenges of implementing artificial intelligence in healthcare. The article explores the ethical, legal, and social implications of AI adoption in healthcare settings. It emphasizes the need for careful consideration of biases, transparency, privacy, and trust in the development and deployment of AI systems. Choi et al. [14] propose a method called "Doctor AI" for predicting clinical events using recurrent neural networks. The study demonstrates the potential of utilizing machine learning algorithms to predict patient outcomes based on electronic health records. The authors showcase the accuracy and clinical utility of the proposed approach in predicting adverse events in a hospital setting in 2016. Liao et al. [15] (2019) 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. In 2015, LeCun et al. [16] provide an in-depth review of deep learning, a subfield of machine learning that utilizes artificial neural networks with multiple layers. The authors discuss the fundamental concepts, architectures, and training algorithms of deep learning models. They also highlight the impact of deep learning in various domains, including computer vision, natural language processing, and healthcare. Tang et al. [17] in 2018 present a white paper by the Canadian Association of Radiologists on the use of artificial intelligence in radiology. The paper explores the potential applications of AI in radiology, such as image interpretation, decision support, workflow optimization, and quality improvement. It discusses the challenges and opportunities associated with integrating AI into radiology practice. Bates et al.[18] discuss the role of information technology in improving patient safety. The article emphasizes the potential of technology, including AI, to enhance healthcare safety by reducing errors, improving communication, and providing decision support to healthcare providers in 2017.

3.Implementation:

The algorithmic design of an AI doctor assistant system by bayes network plays a crucial role in its ability to provide intelligent medical support. Here are some key algorithms commonly employed in AI doctor assistant systems In this chapter will discuss about the algorithm and sample work using bayes network with comparison study.

3.1 Algorithm

The questionnaire can be generated by the following method with using the delphi method.

$$h_i = l_i(wl_{i-1} + Uy_i) \tag{1}$$

Where w and U are matrixes with network weight. li is the activation hyperbolic tangent function (non linear). Based on the existing word, next work can be predicted using the following formula.

$$P(y_{ij} / y_{i-1} \dots y_i) = \frac{\exp(a_i h_j)}{\sum_{j=1}^{k} \exp(a_j h_i)} \tag{2}$$

Where $a_j \in A \,\&\, A$ is the weight of the solfmom function and all possible words is j=1,2,3…

$y_{i-1} \dots y_i$ are input sequence. in RNN of step i , hidden state is l_i then by back propagation algorithm the network are trained.

The error is calculated in the back propagation by cross entropy function by the following formula**.**

$$L(v_i, \hat{v}_i) = -v_i \log(\hat{v}_i) \tag{3}$$

Where v_i probability of predicted works over all the words and v_i is linear victor function.

Using the back probation the weight is optimized by stochastic gradient decent method which is given below.

$E : R^n \to R$ at is the vector of first derivatives of the objective function E. The gradient function is given by

$$gf(\theta)(\nabla E(\theta)) = \left[\frac{\partial E(\theta)}{\partial \theta}, \frac{\partial E(\theta)}{\partial \theta_2}, \frac{\partial E(\theta)}{\partial \theta_3} \cdots \frac{\partial E(\theta)}{\partial \theta_n} \right] \tag{4}$$

$$\eta^* = \arg \min_{\eta > 0} \varphi(\eta) \tag{5}$$

$$\varphi(\eta) = E(\theta_{now} + \eta d) \tag{6}$$

Where η^* one dimensional search of word, d is is the difference between the current word and next word. By the generalization principle we can get

$$\varphi'(\theta) = \left. \frac{dE(\theta_{now} + \eta d)}{d\eta} \right|_{\eta=0} = g^T d = g^T \|d\| \cos(\xi(\theta_{now}) < 0 \tag{7}$$

Here ξ is the difference between g and d $\xi(\theta_{now})$ is the difference between g_{now} *and* d the current word is θ_{now}

$$P(p_1.p_2 \dots p_N / q_1.q_2 \dots q_N) = \prod_{i=1}^{N} P(q_i / v, q_1.q_2 \dots q_{N-1}) \tag{8}$$

The objective validate the condition probability $P(p_1.p_2 \dots p_N / q_1.q_2 \dots q_N)$ where $q_1.q_2 \dots q_N$ is the input and the output sequence of word $p_1.p_2 \dots p_N$. Here two different RNN are used by the equation (8) trained the RNN correct sequence T given sourse of sequence R is maximal.

$$\frac{1}{R}\sum_{T,R\in R}\log\left(P\left(T/R\right)\right) \quad (9)$$

Here S is a trained set using the backpropagation the error can be calculated and the optimum solution can by obtained by stochastic gradient method (3).

To get the generated predicted words as a output by using the Roulete Wheel solution [1998]. By this method words can be generated by the probability softmax function given below (10).

$$\hat{T} = \arg MaxP\left(T/R\right) \quad (10)$$

Where T is the target sequence of words and R is the source of sentence. Text to voice can done by the following Deep Learning Model.

Based on the data set its related to heart issues and the symptoms are represented as a node. The nodes can able to from the network and form conditions probability table.

The bayes network in a graphical model represents the relationship between the variables.

Let $A = \{a_1, a_2, ..a_n\}$ set of variables in the bayes network. The network is based on the following conditions.

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

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

- The joint distribution over A represent CPT of the variables.Here Using the property of morkov blankets is discussed as follows.

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

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

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

$$(DR)\,Diagonesis\ \mathrm{Re}\,sult = \arg\underset{d\in D}{Max}\left(D = d / Mb(Diseases)\right) \quad (14)$$

- Using the markov blankets, the nodes of bayes network then the reset as follows. Here the Markov blanks is the subset of the symptoms.

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

- By the markov blanket property

$$P\left(D / MB(D)\right) = P\left(D / c_i..c_n\right) = \frac{P(D, c_i..c_n)}{P(c_1..c_n)} \quad (16)$$

$$\frac{P(D, c_i..c_n)}{P(c_1..c_n)} = KP\left(D / c_i..c_n\right) =$$

$$KP\left(D,\ c_1..c_n\right) = K\prod_{a_i\in(D,c_i...c_n)} P(a_i / \pi(a_i))$$

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

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

Using the equation(16) and (17) will get the suggestion to the doctor for the better results. In this sample work we used the bayes network with morkov blankets. The identified attributes are given below, which are represented as nodes in the Bayes network. The attributes represented as nodes.

- Age: Represents the age of the patient.
- Sex: Represents the gender of the patient.
- Chest Pain Type: Represents the type of chest pain experienced by the patient.
- Resting Blood Pressure: Represents the resting blood pressure of the patient.
- Cholesterol: Represents the cholesterol level of the patient.
- Fasting Blood Sugar: Represents the fasting blood sugar level of the patient.
- Electrocardiographic Results: Represents the electrocardiographic results of the patient.
- Maximum Heart Rate Achieved: Represents the maximum heart rate achieved by the patient during exercise.
- Exercise Induced Angina: Represents whether the patient experiences angina during exercise.

- ST Depression Induced by Exercise: Represents the ST depression induced by exercise relative to rest.
- Slope of the Peak Exercise ST Segment: Represents the slope of the peak exercise ST segment.
- Number of Major Vessels: Represents the number of major vessels colored by fluoroscopy.
- Thallium Stress Test: Represents the results of the thallium stress test.
- 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 coditional 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. After completing the processes the information of the patient data are stored with in secured manner.

Table- 1 Comparison Study

S.No	AI doctor	Traditional
1	High accuracy through probabilistic 520odelling, leveraging Bayesian Networks.	Dependent on individual clinician expertise, may vary in accuracy.
2	Rapid data processing facilitates timely insights	Time-intensive processes, potential delays in decision-making.
3	Real-time updates and learning from new data.	Relies on periodic training and updates.
4	Transparent decision-making with clear probabilistic reasoning.	Decision-making may lack transparency
5	Seamless integration for comprehensive patient records.	Limited integration, potential data silos
6	Optimizes resource allocation through prioritization	Not optimized
7	Promotes patient engagement and individualized care.	Limited patient involvement in decision-making
8	Contributes to research with data-driven insights	Limited data-driven insights for research
9	Mitigates cognitive biases, potentially reducing errors	Susceptible to cognitive biases, potential for diagnostic errors.

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 the following table-6. Here the scale is fixed by making the feedback system questioners for the research purpose only.

Table 2. Units for magnetic properties

Aspects	A I Doctor Assistant	Existing Traditional method
Decision-making capabilities	9	6
Diagnoses and treatment support	8	7
Data analysis and processing	10	5
Patient interaction and engagement	9	4
Integration of medical research	9	6
Speed and efficiency of workflows	9	5
Continual learning and improvement	9	3
Cost-effectiveness	8	6
Challenges and ethical considerations	9	6

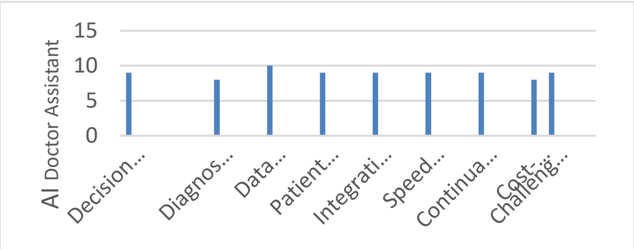

Fig-1

From the table and figure-1,we can observe that integration of an Artificial Intelligence (AI) Doctor Assistant utilizing Bayesian Networks presents a paradigm shift in healthcare, offering a range of advantages over traditional systems. The inherent strengths of Bayesian Networks, combined with AI capabilities, contribute to a more efficient, accurate, and patient-centric healthcare ecosystem.

The Bayesian approach enables the AI Doctor Assistant to provide high diagnostic accuracy by modeling complex relationships among medical variables and incorporating probabilistic reasoning. This ensures a more nuanced understanding of patient conditions, facilitating tailored and personalized treatment recommendations based on individual health profiles.

The efficiency gains achieved through rapid data processing and real-time learning contribute to timely insights and adaptive decision-making. This not only optimizes resource allocation but also addresses the dynamic nature of medical knowledge, ensuring the system remains at the forefront of evidence-based practices.

Transparency and explainability, hallmarks of Bayesian Networks, foster trust among healthcare professionals by providing clear insights into the reasoning behind diagnostic and treatment recommendations. The integration with Electronic Health Records (EHR) further streamlines the decision-making process, creating a comprehensive and accessible repository of patient information.

Despite these advancements, challenges such as ethical considerations, data privacy, and the need for ongoing validation and improvement of AI algorithms persist. Collaborative efforts among technologists, healthcare professionals, and policymakers are essential to address these challenges responsibly and ensure the ethical and secure implementation of AI Doctor Assistants in the healthcare landscape.

4. Conclusion

In conclusion, the Artificial Intelligence Doctor Assistant employing Bayesian Networks stands at the forefront of healthcare innovation. Its probabilistic modeling ensures high diagnostic accuracy and personalized treatment recommendations, fostering more effective and tailored patient care. The system's efficiency, real-time learning, and seamless integration with Electronic Health Records enhance decision-making, optimizing resource allocation. The transparent and explainable nature of Bayesian Networks in stills trust among healthcare professionals. Despite these advancements, ethical considerations and ongoing validation remain critical for responsible implementation. This AI-driven approach holds the potential to revolutionize healthcare, offering a glimpse into a future where technology and human expertise harmoniously contribute to superior patient outcomes.

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