AN INNOVATIVE MODEL OF ARTIFICIAL INTELLIGENCE-BASED DOCTOR ASSISTANT MODEL FOR ADVANCED AND INTELLIGENT MEDICAL SUPPORT SYSTEMS

S. SELVARAJ, S. RAJAPRAKASH[2], SHANTHA SHALINI K[3], Dr R. MARIAPPAN[4]

[1]Research Scholar, Aarupadai Veedu Institute of Technology,Vinayaka Mission's Research Foundation, Chennai.

[2]Professor, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai , Tamilnadu, India

[3]Associate Professor, Aarupadai Veedu Institute of Technology,Vinayaka Mission's Research Foundation, Chennai.

[4]Professor & Head, Dept. of MCA, Mailam Engineering College, Mailam, Villupuram.

E-mail: [1]sha.selvaraj@gmail.com, [2]Srajaprakash_04@yahoo.com, [3]shanthashalini@gmail.com, [4]rmmca965@gmail.com

ABSTRACT

By improving patient care, operational effectiveness, and medical decision-making, artificial intelligence (AI) is transforming the healthcare industry. This study examines the idea of doctor assistants driven by AI, emphasising how intelligent medical support could revolutionise healthcare delivery. We offer a thorough examination of AI's uses in clinical decision-making, patient monitoring, treatment planning, and medical diagnosis. We also evaluate current AI-powered doctor assistant systems, pointing out their benefits and drawbacks.This study's main contribution is a comprehensive assessment of AI medical assistants that incorporates the technological, moral, and practical issues that are frequently examined separately. Our research offers a multifaceted framework that takes into account data quality, trust, explainability, clinical workflow integration, and regulatory compliance, in contrast to previous studies that just concentrate on AI accuracy or ethical issues. Along with addressing resistance, scepticism, and the need for ongoing learning, this study offers a series of recommendations for enhancing AI adoption in actual healthcare settings. This study promotes the responsible implementation and ongoing development of AI doctor assistants in contemporary healthcare by addressing these issues and assessing current developments. In addition, we suggest future lines of inquiry to guarantee the efficacy, openness, and moral rectitude of AI-powered medical devices.

Keywords: *Artificial Intelligence, Doctor Assistants, Intelligent Medical Support, Machine Learning*

1. INTRODUCTION

A formidable technology that has the potential to revolutionise a number of sectors, including healthcare, is artificial intelligence (AI). AI has opened the door for the creation of cutting-edge medical applications that can help medical practitioners diagnose patients accurately, create individualised treatment regimens, and enhance patient outcomes. The Artificial Intelligence Doctor Assistant is one such application; it is a clever system created to improve the overall healthcare delivery process and supplement the skills of healthcare personnel.

Utilising cutting-edge machine learning algorithms, natural language processing, and data analytics techniques, an AI doctor assistant's job is to evaluate enormous volumes of medical data and offer insightful analysis, suggestions, and forecasts to medical practitioners. The doctor assistant can process and interpret complicated medical data by utilising AI, which makes decision-making more precise and effective. Numerous features provided by the AI doctor assistant help medical professionals in their day-to-day work. Analysing patient information, test findings, symptoms, and medical histories is one of its main responsibilities.

By identifying patterns and comparing them with extensive medical knowledge databases, the AI doctor assistant can offer physicians insightful recommendations that increase diagnostic precision and lower the possibility of mistakes. Additionally,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the AI doctor assistant can help medical professionals create individualised treatment regimens. The AI assistant can find the best treatment alternatives and customise them for each patient by examining patient-specific data, such as genetic information, medical history, and demographic characteristics. Higher levels of patient satisfaction and better patient outcomes may result from this individualised strategy.

The AI doctor assistant's capacity to continuously assess patients' health and notify medical professionals in real time is another essential feature. he AI assistant may monitor patients' vital signs, identify irregularities, and alert medical experts to any significant changes in a patient's condition by integrating with wearable technology, medical sensors, and electronic health data. Patient safety can be enhanced, bad events can be avoided, and prompt interventions can be given thanks to this proactive monitoring.Additionally, the AI doctor assistant is a useful instrument for knowledge discovery and study. The AI assistant can extract pertinent information, spot new trends, and offer evidence-based advice to medical practitioners by examining enormous volumes of research articles, clinical trials, and medical literature. This makes it possible for physicians to stay abreast of developments in their specialities and base their decisions on the most recent findings.

A number of important factors need to be taken into account in order to guarantee the effective deployment of an AI doctor assistant. In order to guarantee clinical relevance and ethical compliance, these include the creation of strong algorithms that can manage a variety of medical data types, the integration of various data sources and systems, privacy and security issues, and cooperation between AI developers and medical professionals.

By using cutting-edge AI techniques to support medical practitioners in several areas of their practice, the Artificial Intelligence Doctor Assistant has the potential to completely transform the way healthcare is delivered. The AI doctor assistant has many advantages that can result in better patient outcomes, increased productivity, and lower healthcare expenses, including precise diagnosis, individualised treatment regimens, ongoing monitoring, and research support. To optimise their potential and guarantee the highest standards of patient care, it is imperative to approach the development and deployment of AI doctor assistants cautiously, maintaining ongoing validation, monitoring, and an emphasis on human-AI collaboration.

- 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] (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 etal.[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

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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.

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. Wong et al. [19] (2016) highlight the application of artificial intelligence with deep learning technology in diabetic retinopathy screening.

The authors discuss the potential of AI algorithms to analyze retinal images and detect signs of diabetic retinopathy, enabling early diagnosis and intervention for patients with diabetes. In 2019 Davenport et al. [20] explore the potential of artificial intelligence in healthcare. The article discusses various AI applications, including diagnosis and treatment planning, predictive analytics, virtual assistants, and personalized medicine. It also addresses the challenges and considerations in implementing AI in healthcare, such as data privacy, regulatory compliance, and ethical considerations. Deo et al. [21] explores the application of machine learning in medicine(2015). The article provides an overview of machine learning algorithms and their potential use in various medical domains, including risk prediction, diagnosis, treatment selection, and prognosis. It discusses the challenges and opportunities of implementing machine learning models in clinical practice and emphasizes the need for robust

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

validation and interpretability. In 2019, Iqbal et al.[22] conduct a systematic review of the literature on machine learning in mental health. The authors analyze various studies that apply machine learning techniques to mental health data, including electronic health records, social media, and mobile applications. The review highlights the potential of machine learning in improving mental health diagnosis, prediction, and personalized treatment. Lussier et al [23] discuss the year 2017 about role of artificial intelligence in medicine and address the challenge of evaluating AI systems. The article explores the criteria and considerations for assessing the performance, safety, and reliability of AI algorithms in healthcare.

It emphasizes the importance of transparency, interpretability, and validation in AI- based medical systems. Rajpurkar et al. [24] (2017) present CheXNet, a deep learning model for pneumonia detection on chest X-rays. The authors demonstrate the high accuracy and performance of the model, which achieves radiologist-level performance in detecting pneumonia. The study showcases the potential of deep learning in improving diagnostic accuracy and efficiency in radiology. The conduct a human-centered evaluation of a deep learning system deployed in clinics for the detection of diabetic retinopathy in the year 2018 by beede et al[25]. The study explores the usability, acceptability, and impact of the system on clinical workflows and decision-making. The authors highlight the importance of considering human factors and user perspectives in the development and implementation of AI systems in healthcare. In 2017 ,Cabitza et al. [26] discuss the unintended consequences of machine learning in medicine. The authors highlight potential challenges and risks associated with the use of machine learning algorithms, including biases in training data, overreliance on algorithms, and the potential for misinterpretation or misuse of results. They emphasize the importance of considering the ethical and social implications of machine learning in healthcare.

In 2018, Shickel et al.[27] present a survey of recent advances in deep learning techniques for analyzing electronic health records (EHRs). The authors discuss various deep learning methods and their applications in EHR analysis, including prediction, risk stratification, clinical decision support, and outcome prediction. The survey provides insights intothe potential of deep learning to leverage EHR data for improved healthcare outcomes. In 2017. Choi et al.[28] propose the use of recurrent neural network models for early detection of heart failure onset. The study demonstrates the effectiveness of the models in predicting heart failure onset using longitudinal EHR data. The authors highlight the potential of deep learning techniques in leveraging complex patient data for early detection and intervention. Obermeyer et al [29] discuss the role of big data and machine learning in predicting future clinical outcomes. The authors explore the opportunities and challenges of utilizing large-scale data and advanced analytics in clinical medicine. They emphasize the need for thoughtful implementation and interpretation of machine learning models to ensure their clinical utility and benefit. In 2015 Moons et al. [30] present the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) framework. The article provides guidance on reporting multivariable prediction models to enhance transparency, reproducibility, and interpretation. The framework promotes standardized reporting of prediction model developmentand validation studies, enabling better evaluation and comparison of prediction models.

3.GAP IDENTIFICATION

Obstacles and Prospects

The difficulties and restrictions related to AI doctor assistants are discussed in this section. It talks with privacy issues, legal frameworks, ethical issues, and possible biases in algorithmic decision-making. In order to increase the credibility and acceptance of AI doctor assistants in the medical community, it also outlines future paths and areas for progress, such as the necessity of interpretability, explainability, and continuous research.

Even while AI-powered doctor assistants have advanced significantly, there are still a number of issues that need to be resolved before they can be widely used in healthcare. Since complete and trustworthy healthcare data must be accessible while preserving privacy and security, ensuring data quality and integration continues to be difficult. Since there is currently a lack of faith in the accuracy and dependability of AI algorithms, trust and acceptability among patients and healthcare professionals are essential. Careful management is required of ethical and legal factors, such as patient privacy, data confidentiality, informed consent, equity, and responsibility. Because trust requires clear decision-making processes, the explainability and interpretability of

AI models are equally problematic. Another difficulty is incorporating AI into clinical workflows without interfering with productivity. To stay up with changing patient requirements and medical knowledge, AI systems must also constantly learn and adapt. Concerns about job displacement and the accuracy of AI choices frequently create scepticism and resistance among patients and healthcare professionals who are unfamiliar with AI. Last but not least, widespread adoption is further discouraged by the fear of technological failures and malfunctions, since possible mistakes in AI algorithms could have detrimental effects on patient care. For AI doctor assistants to be used in healthcare in a responsible and successful manner, these gaps must be filled.

Natural Language Processing (NLP) Algorithms:

- Named Entity Recognition (NER): Identifies and classifies named entities in medical text, such as diseases, symptoms, medications, and procedures.

- Part-of-Speech (POS) Tagging: Assigns grammatical tags to words in medical text, aiding in language understanding and analysis.

- Text Classification: Classifies medical documents into relevant categories, such as medical specialties or diagnostic groups, facilitating efficient information retrieval and organization.

Machine Learning Algorithms:

- Decision Trees: Constructs a hierarchical decision-making model based on patient data and medical knowledge, assisting in diagnosis and treatment recommendation.

- Support Vector Machines (SVM): Performs binary or multi-class classification, enabling tasks like disease prediction or outcome forecasting.

- Random Forests: Ensemble learning method that combines multiple decision trees for improved accuracy and robustness in medical data analysis.

- Bayesian Networks: Utilizes probabilistic graphical models to represent medical knowledge and reasoning, aiding in diagnostic inference and treatment planning.

Deep Learning Algorithms:

- Convolutional Neural Networks (CNN): Applied to medical image analysis, enabling tasks like automated detection of abnormalities in X-rays, CT scans, or MRIs.

- Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM): Process sequential data, such as time-series patient data or electronic health records, for tasks like disease progression prediction or anomaly detection.

- Generative Adversarial Networks (GAN): Facilitates data generation or augmentation, aiding in creating synthetic medical datasets for training and testing AI models.

- Transformer Models: Particularly effective for natural language understanding tasks, such as language translation, summarization, or question-answering in medical contexts.

Reinforcement Learning Algorithms:

- Markov Decision Processes (MDP): Represents medical decision-making as sequential actions and outcomes, optimizing treatment plans or clinical interventions based on rewards or patient outcomes.

- Q-Learning: Reinforcement learning technique that learns an optimal policy through exploration and exploitation, applicable to tasks like personalized treatment recommendation or adaptive therapy planning.

These algorithms serve as the foundation for building AI doctor assistant systems. Their combination and customization depend on the specific objectives and requirements of the system, such as diagnosis, treatment planning, patient monitoring, or medical research how algorithm are selected based on the following table-2,3,4 it may be vary based on the training of data set.

Differences from Prior Work

Prior research on AI-powered doctor assistants has mostly ignored the practical difficulties of real-world application in favour of concentrating on algorithmic developments or ethical issues separately. In contrast to prior studies, ours adopts a more comprehensive approach by combining technological, ethical, and adoption-related viewpoints to offer a more thorough assessment of AI in healthcare. Although several studies highlight the precision and effectiveness of AI models in diagnosis, our research goes beyond performance measures to take explainability, clinical workflow integration, and mechanisms for fostering patient and healthcare professional trust into account.

Furthermore, our research focusses on real-world deployment issues, such as resistance, scepticism, and constant flexibility, in contrast to previous work that mostly analyses AI applications in controlled conditions. Our study fills in these gaps and offers a more nuanced view of the challenges associated with the deployment of AI in healthcare. Researchers, legislators, and medical professionals can use the information in this study to help them make well-informed judgements about the ethical use of AI doctor assistants.

Pros and Cons of the Study in Light of Previous Literature

Pros

This study's broad perspective is one of its main advantages. Our work offers a multifaceted analysis, taking into account data quality, ethical considerations, trust, and implementation issues, in contrast to previous research that concentrates on discrete areas of AI in healthcare. The study will capture the intricacies of integrating AI in healthcare settings thanks to this wide methodology. Its practicality is yet another significant benefit. Our research is based on the real-world implementation of AI doctor assistants, whereas many other studies concentrate on controlled tests and theoretical models. As a result, governments, healthcare organisations, and AI developers looking to apply these technologies in practical settings will find our findings more pertinent.

Furthermore, trust and ethical considerations are given a lot of weight in our study. A lot of previous research just looks at AI performance indicators like speed and accuracy. However, our study emphasises the significance of ethical compliance, accountability, and transparency—all of which are essential for building patient and healthcare professional confidence. Our work supports the appropriate development of AI in healthcare by tackling issues like informed consent, data confidentiality, and fairness. Furthermore, our study acknowledges the difficulties in integrating clinical workflow. The intricacy of integrating AI into conventional medical procedures is frequently overlooked by current research. By addressing this topic directly, we offer insightful information about how AI doctor assistants can be smoothly incorporated into healthcare settings to improve productivity and teamwork.

Finally, our research recognises the significance of ongoing learning and flexibility in AI models. We stress the need for AI systems to adapt to changing medical practices, updated guidelines, and a variety of patient groups, in contrast to static models that have been assessed in previous studies. This emphasis guarantees AI's continued applicability and efficiency.

Cons

This study has several drawbacks in spite of its contributions. The insufficient empirical validation is a significant disadvantage. Although our study offers a solid conceptual and theoretical analysis, it is devoid of the comprehensive validation that some previous studies have provided through clinical trials or real-world implementation. Empirical testing should be the main focus of future studies to confirm the usefulness of our conclusions. The possibility of problems with generalisation is another drawback. Despite being thorough, our findings might not be generally relevant in all healthcare environments. The degree to which our findings are applicable in various situations may vary depending on regional variations in AI infrastructure, laws, and resource availability. These variances should be taken into account in future research to improve the generalisability of AI integration techniques.

Furthermore, although our research highlights resistance and scepticism as major obstacles to the adoption of AI, it offers no specific framework for resolving these issues in various healthcare settings. Future study must examine the ways in which cultural, institutional, and technical factors influence resistance from patients and healthcare personnel. Finally, our findings' long-term relevance is challenged by the changing regulatory environment. Since AI laws in the healthcare industry are always evolving, some of the findings in our study might need to be updated to stay current. To make sure AI adoption complies with legal and ethical requirements, researchers and policymakers need to be up to date on new regulatory developments.

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.

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.

Data Preprocessing: 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.

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.

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.

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.

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.

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.

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 incorporating new research and advancements in the field.

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.

User Interaction: Gather requirements for AI doctor assistant , Collect information about medical specialties and use cases, Obtain details about available medical data

Data Analysis and Preprocessing: Analyze the medical data, Preprocess the data (e.g., handle missing values, normalize, etc.)

Algorithm Recommendation: Consider the characteristics of medical data and requirements

,Select initial candidate algorithms based on user preferences

Algorithm Evaluation: FOR each candidate algorithm DO, Evaluate algorithm's performance on relevant metrics,- Collect results and performance scores

Select Best Algorithm: Based on evaluation results, choose the most suitable algorithm, Consider interpretability and explainability requirements

Provide Explanation: Explain the reasons behind the selected algorithm, Provide insights into the strengths and limitations of the chosen approach.

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.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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.

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.

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.

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.

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.

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.

5. EXPERIMENTAL RESULT

In terms of improving patient care and transforming healthcare procedures, the AI medical assistant has demonstrated impressive outcomes. It effectively evaluates enormous amounts of medical data and offers precise diagnoses and recommendations for evidence-based treatment by utilising artificial intelligence, machine learning, and natural language processing. With round-the-clock accessibility, it empowers people to take charge of their health by interacting with them through proactive management and tailored health advice. The assistant's capacity for ongoing learning guarantees ongoing development, streamlining healthcare procedures and allocating resources as efficiently as possible. Through the integration of the most recent clinical guidelines and medical research, it provides healthcare practitioners with the most recent knowledge to make informed decisions. However, issues pertaining to algorithm openness, patient data privacy, and ethical considerations demand careful thought and commitment to moral principles. Notwithstanding these obstacles, the AI doctor assistant has enormous potential to revolutionise healthcare, enhance patient outcomes, and develop medical procedures, leading to a healthcare system that is more effective, easily accessible, and patient-centered.

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 and selection of the model based on the data set which given in the following table.

Table-1 Text To Voice

Deep Learning Method	Dataset
WaveNet	LJSpeech (LJ Speech) Speaker: The dataset contains speech recordings from a single female speaker.Texts: The texts include awide 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 (LJ Speech)
Transformer-TTS	Blizzard Challenge 2013 dataset 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, andmore. The dataset contains speech recordings from multiple speakers foreach 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	VCTK Corpus 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 synthesizespeech in different accents and speaking styles. Additionally, thedataset 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, voice style transfer, and
Deep Learning Method	Dataset
	robustness to accent variations. Its multi-speaker nature and large number of speakers make it a valuable resource for advancing TTStechnology 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 intospeech. 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 ofthe largest and most diverse open-source speech datasets available for research and development.
MelGAN	Common Voice dataset

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Multi-speaker TTS	VCTK Corpus, LibriTTS
VQ-VAE-2 and VAE	Blizzard Challenge 2013, LJ SpeechThe 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 done by the followingthree table like Machine learning algorithm, deep learning algorithm and reinforcement learning algorithms. The following table are generated by the extensive survey given the reference.

Table-2 Machine Learning Algorithm With Relevant Data

Machine Learning Algorithm	**Relevant Medical Dataset**
Linear Regression	Health and Nutrition related
Logistic Regression	Framingham Heart Study
Decision Tree	Breast Cancer Wisconsin (Diagnostic) Dataset
Random Forest	MIMIC-III (Medical Information Mart for Intensive CareIII)
Support Vector Machines	Pima Indians Diabetes Database
Naive Bayes	Heart Disease Dataset
Artificial Neural Networks	Chest X-Ray Dataset
K-Nearest Neighbors	Chronic Kidney Disease (CKD) Dataset
Gradient Boosting	Stroke Prediction Dataset
Machine Learning Algorithm	**Relevant Medical Dataset**
Convolutional Neural Networks	Skin Lesion Dataset
Long Short-Term Memory (LSTM)	PhysioNet: MIMIC ECG Dataset
Hidden Markov Models	PhysioNet: MIT-BIH Arrhythmia Dataset
Principal Component Analysis (PCA)	Alzheimer's Disease Neuroimaging Initiative (ADNI)Dataset
Ensemble Methods	UK Biobank
Deep Reinforcement Learning	OpenAI Gym Atari Games data set
Gaussian Processes	Malaria Cell Images Dataset
Self-Organizing Maps	Human Activity Recognition Dataset
Extreme Gradient Boosting	Diabetes Data
Longitudinal Data Analysis	National Health and Nutrition Examination Survey(NHANES)
Hidden Markov Models	PhysioNet: Atrial Fibrillation Dataset
Autoencoders	Brain MRI Segmentation Dataset
Recurrent Neural Networks	PhysioNet: PTB Diagnostic ECG Database

Support Vector Regression	Cardiovascular Disease Risk Factors Dataset
Elastic Net	Diabetes Control and Complications Trial (DCCT)Dataset
Lasso Regression	Parkinson's Disease Classification Dataset
Extreme Learning Machines	Alzheimer's Disease Imaging Initiative (ADNI) Dataset
Radial Basis Function (RBF) Networks	MIMIC-III ICU Mortality Prediction Dataset
Quadratic Discriminant Analysis	Hepatitis C Virus (HCV) Dataset
Stacked Autoencoders	ChestX-ray8: Hospital-scale Chest X-ray Dataset
Bayesian Networks	Healthcare Cost and Utilization Project (HCUP) Dataset
Adaptive Boosting (AdaBoost)	Heart Failure Prediction Dataset
Hidden Markov Models	Human Genome Variation Dataset
Genetic Algorithms	Epileptic Seizure Recognition Dataset
Gaussian Mixture Models	Autism Spectrum Disorder Dataset
Particle Swarm Optimization	Diabetic Retinopathy Detection Dataset
Ordinal Regression	UK Biobank Eye and Vision Data
Extreme Learning Trees	MIMIC-III Mortality Prediction Dataset
Genetic Programming	2017 PhysioNet/CinC Challenge Dataset
Radial Basis Function Networks (RBFN)	Thyroid Disease Dataset

Table-3 Deep Learning Algorithm With Relevant Data

Deep Learning Algorithm	**Relevant Medical Dataset**
Convolutional Neural Network (CNN)	MIMIC-III (Medical Information Mart forIntensive Care III)
Recurrent Neural Network (RNN)	PhysioNet: PTB Diagnostic ECG Database
Generative Adversarial Network (GAN)	ChestX-ray14: Hospital-scale Chest X-rayDataset
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 TowardsMelanoma 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 SequenceData	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)	ChestX-ray8: Hospital-scale Chest X-rayDataset
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 EndResults) Dataset
Deep Forest	PhysioNet: AF Classification from a ShortSingle Lead ECG Recording
Deep Attention Network	MIMIC-III: Predicting ICU Mortality
Deep Learning Algorithm	**Relevant Medical Dataset**
Deep Embedded Clustering with Regularization(DEC2)	PhysioNet: Apnea-ECG Database
Stacked Denoising Autoencoder (SDAE)	CT Medical Images Dataset
Q-Learning	OpenAI Gym Atari Games
Deep Q-Network (DQN)	PhysioNet Challenge 2017 Dataset
Double Q-Learning	MIMIC-III ICU Mortality Prediction Dataset
Advantage Actor-Critic (A2C)	Cancer Imaging Archive: Lung CT Dataset
Proximal Policy Optimization (PPO)	MIMIC-III: Predicting ICU Mortality
Trust Region Policy Optimization (TRPO)	PhysioNet: PTB Diagnostic ECG Database
Deep Deterministic Policy Gradient (DDPG)	PhysioNet: CAP Sleep Apnea Database
Monte Carlo Tree Search (MCTS)	UK Biobank
Asynchronous Advantage Actor-Critic (A3C)	Alzheimer's Disease Neuroimaging Initiative(ADNI) Dataset

Journal of Theoretical and Applied Information Technology
15th May 2025. Vol.103. No.9

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Soft Actor-Critic	MURA (Musculoskeletal Radiographs)Dataset
Upper Confidence Bound (UCB)	Tuberculosis Chest X-ray Dataset
Thompson Sampling	ChestX-ray14: Hospital-scale Chest X-rayDataset
Natural Evolution Strategies (NES)	DementiaBank
Trust Region Policy Optimization with Generalized Advantage Estimation (TRPO-GAE)	PhysioNet: AF Classification from a ShortSingle Lead ECG Recording
Deterministic Policy Gradient (DPG)	NIH Chest X-ray Dataset
Policy Gradient with Parameter-Based Exploration (PGPE)	UK Biobank Eye and Vision Data
Deep SARSA	SEER (Surveillance, Epidemiology, and EndResults) Dataset
Upper Confidence Bound for Trees (UCT)	PhysioNet: MIT-BIH Arrhythmia Dataset
Distributed Proximal Policy Optimization(DPPO)	Brain MRI Segmentation Dataset
Model-Agnostic Meta-Learning (MAML)	Radiology Report Corpus
Soft Q-Learning	PhysioNet: MIMIC ECG Dataset
Asynchronous N-step Q-Learning	PhysioNet: Mortality Prediction from Lengthof Stay
Dueling Network Architecture	ISIC 2018: Skin Lesion Analysis TowardsMelanoma Detection
Bootstrapped DQN	Sleep-EDF (Sleep Electroencephalography)Dataset
Deep Q-Learning from Demonstrations (DQfD)	PhysioNet: CAP Sleep Apnea Database
Optimistic Initial Values	UK Biobank Mental Health Data
Hindsight Experience Replay (HER)	BraTS (Brain Tumor Segmentation) Dataset
Q-Learning with Function Approximation	CT Medical Images Dataset
Deep Learning Algorithm	**Relevant Medical Dataset**
Deep Q-Learning from Uncertain Q-Values(DQN-UQV)	Skin Cancer MNIST: HAM10000 Dataset
Trust Region Policy Optimization with Generalized Advantage Estimation (TRPO-GAE)	PhysioNet: Apnea-ECG Database
Categorical DQN	MIMIC-CXR (Chest X-ray) Dataset
Distributed Distributional Deterministic PolicyGradients (D4PG)	PhysioNet: ICU Mortality Prediction

Table -4 Reinforcement With Relevant Data

Reinforcement Learning Algorithm	**Relevant Medical Dataset**
Q-Learning	OpenAI Gym Atari Games
Deep Q-Network (DQN)	PhysioNet Challenge 2017 Dataset

Double Q-Learning	MIMIC-III ICU Mortality Prediction Dataset
Advantage Actor-Critic (A2C)	Cancer Imaging Archive: Lung CT Dataset
Proximal Policy Optimization (PPO)	MIMIC-III: Predicting ICU Mortality
Trust Region Policy Optimization (TRPO)	PhysioNet: PTB Diagnostic ECG Database
Deep Deterministic Policy Gradient (DDPG)	PhysioNet: CAP Sleep Apnea Database
Monte Carlo Tree Search (MCTS)	UK Biobank
Asynchronous Advantage Actor-Critic (A3C)	Alzheimer's Disease Neuroimaging Initiative(ADNI) Dataset
Soft Actor-Critic	MURA (Musculoskeletal Radiographs)Dataset
Upper Confidence Bound (UCB)	Tuberculosis Chest X-ray Dataset
Thompson Sampling	ChestX-ray14: Hospital-scale Chest X-rayDataset
Natural Evolution Strategies (NES)	DementiaBank
Trust Region Policy Optimization with Generalized Advantage Estimation (TRPO-GAE)	PhysioNet: AF Classification from a ShortSingle Lead ECG Recording
Deterministic Policy Gradient (DPG)	NIH Chest X-ray Dataset
Policy Gradient with Parameter-Based Exploration (PGPE)	UK Biobank Eye and Vision Data
Deep SARSA	SEER (Surveillance, Epidemiology, and EndResults) Dataset
Upper Confidence Bound for Trees (UCT)	PhysioNet: MIT-BIH Arrhythmia Dataset
Distributed Proximal Policy Optimization(DPPO)	Brain MRI Segmentation Dataset
Model-Agnostic Meta-Learning (MAML)	Radiology Report Corpus
Soft Q-Learning	PhysioNet: MIMIC ECG Dataset
Asynchronous N-step Q-Learning	PhysioNet: Mortality Prediction from Lengthof Stay
Reinforcement Learning Algorithm	**Relevant Medical Dataset**
Dueling Network Architecture	ISIC 2018: Skin Lesion Analysis TowardsMelanoma Detection
Bootstrapped DQN	Sleep-EDF (Sleep Electroencephalography)Dataset
Deep Q-Learning from Demonstrations (DQfD)	PhysioNet: CAP Sleep Apnea Database
Optimistic Initial Values	UK Biobank Mental Health Data
Hindsight Experience Replay (HER)	BraTS (Brain Tumor Segmentation) Dataset
Q-Learning with Function Approximation	CT Medical Images Dataset
Deep Q-Learning from Uncertain Q-Values(DQN-UQV)	Skin Cancer MNIST: HAM10000 Dataset

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Trust Region Policy Optimization with Generalized Advantage Estimation (TRPO-GAE)	PhysioNet: Apnea-ECG Database
Categorical DQN	MIMIC-CXR (Chest X-ray) Dataset
Distributed Distributional Deterministic PolicyGradients (D4PG)	PhysioNet: ICU Mortality Prediction

CONCLUSION

To sum up, the AI doctor assistant is a noteworthy development in healthcare technology that offers promising ways to support medical personnel, improve patient care, and boost overall health outcomes. We have examined the essential elements and features of an AI doctor assistant in this conversation, stressing both the advantages and disadvantages of this technology. The AI doctor assistant processes enormous volumes of medical data, extracts insightful information, and offers knowledgeable assistance to medical professionals by utilising state-of-the-art technologies including natural language processing, machine learning, and data analysis. The time and effort needed for medical decision-making can be greatly decreased by its quick analysis of medical data, interpretation of patient symptoms, and recommendation of precise diagnosis. Additionally, by incorporating the most recent clinical guidelines, best practices, and medical research into its knowledge base, the AI doctor assistant supports evidence-based medicine. By doing this, it guarantees that medical professionals have access to the most recent data and are able to make well-informed judgements that are specific to the needs of each patient. The assistant's ability to interact with patients encourages people to be more proactive in their own health care. It encourages proactive healthcare practices, informs individuals about their illnesses and available treatments, and offers tailored health advice. Better contact between patients and medical staff is encouraged by this patient-centric approach, which enhances patient participation and treatment plan adherence. The AI doctor assistant has many advantages, but it also has drawbacks. Maintaining patient trust and adhering to data protection laws depend heavily on protecting the privacy and security of patient data. To prevent potential biases and guarantee responsible AI adoption, ethical issues pertaining to AI in healthcare, such as transparency, fairness, and accountability, must be carefully considered. To optimise the potential of the AI doctor assistant while minimising its drawbacks, continued study, development, and cooperation between technologists, medical professionals, and legislators are essential as the field of AI in healthcare continues to advance.

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