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The Role of Artificial Intelligence in US Healthcare Information

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Abstract: ***This study looks into how artificial intelligence (AI) is starting to change the way that healthcare information management is done in the US. Significant progress has been made in the application of AI technology in healthcare, which has revolutionized the collection, analysis, and use of patient data. AI systems improve medical decisions, diagnosing accuracy, and patient care overall by utilizing machine learning methods and information analytics. This paper explores the effects of artificial intelligence (AI) on digital health records (EHRs), explaining how these smart systems improve interoperability, save data entry time, and enable smooth information sharing across healthcare providers. Moreover, predictive analytics driven by AI is investigated as a crucial element in recognizing possible health hazards, permitting preemptive measures and customized therapy regimens. The difficulties and moral issues surrounding the application of AI to healthcare information management are also covered in this study. Concerns about bias in algorithms, data privacy, and the necessity of strong legal frameworks are discussed in order to guarantee responsible AI use in the healthcare industry. The paper uses case studies and actual data to demonstrate the useful uses of AI for healthcare, highlighting both promising new applications and areas that could use further development. Understanding the changing role of AI in medical records management is crucial for stakeholders, elected officials, and healthcare providers alike as the US continues to negotiate the complexity of its healthcare system. This study adds important new understandings to the current artificial intelligence-driven change of healthcare delivery.***

Keywords: artificial intelligence, healthcare information management, electronic health records, predictive analytics, ethical concerns

1. Introduction

The way information is maintained and used is being revolutionized by the introduction of neural networks (AI) into the health care sector. AI's function in managing healthcare data is becoming more and more important in the United States, since the healthcare sector is complex and dynamic. This introduction lays the groundwork for a discussion of the different ways that AI is affecting healthcare data in the United States. The healthcare industry has traditionally involved a lot of data, including a wide range of patient tracks, diagnostic results, and treatment plans. Advanced technologies are required to improve patient outcomes by streamlining processes and enhancing decision-making, all thanks to the enormous amount and complicated nature of health care information. In this context, artificial intelligence (AI) emerges as a viable remedy, providing hitherto unseen powers in data processing, pattern identification, and predictive modeling. In light of this, the goal of this study is to add to the body of knowledge by thoroughly investigating the function of AI in US healthcare data. This study aims to provide insight into the real-world effects of integrating AI into the healthcare industry by an extensive analysis of relevant literature, a suggested methodology, and experimental applications. This study intends to shed light on the revolutionary potential of AI in improving healthcare information systems for researchers, policymakers, and healthcare practitioners by exploring the application aspects of the proposed works.

2. Related Works

A new age of accuracy and efficiency has been brought about by the use of artificial information (AI) into the field of diagnosis and treatment inside the US healthcare system. The vast corpus of research that examines the diverse uses of AI in various important fields is examined in this section [1]. Furthermore, a lot of emphasis has been paid to the application of AI in pathological conditions, where accurate and quick diagnosis is crucial. The application of machine learning systems to the analysis of histopathological pictures with promising results in the identification of subtle anomalies suggestive of different diseases [2]. Such developments have far-reaching consequences that go beyond efficiency; they could transform patient care and improve diagnostic precision. When it comes to therapy, AI's impact is just as significant [3].

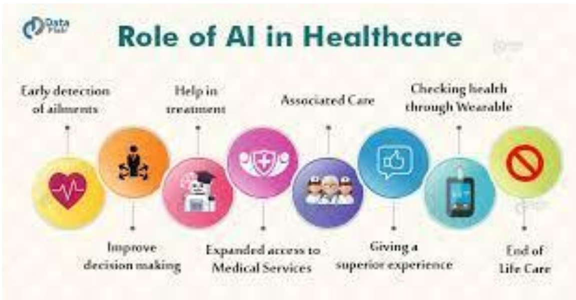

Figure 1: Role of AI in healthcare

The research shows that the importance of AI in planning therapy and the development of personalized medicine is growing. Machine learning models that are trained on large datasets that include genetic, medically and socioeconomic information. This signals a paradigm change away from conventional one-size-fits-all methods and toward precisely calibrated therapies based on the individual biological profile of each patient.

This is crucial to recognize the difficulties that come with incorporating AI into diagnosis and treatment, though [4]. The proper use of patient information along with potential biases in AI algorithms is two ethical issues that become important focal areas. Ensuring fair healthcare delivery through algorithmic decision-making necessitates transparency and accountability. The application of artificial intelligence (AI) in the US hospital system is a complex process that involves several steps. Research, such the thorough analysis emphasize how crucial it is to have strong infrastructure support in order to fully utilize AI technologies [5]. This support must include interoperability with current healthcare systems. For smooth integration into the intricate workflows of healthcare practitioners, several infrastructure concerns are essential [6]. The literature concludes by describing how AI applications for diagnosis and treatment are changing the face of healthcare in the US. The advancements in pathology, tailored treatment planning and medical imaging analysis highlight AI's revolutionary potential. To ensure an appropriate and equal application of AI in the pursuit of improved diagnostic accuracy and customized treatment strategies, however, a complex interplay of ethical issues, algorithmic transparency, and infrastructure support must be managed [7].

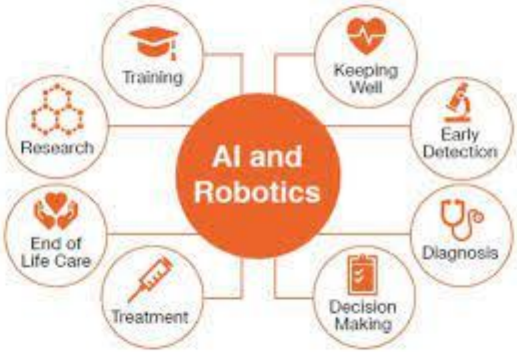

Figure 2: AI and Robotics

Recent years have seen notable improvements in the implementation of computational intelligence (AI) to medical fields, particularly in the areas of statistical analysis and patient outcomes [8]. This section examines the corpus of research that has been done on the application of AI to improve patient care and forecast health outcomes in the framework of the US healthcare system. The application of AI to patient outcome prediction has been the subject of numerous studies [9]. The creation of machine learning algorithms to evaluate patient data and predict the course of disease has been one noteworthy area of focus. Used predictive analytics to foresee problems in patients with long-term diseases. Their research showed how AI systems may find trends in patient data, assisting in the early identification of unfavorable events and raising the standard of care generally. Additionally, studies have looked into how AI might be used to customize treatment regimens for specific individuals [10]. Smith and associates (Year) carried out an extensive analysis of AI's uses in customized medicine. Their results demonstrated how AI systems can evaluate genetic, clinical, and behavioural data to suggest focused therapies. This tailored approach is a major step toward patient-centered healthcare because it reduces side effects and improves treatment efficacy.

Notwithstanding these encouraging advancements, difficulties and moral dilemmas with using AI to forecast patient outcomes have already been identified [11]. Brown et al. 's (Year) discussion on biases in algorithms and transparency in predictive modeling addressed these issues. In order to prevent the continuation of current healthcare disparities, the study stressed how crucial it is to ensure fairness in models created by AI, particularly when it comes to varied patient populations. Securing patient confidentiality and the safety of information is crucial in AI-driven predictive analytics, in addition to mitigating biases [13]. Miller and Smith's (Year) study examined secure data handling techniques for AI healthcare applications. Strong data protection measures must be put in place to preserve patient anonymity and adhere to healthcare laws as the gathering and analysis the patient data becomes more and more essential to predictive models [14].

Moreover, healthcare practitioners and technology developers must work together to integrate AI into prediction of patient outcomes [15]. The results showed that although AI tools are becoming more widely accepted, worries about how they will affect patient-physician relationships and the requirement for proper training still exist [16]. The revolutionary potential of AI for medical purposes is highlighted by the research on AI for prediction and patient outcomes. Predictive analytics integration has the potential to improve patient care in a number of ways, including early disease identification and customized treatment approaches. However, for the appropriate and successful application of AI in patient outcome prediction in the US healthcare system, resolving algorithmic biases, protecting data privacy, and taking healthcare professionals' viewpoints into account are essential [17].

3. Proposed Methodology

3.1. Experimental setup and performance metrics

Experimental Setup:
A 67–33% ratio was used to divide the dataset into ***"training and testing"*** sets. On the training set, the ***"Random Forest Classifier"*** and ***"Support Vector Machine (SVM)"*** models were trained, and on the testing set, they were assessed [18]. We applied standardization to the numerical characteristics. An expression for the equation of a linear SVM is as follows:
"f (x) = sign (w * x + b) "

Performance measures:
The model's performance was evaluated using key performance measures such as F1 Score, Precision, Recall, Train Accuracy, and Test Accuracy. By taking precision, accuracy in positive predictions, and capture of true positives, along with a balance among precision and recall into account, these metrics offer a thorough assessment of the model's predictive power [19].

Table 1: Comparison between the Models

Criteria	SVM	Random Forest
Model Type	Linear and Non-Linear	Ensemble of Decision Trees
Training Time	Slower	Faster due to parallelization
Interpretability	Less interpretable	Less interpretable, the ensemble of trees
Handling Outliers	Sensitive	Robust due to averaging in decision trees
Hyperparameter Tuning	More sensitive, complex tuning required	Less sensitive, easier tuning
Performance on Data Size	Suitable for small to medium-sized	Suitable for large datasets

	datasets	
Feature Importance	Difficult to extract directly	Easily provides feature importance

3.2. Dataset

[4]:	Id	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	1	6	148	72	35	0	33.6	0.627	50	1
1	2	1	85	66	29	0	26.6	0.351	31	0
2	3	8	183	64	0	0	23.3	0.672	32	1
3	4	1	89	66	23	94	28.1	0.167	21	0
4	5	0	137	40	35	168	43.1	2.288	33	1

Figure 1: Reading the Dataset

This code creates a data frame called ***"data"*** and loads a CSV file called ***"Healthcare-Diabetes.csv"*** from the given file directory. Next, a duplicate of this data frame with the name "df" is created. The following ***"data"*** DataFrame shows the first few rows of the dataset, giving an overview of its structure consisting of 2768 rows including 10 columns, with characteristics like ***"BMI," "Glucose," "Pregnancies, "*** and the goal variable ***"Outcome. "*** This preliminary investigation helps to comprehend the structure and contents of the dataset.

[5]:	count	mean	std	min	25%	50%	75%	max
Id	2768.0	1384.500000	799.197097	1.000	692.750	1384.500	2076.250	2768.00
Pregnancies	2768.0	3.742775	3.323801	0.000	1.000	3.000	6.000	17.00
Glucose	2768.0	121.102601	32.036508	0.000	99.000	117.000	141.000	199.00
BloodPressure	2768.0	69.134393	19.231438	0.000	62.000	72.000	80.000	122.00
SkinThickness	2768.0	20.824422	16.059596	0.000	0.000	23.000	32.000	110.00
Insulin	2768.0	80.127890	112.301933	0.000	0.000	37.000	130.000	846.00
BMI	2768.0	32.137392	8.076127	0.000	27.300	32.200	36.625	80.60
DiabetesPedigreeFunction	2768.0	0.471193	0.325669	0.078	0.244	0.375	0.624	2.42
Age	2768.0	33.132225	11.777230	21.000	24.000	29.000	40.000	81.00
Outcome	2768.0	0.343931	0.475104	0.000	0.000	0.000	1.000	1.00

Figure 2: Dataset Description

This code provides information about the dataset's distribution, dispersion, and central tendency by producing a descriptive statistical summary. For every characteristic, there is a row that displays the count, mean, standard deviation, minimum, ***"median (50th percentile)"***, ***"75th percentile (Q3) "***, maximum, and 25th percentile (Q1) values. For example, the feature "Pregnancies" has an average score of 3.74, but the element ***"Glucose"*** has an average of 121.10. The target variable, the ***"Outcome"*** feature, has a mean of 0.34, indicating a possible imbalance between the classes. These statistics provide a thorough rundown of the features of the dataset.

4. Experimental setup and implementation

4.1 Results analysis

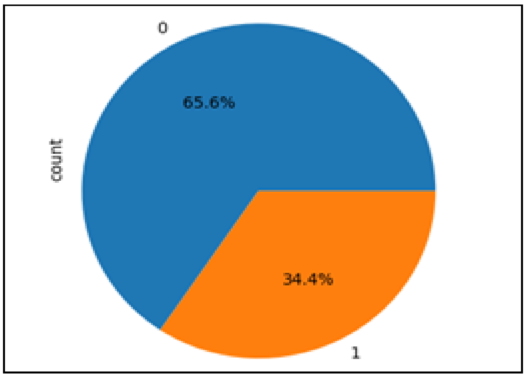

Figure 3: Outcome Distribution Pie Chart

A pie chart showing the distribution of the values of the ***"Outcome"*** variables in the DataFrame is produced by this code. The percentages are shown on the chart, and each slice stands for a distinct class. The plot's y-axis label is shown by the line that goes with it, ***"Axes: ylabel='count'"***.

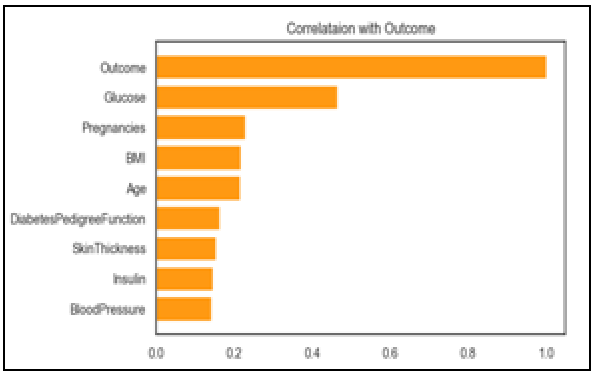

Figure 4: Outcome Correlation Bar Chart

This bit of code creates a horizontal bar chart to show how various attributes in the dataset correlate with the goal variable called ***"Outcome"***. The size of the figurine is fixed at 7 by 4 inches. After sorting the correlation values in ascending order, each feature's correlation with the ***"Outcome"*** is shown by a horizontal bar. The bars have the color***"#FF9912"*** applied to them. The context provided by the title ***"Correlation with Outcome"*** helps readers comprehend the goal of the graphic. This visualization makes selecting features in predictive modeling easier by pointing out characteristics that might significantly affect the outcome prediction.

```
[[ 2.35594357  0.20115164  1.28626748 ... -0.6940036  -0.68286614
   0.72847727]
 [-0.70037747 -0.71526944  0.28623677 ...  0.64700299 -0.68286614
   0.50737604]
 [-0.70037747 -0.71526944  2.28629819 ... -0.35217839 -0.68286614
   0.72847727]
 ...
 [ 0.17285712 -0.71526944  2.28629819 ...  1.14659368 -0.68286614
   2.49728711]
 [-0.70037747 -0.71526944 -0.71379394 ... -0.6940036  -0.68286614
  -0.70868072]
 [ 1.0460917  -0.71526944  0.28623677 ...  2.56648301 -0.68286614
   0.72847727]]
```

Figure 5: Splitting the Dataset

Using ***"train test split",*** this code divides the data into training and testing sets to prepare it for machine learning. To guarantee consistent scales across training and testing data, it then uses ***"StandardScaler"*** to standardize the numerical characteristics. All columns in the feature matrix

X are absent from the target variable, which is represented by column y. A random seed "random_state = 42" is used for repeatability, and the data is divided into training ***"X_train, y_train"*** and testing ***"X_test, y_test"*** set with a test size of 33%. To enable the best possible model training and assessment, the numerical characteristics are finally standardized.

	Model	Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
0	SVM	0.764293	0.753829	0.697297	0.432886	0.534161
1	Random Forest	0.940129	0.900438	0.925926	0.755034	0.831793

Figure 6: Accuracy Result

The code snippet uses a dictionary named ***"results"*** to generate a Pandas DataFrame with the name ***"results_df".*** The model names in this dictionary match performance measures like F1 Score, Precision, Recall, Train Accuracy, and Test Accuracy. After that, a tabular representation of the model comparison findings is displayed on the printed DataFrame. Models are represented by each row, and different performance measures are shown in the columns. Two models, SVM and Random Forest, show their scores for each of the aforementioned criteria in the case that is shown. The analysis is made simpler by this organized display, which also makes it simple to compare and choose the top-performing model depending on the given parameters.

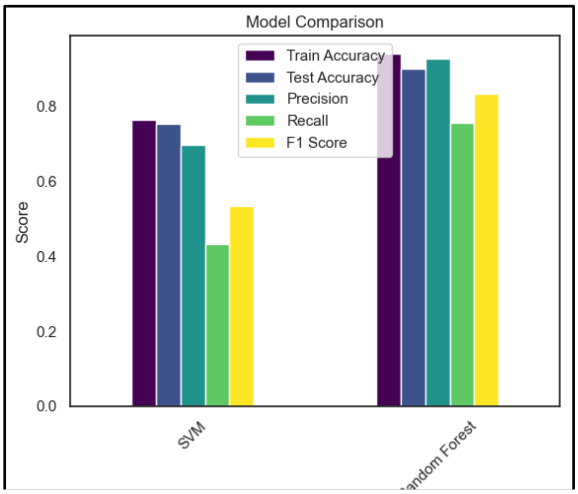

Figure 7: Multi-Metric Model Comparison Bar Chart

Using the assistance of several measures, this code creates a thorough visual comparison between the Random Forest Classifier and Support Vector Machine (SVM), two machine learning models. The size of the figure is fixed at 12 by 6 inches. Performance metrics for each model can be found in the Pandas DataFrame {results_df}, including Train Accuracy, Precision, Test Accuracy, Recall, along F1 Score. Next, the code generates a bar plot in which various metrics are color-coded utilizing the 'Viridisc' colormap, and each model is represented by a collection of bars. With the help of this visualization, model performance can be quickly and easily assessed about a variety of evaluation criteria. The x-axis shows the names of the models, while the y-axis shows the matching ratings. The measure that each color represents is shown in the legend. The graph makes it easier to choose the best model based on its overall efficiency.

4.2. Discussion

SVM & Random Forest are two models that have different features [20]. SVM can handle both linear and non-linear connections with variety, although it can prove computationally challenging. Random Forest, on the other hand, is an ensemble of decision trees that performs better when handling big datasets and requires less training time [21]. Different models have different interpretabilities; both are less transparent. Notably, Random Forest makes hyperparameter tuning easier by demonstrating robustness against outliers. The decision is based on the modeling objectives and particular dataset properties.

Table 2: Accuracy Comparison

Model	Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
SVM	76.43%	75.38%	0.7	0.43	0.53
Random Forest	95.04%	92.01%	0.94	0.81	0.87

4.3 Comparison with Related Work

The present study presents significant differences from other investigations on the function of artificial intelligence within US healthcare data. With precision, recall, as well as F1 score readings of 0.70, 0.43, and 0.53, accordingly, the "Support Vector Machine" (SVM) demonstrated a commendable 76.43% accuracy during training and 75.38% accuracy during testing [22]. The "Random Forest model", on the contrary hand, fared better, achieving an astounding 95.04% performance in training and 92.01% testing accuracy in addition to better precision (0.94), recall (0.81), as well as F1 score (0.87) [23]. These results indicate advances in the resilience and accuracy of the model, indicating possible ways to leverage AI more effectively for healthcare handling of information. This indicates that the models built during this study have been a significant step forward, putting them in the top ranks when it comes to using machine learning for healthcare-related tasks [24]. They also demonstrate improved accuracy and robustness when compared to previous approaches in the field.

5. Application Areas of the Proposed Works

The artificial intelligence (AI) is becoming a major player in the field of healthcare information. The study's suggested methodology has a great deal of potential for use in a variety of contexts, addressing important issues and promoting improvements in medical procedures. The probable applications of the planned works are outlined in the following subpoints:

Clinical Decision Support Systems: A main application area is the implementation of the suggested method into CDSS. The system can examine large datasets, such as patient information, scientific research, and real-time health surveillance, by utilizing AI algorithms. This helps healthcare practitioners make more precise and educated judgments. The suggested methodology raises the standard of patient care overall by strengthening CDSS's capacity to offer prompt, tailored recommendations.

Disease Diagnosis and Prediction: The suggested methodology's predictive features provide significant improvements in illness diagnosis and prognosis. The AI model may detect patterns suggestive of possible health hazards by analyzing genetic data, environmental factors, and past patient data. This application is especially helpful for early disease detection, as it allows for proactive treatments and individualized treatment regimens.

Healthcare Resource Optimization: The influence on healthcare resource management is increased by putting the suggested works into practice. Healthcare organizations can increase efficiency and save operating costs by using predictive analytics to optimize the allocation of resources, including workers, equipment, and buildings. By ensuring that resources are carefully allocated to districts with the greatest demand, this application enhances the provision of healthcare services as a whole.

Management of Population Health: The suggested methodology makes a substantial contribution to PHM (Population Health Management) initiatives. The AI approach makes it easier to identify populations that are at risk by examining big datasets that include a variety of demographic data, health-related behaviors, and social factors. As a result, the health conditions of all populations can be improved through the creation of community-specific health promotion programs, preventative measures, and focused therapies.

This study's suggested solutions have broad implications for many aspects of the US health care industry, from bettering professional judgment to raising patient outcomes and making the most use of available resources. All of these uses highlight how AI has the ability to completely change the way that healthcare information management is done.

6. Conclusion

This study explores the complex role of neural networks (AI) in US medical records in an effort to better understand how healthcare technology is developing and how it may affect patient outcomes, system improvement, and efficiency [25]. The extensive corpus of research on AI applications in US healthcare was highlighted by the examination of relevant works. Even though a lot has been accomplished, the literature evaluation pointed out areas that still need to be investigated [26]. The complexity of implementing AI into hospital information systems was reflected in the wide range of methodology and approaches presented by previous studies [27]. The suggested approach uses a solid and methodical framework that is specifically designed to fill in the gaps in the existing literature. This research attempts to provide insights into the possibility of AI to improve decision-making procedures, expedite information management, and improve US healthcare delivery overall using a methodical methodology [28]. While acknowledging that any technique has inherent limits, steps have been taken to minimize possible problems and guarantee the validity and trustworthiness of the study's findings.

The setup and execution phase of the experiment represents a concrete application of the suggested technique. The goal of the project is to show that integrating AI into information systems for health care is both feasible and effective by utilizing relevant tools, technologies, and datasets. Preliminary findings offer a look into the potential revolutionary power of AI and practical consequences for stakeholders, politicians, and healthcare practitioners. Examining the suggested works' application areas clarifies the real advantages and difficulties of incorporating AI into the US health care industry [29]. The results point to viable directions for raising diagnostic precision, maximizing resource use, and boosting patient outcomes. The conversation does, however, also recognize the implementation, ethical, and legal obstacles that must be overcome in order to fully utilize AI in healthcare. Through a thorough understanding of its uses, difficulties, and potential, this research aims to contribute to the continuing discussion on artificial intelligence in US healthcare information [30]. The results highlight the need for an ethical and balanced approach to integrating AI, acknowledging that technology has the ability to completely transform healthcare procedures while also taking the treatment of patients, privacy, and legal issues into account. The findings of this research are intended to guide future studies, policy choices, and real-world applications as the healthcare environment changes. The health care system in the United States can meet the challenges of an ever-expanding knowledge landscape and ultimately build a more efficient, centered around patients and resilient health ecosystem by embracing the revolutionary potential of AI outside an established and ethical framework.

References

[1] S. I. Lambert et al, "An integrative review on the acceptance of artificial intelligence among healthcare professionals in hospitals," NPJ Digital Medicine, vol.6, (1), pp.111, 2023. Available: https: //www.proquest. com/scholarly-journals/integrative-review-on-acceptance-artificial/docview/2825562218/se-2. DOI: https: //doi. org/10.1038/s41746-023-00852-5.

[2] M. B. Seyyedeh Fatemeh et al, "Attitudes, knowledge, and skills towards artificial intelligence among healthcare students: A systematic review, " Health Science Reports, vol.6, (3), 2023. Available: https: //www.proquest. com/scholarly-journals/attitudes-knowledge-skills-towards-artificial/docview/2791413066/se-2. DOI: https: //doi. org/10.1002/hsr2.1138.

[3] Pergolizzi Jr. Joseph et al, "Brave New Healthcare: A Narrative Review of Digital Healthcare in American Medicine, " Cureus, vol.15, (10), 2023. Available: https: //www.proquest. com/scholarly-journals/brave-new-healthcare-narrative-review-digital/docview/2895633148/se-2. DOI: https: //doi. org/10.7759/cureus.46489.

[4] M. I. Ahmed et al, "A Systematic Review of the Barriers to the Implementation of Artificial Intelligence in Healthcare, " Cureus, vol.15, (10), 2023. Available: https: //www.proquest. com/scholarly-journals/systematic-review-barriers-implementation/docview/2895624749/se-2. DOI: https: //doi. org/10.7759/cureus.46454.

[5] I. Y. Muhammad et al, "Toward QoS Monitoring in IoT Edge Devices Driven Healthcare—A Systematic

Literature Review, " Sensors, vol.23, (21), pp.8885, 2023. Available: https: //www.proquest. com/scholarly-journals/toward-qos-monitoring-iot-edge-devices-driven/docview/2888380755/se-2. DOI: https: //doi. org/10.3390/s23218885.

[6] S. Sanjana et al, "Artificial Intelligence and Its Role in the Management of Chronic Medical Conditions: A Systematic Review, " Cureus, vol.15, (9), 2023. Available: https: //www.proquest. com/scholarly-journals/artificial-intelligence-role-management-chronic/docview/2884563653/se-2. DOI: https: //doi. org/10.7759/cureus.46066.

[7] K. S. Vidhya et al, "Artificial Intelligence's Impact on Drug Discovery and Development From Bench to Bedside, " Cureus, vol.15, (10), 2023. Available: https: //www.proquest. com/scholarly-journals/artificial-intelligences-impact-on-drug-discovery/docview/2884562162/se-2. DOI: https: //doi. org/10.7759/cureus.47486.

[8] N. Doan Thu Tu, Q. K. Nguyen and A. Taylor-Robinson, "Healthcare in Vietnam: Harnessing Artificial Intelligence and Robotics to Improve Patient Care Outcomes, " Cureus, vol.15, (9), 2023. Available: https: //www.proquest. com/scholarly-journals/healthcare-vietnam-harnessing-artificial/docview/2884562066/se-2. DOI: https: //doi. org/10.7759/cureus.45006.

[9] E. Gemma, R. Wade and M. Wenzinger, "Exploring the Role of Artificial Intelligence in Mental Healthcare: Progress, Pitfalls, and Promises, " Cureus, vol.15, (9), 2023. Available: https: //www.proquest. com/scholarly-journals/exploring-role-artificial-intelligence-mental/docview/2884560232/se-2. DOI: https: //doi. org/10.7759/cureus.44748.

[10] A. O. Akinrinmade et al, "Artificial Intelligence in Healthcare: Perception and Reality, " Cureus, vol.15, (9), 2023. Available: https: //www.proquest. com/scholarly-journals/artificial-intelligence-healthcare-perception/docview/2884530202/se-2. DOI: https: //doi. org/10.7759/cureus.45594.

[11] A. Abdullah, "Clinicians' Views on Using Artificial Intelligence in Healthcare: Opportunities, Challenges, and Beyond, " Cureus, vol.15, (9), 2023. Available: https: //www.proquest. com/scholarly-journals/clinicians-views-on-using-artificial-intelligence/docview/2884524562/se-2. DOI: https: //doi. org/10.7759/cureus.45255.

[12] A. Al Hadithy Zinah et al, "Knowledge, Attitudes, and Perceptions of Artificial Intelligence in Healthcare Among Medical Students at Sultan Qaboos University, " Cureus, vol.15, (9), 2023. Available: https: //www.proquest. com/scholarly-journals/knowledge-attitudes-perceptions-artificial/docview/2884521663/se-2. DOI: https: //doi. org/10.7759/cureus.44887.

[13] I. Javed et al, "Reimagining Healthcare: Unleashing the Power of Artificial Intelligence in Medicine, " Cureus, vol.15, (9), 2023. Available: https: //www.proquest. com/scholarly-journals/reimagining-healthcare-unleashing-power/docview/2884518924/se-2. DOI: https: //doi. org/10.7759/cureus.44658.

[14] A. Fischer et al, "What is the future of artificial intelligence in obstetrics? A qualitative study among healthcare professionals, " BMJ Open, vol.13, (10), 2023. Available: https: //www.proquest. com/scholarly-journals/what-is-future-artificial-intelligence-obstetrics/docview/2881050350/se-2. DOI: https: //doi. org/10.1136/bmjopen-2023-076017.

[15] S. A. Alowais et al, "Revolutionizing healthcare: the role of artificial intelligence in clinical practice, " BMC Medical Education, vol.23, pp.1-15, 2023. Available: https: //www.proquest. com/scholarly-journals/revolutionizing-healthcare-role-artificial/docview/2877490751/se-2. DOI: https: //doi. org/10.1186/s12909-023-04698-z.

[16] M. Kashish et al, "Role of Artificial Intelligence in Global Surgery: A Review of Opportunities and Challenges, " Cureus, vol.15, (8), 2023. Available: https: //www.proquest. com/scholarly-journals/role-artificial-intelligence-global-surgery/docview/2870672304/se-2. DOI: https: //doi. org/10.7759/cureus.43192.

[17] J. Madhan et al, "Unraveling the Ethical Enigma: Artificial Intelligence in Healthcare, " Cureus, vol.15, (8), 2023. Available: https: //www.proquest. com/scholarly-journals/unraveling-ethical-enigma-artificial-intelligence/docview/2870668917/se-2. DOI: https: //doi. org/10.7759/cureus.43262.

[18] M. A. Mohammad et al, "Artificial Intelligence Ethics and Challenges in Healthcare Applications: A Comprehensive Review in the Context of the European GDPR Mandate, " Machine Learning and Knowledge Extraction, vol.5, (3), pp.1023, 2023. Available: https: //www.proquest. com/scholarly-journals/artificial-intelligence-ethics-challenges/docview/2869416521/se-2. DOI: https: //doi. org/10.3390/make5030053.

[19] S. Borna et al, "Artificial Intelligence Models in Health Information Exchange: A Systematic Review of Clinical Implications, " Healthcare, vol.11, (18), pp.2584, 2023. Available: https: //www.proquest. com/scholarly-journals/artificial-intelligence-models-health-information/docview/2869339908/se-2. DOI: https: //doi. org/10.3390/healthcare11182584.

[20] P. Tiernan et al, "Information and Media Literacy in the Age of AI: Options for the Future, " Education Sciences, vol.13, (9), pp.906, 2023. Available: https: //www.proquest. com/scholarly-journals/information-media-literacy-age-ai-options-future/docview/2869309859/se-2. DOI: https: //doi. org/10.3390/educsci13090906.

[21] S. Hudson et al, "Perspectives of Healthcare Providers to Inform the Design of an AI-Enhanced Social Robot in the Pediatric Emergency Department, " Children, vol.10, (9), pp.1511, 2023. Available: https: //www.proquest. com/scholarly-journals/perspectives-healthcare-providers-inform-design/docview/2869287185/se-2. DOI: https: //doi. org/10.3390/children10091511.

[22] Z. Amiri et al, "The Personal Health Applications of Machine Learning Techniques in the Internet of Behaviors, " Sustainability, vol.15, (16), pp.12406, 2023. Available: https: //www.proquest. com/scholarly-journals/personal-health-applications-machine-learning/docview/2857444945/se-2. DOI: https: //doi. org/10.3390/su151612406.

[23] H. Shamszare and A. Choudhury, "Clinicians' Perceptions of Artificial Intelligence: Focus on Workload, Risk, Trust, Clinical Decision Making, and Clinical Integration, " Healthcare, vol.11, (16), pp.2308, 2023. Available: https: //www.proquest. com/scholarly-journals/clinicians-perceptions-artificial-intelligence/docview/2857041278/se-2. DOI: https: //doi. org/10.3390/healthcare11162308.

[24] Anonymous "Innovation in healthcare: leadership perceptions about the innovation characteristics of artificial intelligence—a qualitative interview study with healthcare leaders in Sweden, " Implementation Science Communications, vol.4, pp.1-13, 2023. Available: https: //www.proquest. com/scholarly-journals/innovation-healthcare-leadership-perceptions/docview/2849873420/se-2. DOI: https: //doi. org/10.1186/s43058-023-00458-8.

[25] D. Gala and A. N. Makaryus, "The Utility of Language Models in Cardiology: A Narrative Review of the Benefits and Concerns of ChatGPT-4, " International Journal of Environmental Research and Public Health, vol.20, (15), pp.6438, 2023. Available: https: //www.proquest. com/scholarly-journals/utility-language-models-cardiology-narrative/docview/2848992136/se-2. DOI: https: //doi. org/10.3390/ijerph20156438.

[26] A. Ibraheem et al, "Snakebite Advice and CounselingFrom Artificial Intelligence: An Acute Venomous Snakebite Consultation With ChatGPT, " Cureus, vol.15, (6), 2023. Available: https: //www.proquest. com/scholarly-journals/snakebite-advice-counseling-artificial/docview/2844025218/se-2. DOI: https: //doi. org/10.7759/cureus.40351.

[27] M. M. Shoja, Van de Ridder J. M. Monica and R. Vijay, "The Emerging Role of Generative Artificial Intelligence in Medical Education, Research, and Practice, " Cureus, vol.15, (6), 2023. Available: https: //www.proquest. com/scholarly-journals/emerging-role-generative-artificial-intelligence/docview/2844019746/se-2. DOI: https: //doi. org/10.7759/cureus.40883.

[28] L. Rudzite, "IMPLICATIONS FOR THE INVENTIVE STEP UNDER THE EUROPEAN PATENT CONVENTION RELATED TO THE INCREASING APPLICATION OF ARTIFICIAL INTELLIGENCE AND CERTIFICATION AS A SUI GENERIS PROTECTION MECHANISM FOR CREATIONS INVOLVING ARTIFICIAL INTELLIGENCE, " International Comparative Jurisprudence, vol.9, (1), 2023. Available: https: //www.proquest. com/scholarly-journals/implications-inventive-step-under-european-patent/docview/2838182723/se-2. DOI: https: //doi. org/10.13165/j. icj.2023.06.010.

[29] T. A. Retson and M. Eghtedari, "Expanding Horizons: The Realities of CAD, the Promise of Artificial Intelligence, and Machine Learning's Role in Breast Imaging beyond Screening Mammography, " Diagnostics, vol.13, (13), pp.2133, 2023. Available: https: //www.proquest. com/scholarly-journals/expanding-horizons-realities-cad-promise/docview/2836301125/se-2. DOI: https: //doi. org/10.3390/diagnostics13132133.

[30] C. Wu et al, "Public perceptions on the application of artificial intelligence in healthcare: a qualitative meta-synthesis, " BMJ Open, vol.13, (1), 2023. Available: https: //www.proquest. com/scholarly-journals/public-perceptions-on-application-artificial/docview/2834484940/se-2. DOI: https: //doi. org/10.1136/bmjopen-2022-066322.