Mar 31st, 10:30 AM - 11:30 AM

How Technology May be Used for Future Disease Prediction: A Systematic Literature Review

Rich P. Manprisio
Governors State University, rmanprisio@govst.edu

Mohammed Salam

How technology may be used for future disease prediction: A Systematic Literature Review

Abstract

Exasperated by the current pandemic, our healthcare system continues to struggle with the accuracy and effectiveness of disease treatments. However, despite these growing challenges, technological advancements have aided potential disease prediction. There has been a positive correlation between utilizing technologies and leveraging them for disease predictions. Thanks to our continued reliance and technological advancement, current research shows that it has many viable options to aid the healthcare field. This systematic review looks at the current state of how technologies have been and can be used to improve healthcare.

Keywords: Internet of Things (IoT), Internet of Healthcare Things (IoHT), Deep Learning, Artificial Intelligence (AI), Machine Learning (MI)

Authors: Rich Manprisio & Mohammed Salam

Introduction

Our current healthcare system has faced some ongoing challenges, specifically regarding disease treatment and predictions. Research has shown that diseases are much harder to diagnose in their preliminary stages because people often haven't developed symptoms yet, and only trace amounts can be found in their bodies. (*Belle et al., 2015*) . Paired with a precise data collection method to look for future predictors. Another area is the growing differences in the type of care patients access based on their demographics.

Furthermore, the waning effectiveness of medical treatments and the increased length of hospital stays are due to the lack of an effective method for determining diagnoses. Current medical costs have continued to rise without the correct justification. Up to one-third of medical expenses are unnecessary, with only about half of care aligned to evidence-based treatments (*Pavel et al., 2013*). This is mainly because healthcare decisions are subjective and primarily influenced by the experience of the individual clinician who treats the patient. Health information technology may improve the collection and exchange of self-reported information (*Sarmah, 2020*). Due to these challenges (compounded by the current pandemic we are facing), technology has been looked at as a way to alleviate this ongoing strain on the healthcare system. It's this basis on which this research is based.

The Internet of Healthcare Things (IoHT) is a subset of technology that has grown due to the popularity of Internet of Things (IoT) devices. The idea behind IoHT devices is to track various vital signs of patients, including heart rates, blood sugar levels, and more have been used throughout the years to help patients continue to be monitored outside of a clinical setting. However, we are now seeing they can be used for more advanced applications such as improving a patient's recovery time and looking for predictors that could be used to determine if a patient is a candidate for future illness. Knowing that IoHT devices are constantly collecting data from millions of patients, it's this concept that this collected information can be used beyond just a single patient but for many. IoHT devices contain a tremendous amount of unstructured data (i.e., challenging to run queries on, easily accessible, etc.); this is where more technological intervention needs to be brought in. Infectious disease trends are not known, which means prediction is not an easy task (*Chae, Kwon, and Lee, 2018*).

The idea is to take the vast amounts of collected data from IoHT devices, clinician medical records, and input from clinicians and implement an Artificial Intelligence/Machine Learning system. Such systems could be developed to sift through all the data looking for crucial points that could be used. Current practices around collecting, curation, and sharing data make it difficult to apply machine learning to healthcare on a large scale (*Dhindsa, Bhandari, and Sonnadara, 2018*). Artificial Intelligence (AI) / Machine Learning (ML) has continued to advance the way our devices can appear to be learning. ML is critical in healthcare and is increasingly applied to hospitals and clinical settings (*Khare et al., 2017*). By taking the data collected by IoHT devices, AI can put the data into a structured, searchable format that clinicians can evaluate. The collection from these datasets can be used for future disease prediction analysis.

The objective of this research is to see how current technologies have been used to aid the healthcare field to determine where the challenges lie in both the implementations and acceptance for more clinicians and patients. Based on this objective, the following research questions are posed.

R1. What current technologies in the healthcare field can be implemented for long-term prediction?

Under the current prevalence of chronic disease, medical care underperforms in all key indicators (*Martyushev-Poklad, Yankevich, and Petrova, 2022*).

R2. How effective can technologies be used to collect and filter patient data?

The U.S. healthcare field workers are constantly sharing their findings with their colleagues. Many professionals collaborate and then examine the patients according to each one's specialty by analyzing the data collected from such things as IoMT devices (*Dhanvijay and Patil, 2019*). Through this collaboration, IoMT devices and other technologies can provide better treatment for multiple patients suffering from the exact alignments. The issue is often an efficient and accurate method to sift through the wealth of data collected, eliminate all the other clinical static, and make the necessary information available at the right time to the right people (*Almustafa, 2020*).

R3. How can the data collected from various technologies (i.e., the Internet of Healthcare Things) be effectively used for future disease predictions?

Research has shown that Internet of Things (IoT) devices have been “widely identified as a solution to alleviate the increasing pressures on healthcare systems.” (*Baker, Xiang, and Atkinson, 2017*). It's believed that early diagnoses and early intervention can be supported by technologies to enhance the identification of the nature of illnesses (*Karahoca, 2018*).

This paper first provides a background on some examples that have already been successful in aiding disease prediction using technologies. Next, the recommended methods for analyzing the current literature available are considered. From there, the research framework is discussed, outlining the procedures and continuing research while reviewing the recent results. Finally, future research discussion outlines the next steps in the process and where additional areas that have shown gaps in the study are available to point to where a more in-depth analysis can begin.

Background

Since the increased technological advancements, it has continued to be leveraged as a viable tool in disease analysis and prediction. One example is the Non-Invasive Risk Assessment with Machine Learning and Artificial Intelligence (Niramai). This tool leverages previous data collected from breast cancer patients to detect tumors five years earlier than mammography or clinical exams (*Bhattacharya et al., 2019*). By increasing the amount of collected information, one could believe that future detection could be even earlier. It's possible that this concept can be used for other diseases to increase early detection ability.

An additional example of this was done by a startup company called Sensely. They created a digital nurse that organizes patients' symptoms and presents potential alignments to their doctors before meeting with them. This way, the patient's time with the doctors could be reduced if necessary by having the information in a shorter amount of time. Taking this information and combining it with other patients could help see current trends that may be happening in a demographic, age group, etc. (*Nguyen and Do 2019*).

It has been shown that most healthcare decisions are subjective and influenced by the individual clinicians who treat patients and have a large amount of medical knowledge. This leaves a gap in the level of care a patient could get based on who their doctors are. This gap could be detrimental to the care of a patient. However, with more information available, a care provider could make more accurate recommendations (*Pavel et al., 2013*). Several computer-aided methods have been developed for disease predictions. APACHE III is a prognostic scoring system used to predict a patient's likelihood of experiencing heart conditions, digestive disorders, Alzheimer's disease, and cancer (*Nguyen and Do, 2019*). Building on this success shows the validity of continued research utilized by more patients and a broader range of conditions.

Research Methods

Due to its popularity and ties to the healthcare field, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework will be used throughout this paper. “PRISMA includes new reporting guidance that reflects advances in methods to identify, select, appraise and synthesize studies”(*Page et al., 2021*). Systematic reviews and meta-analyses have become increasingly important in healthcare, with clinicians reading them to keep up to date with their specialties (*Page et al., 2021*). These guidelines will help provide structure for a review clearly, transparently, and with sufficient detail to enable reproducibility.

Utilizing PRISM's 2020 checklist will aid in mapping the number of records, what is included and excluded, including the reason behind it. This protocol preparation is an essential component of this Structure Literature Review (SLR), ensuring that this systematic review is carefully planned and that what is intended is explicitly documented before the study starts promoting consistency (*Page et al., 2021*). In addition to using PRISMA, this paper follows the Kitchenham and Charters methodology by covering three main phases (planning, conducting, and reporting).

Conducting the Review

Per Kitchenham and Charter, a review protocol specifies the method used to undertake a specific systematic review. This is crucial in reducing the likelihood of research bias. Based on this proposed protocol, the area to address is the background/rationale for this review. By having a better understanding of what Artificial Intelligence/Machine Learning is and isn't capable of doing, this information could be used to achieve the desired goal. Next is the study selection criteria

that outline which studies will and won't be included in this review. Such criteria include ranging the dates of information collected and only using research from peer-reviewed journals. After determining the requirements, we need to plan out the study selection procedures, explaining how the selection criteria will be applied. This will be broken down in great detail in subsequent sections. Finally, discussed is how the synthesis of the extracted data is handled. Defining the strategy and explaining how the collected data will be evaluated.

Any SLR aims to find as many primary studies relating to the research questions as possible, ensuring unbiased results by varying the information collected (*Kitchenham and Charters, 2007*). The standard approach is to break down research questions, not individual facets. A list of synonyms, abbreviations, and alternative spellings is outlined for keyword search.
Based on this, the following keywords were used to perform the preliminary search (see Table 1)

Deep Learning	Fog Computing	Artificial Intelligence
Internet of Healthcare Things (IoHT)	Disease prediction	Big Data Analytics
Healthcare prediction technologies	Patient technologies	Machine learning
Electronic Health Records (HER)	Wearable technologies	Portable monitors
Telehealth and Apps	Automated health devices	Clinical Decision Support (CDS)

Table 1 Keyword(s) used for search

The critical need for reviewing the collected literature is to define any outlying trends to the current state of information available for technologies in healthcare, the links the literature share regarding their findings, and attempt to find the gaps in existing research available with recommendations for future research possibilities. Based on the literature reviewed, a thematic approach would be recommended. This framework shows where possible connections are present and integrated within the requirements previously outlined.

Classification Scheme

A classification scheme has been utilized to classify the research specific to the topic. This scheme is beneficial to see where the similarities of research have been done regarding advancing disease predictions in healthcare. Using the World Health Organization's (WHO) digital health interventions *(World Health Organization, 2019)* guide, the following classification scheme was developed (*see Figure 1*).

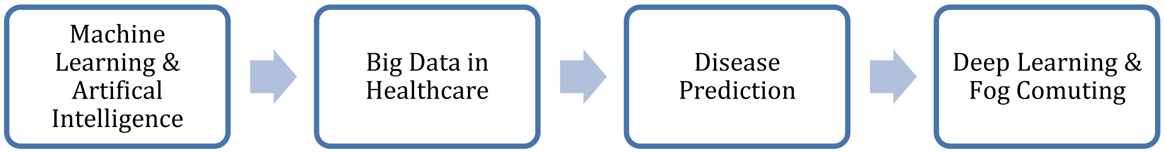

Figure 1 WHO Interventions

- *Machine Learning & Artificial Intelligence*
  - Research shows how artificial intelligence is currently being used to both gather data from parties and share it with healthcare professionals
- *Big Data in Healthcare*
  - Research showing how Big Data (unstructured data) is currently being utilized in healthcare and the various methods used for the collection of data
- *Disease Prediction*
  - How has the data gathered been used to predict future disease
- *Internet of Healthcare Things*
  - How have current IoHT devices been used to collect patient data, and how it ties back into disease prediction

Documenting the Search

Kitchenham and Charter's methods outline the necessity for documenting the search methods. This is necessary for allowing for the search to be replicated by other researchers. The criteria for selecting articles and creating a framework to classify the selected materials came from peer-reviewed journals. The databases cover most academic journals in English available and focus on the technology and healthcare field (*see Table 2*). The search parameters were set starting in 2005 because of the proliferation we began to see with the amount of technology being leveraged in the healthcare field. "The early 2000s was a turning point for the healthcare field with the amount of technology being introduced and clinically tested for patients and their doctors." (*Ahmed et al., 2020*).

Database	Coverage
IEEE	2005 to 2022
Computer Society	2005 to 2022
Internet of Things Journal	2005 to 2022
Computer and Reliability Societies	2005 to 2022
Biomedical Engineering	2005 to 2022
Biomedical and Health Informatics	2005 to 2022
Academic Search Premier	2005 to 2022
International Journal of Environmental Research and Public Health	2005 to 2022
Institute of Physics IOP Science	2005 to 2022
Frontiers in Genetics	2005 to 2022
Journals of Big Data	2005 to 2022

Table 2 Databases and journals used for research

The research area is the academic research on how data collected from IoHT devices can be leveraged using Deep Learning Artificial Intelligence. The goal of this phase is to create a classification framework and to suggest directions for future research. The research scope is literature on fog computing, deep learning, IoHT devices, and big data between 2005 to 2022. It's essential to encompass the time that the previously discussed technologies have been available to determine where it has been implemented and what areas can benefit from them by utilizing previous research.

Since initial searches restored a tremendous amount of information not necessarily relevant to the topics, a more refined study selection process was necessary. This process is used to identify those primary studies that provide the evidence to support the research (*Kitchenham and Charters, 2007*). This idea developed a quality checklist to ensure that each literature review is held to the same standard.

An example of this checklist is as follows

1. Is the literature within the predefined period outlined in the planning phase?
2. Is the literature published in a peer-reviewed journal?
3. Is this literature free of bias of the authors while stating the facts?
4. Are their author's findings quantifiable?
5. Was the sample size sufficient to understand the results?

Reporting on Initial Search

Based on the keyword searches, a tremendous amount of information was returned. Due to this, a series of keywords and operators were used to target the results. The following queries were run.

1. IoHT AND Deep learning
2. IoHT AND Artificial Intelligence OR deep learning
3. Fog computing AND disease prediction
4. Fog computing OR deep learning AND disease prediction
5. Big Data AND disease prediction

For articles to be considered valid candidates, the abstract and title needed to tie directly to the research questions.

Results

Following PRISMA's 2020 diagram, the following papers use the identification of new studies via databases, whereas "n" signifies the number of literature found. Figure 2 shows the flow of the process in which sifting through the collected research was filtered. Initially, 365 papers were inspected. A summary was done from the abstracts of the articles to see if they fell into one of the four classifications (see Figure 1). After duplicate records were removed due to a lack of research on the topic or marked as ineligible by automation tools, exactly 50 articles were left. After reading through the research beyond the abstract, an additional level of filtering was conducted to determine if it fits within the context of the four classification schemes. From

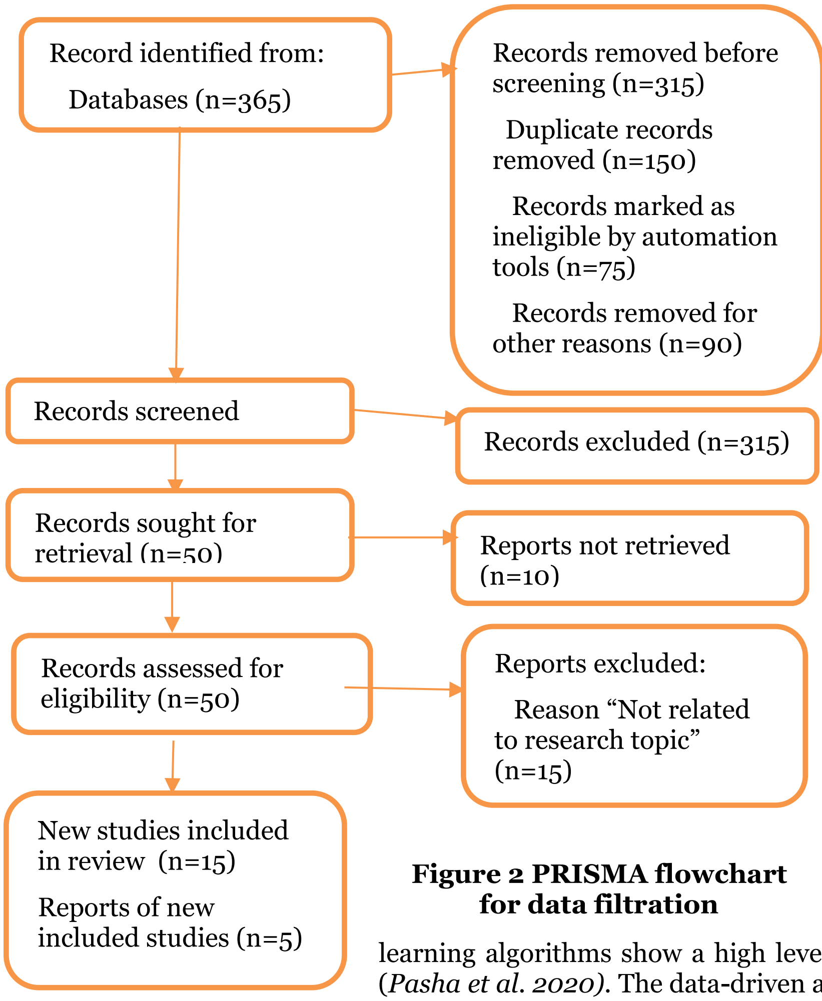

Figure 2 PRISMA flowchart for data filtration

there, what remained was 35 articles that shared common themes and showed that current technologies had been used to aid in future disease predictions. The results of this review are as follows.

Big Data Analytics (BDA) platforms are the best way to analyze the structure and unstructured data gathered from healthcare management systems (*Sahoo, Mohapatra, and Shih-Lin, 2016*). BDA can handle such dynamic data, providing practical and expectantly beneficial output in an actual data application for various organizations (*Basco and Senthilkumar, 2017*).

Medical services have improved with inspirational technologies such as IoT paired with AI. A proposed method called Crow Search Optimization algorithm-based Cascaded Long Short Term Memory (CSO-CLSTM) shows a 97.25% accuracy in diagnosing heart disease and diabetes (*Mansour et al., 2021*). Accuracy levels of various machine learning are promising through the use of Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Trees (DT). That shows how learning algorithms show a high level of forecasting heart attacks in patients (*Pasha et al. 2020)*. The data-driven approach of machine learning is currently being used to identify nonlinear associate and complex interactions between variables without the need to pre-specify these relations in atrial fibrillation (*Hill et al., 2019*).

Data mining devices (such as IoHT) have been shown to collect data to successfully predict and make informed decisions when considering continued time-series measurements for ongoing healthcare. (*Banaee, Ahmed, and Loutfi, 2013*). With the continued reliance on wearable IoHT devices, a particular emphasis has been given to mining patient data to offload to a fog computing device to handle the security and collection before transmission (*Gardasevic et al., 2020*).

With the recent pandemic, many resources have been placed on looking at real-time COVID-19 monitoring systems as an IoHT device to monitor the wearer's body temperature and blood oxygen levels to predict future infections (*Ennafiri and Mazri, 2020*). Deep Learning approaches such as Convolution Neural Networks (CNN), or Recurrent Neural Networks (RNN) have been yielding results in predictive disease prediction in Alzheimer's of up to 96.0% (*Jo, Nho, and Saykin, 2019*).

The use of Blockchain technologies for data distribution (*Marbury, 2018*). Although used in cryptocurrency, Blockchain technologies have been growing in popularity in sharing large amounts of data with various healthcare providers Creating a way to aggregate heterogeneous data from different sources (*Ngiam and Khor, 2019*). We are dealing with an ongoing issue of taking data from different devices and allowing access to collected data to advance AI across other manufacturers.

Implementing Health 2.0's technologies (Software Defined Networks (SDN), Nanotechnologies, and Point-of-Care Devices (PoCD)) (*Gong, Zhang, and Chen, 2020*). Most research points to the need to offload the AI functionality outside of the IoHT devices to more reliable devices.

The preliminary research shows that while the initial idea of Artificial Intelligence is prevalent in medical devices, other areas could be particularly beneficial. An additional area that nearly all the research discussed was the sheer amount of produced and collected data. Looking at a single sensor could collect millions of bytes of data that could be used to improve upon the complexity and learning capabilities of AI (*Chen, 2020*). The concept is like that of what doctors do. A doctor will look at past medical conditions to recommend the correct medication and treatment for a patient. However, they have yet to leap to analyzing the data collected by IoHT devices. Doctors typically don't analyze real-time steaming e-health data; data mining these historical records allows a clinician to examine conditions that could be common across subpopulations and regions to understand health trends (*Chen et al. 2017*)

It doesn't necessarily seem to be an issue with collecting data but how to share it with those that can benefit from it the most. Typically, the data gathered stays in some local environment, which inherently limits the value you can derive from it (*Kitchenham and Charters, 2007*). Knowing this could lead to a discussion on eliminating these data silos where the data is only beneficial to a small group.

This is by no means a complete list since advancements in image processing and pattern recognition show promise for aiding prediction analysis. Due to the limitations of the search, it has been limited to the themes discussed. However, future research should include this as a viable technology.

Conclusions and Future Research

Based on all of the research completed up to this point, it's apparent that additional research into the field of IoMT would benefit the industry by providing the following contributions. *Survey/research results could be used to identify the gaps in the usage of IoMT devices.* Because of the vast availability of data, there has been an additional occurrence in the healthcare industry and a need for increasing studies that aim to leverage the data collected to improve healthcare (*Harerimana, 2018*). *Research could open up the possibility of collecting data from patients and how to use the data in disease predictions*. Collected data could solve many clinical problems, such as tracking outcomes of surgical treatments and determining early warning signs of chronic illness. This information could be aggregated, looking for symptom outliers (*Ngiam and Khor, 2019*). By conducting my proposed research, it could show the validity of IoMT and how it could be advantageous in the future aggregation of data collected for potential disease predictions.

This is where the deep learning side could be where fog computing could be used as a form of filtration. It's not feasible to expect IoHT devices to have a fine-grained level of data filtration, so the data could be sent to a fog computing device where filtering the data and posting it to the appropriate people could happen. This, paired with deep learning, where the fog computing devices would increase their intelligence, could reduce the 'static' data collected (*Chui, 2017)*.

Additional areas where gaps have been seen are how to store the data to be easily assessable while ensuring integrity has been maintained. With large volumes of data and other patient information, sophisticated storage methods for such data are critical. Since storing all this information and retrieving it can be taxing to a network (both in terms of time expense sending and retrieving data and computer speeds), it's essential to have a storage and retrieval system that can facilitate rapid data pull and commits based on analytic demands (*Dash et al. 2019*). Another area that warrants further investigation is leveraging IoHT devices for short- and long-term communications paired with cloud computing technologies (*Baker, Wei, and Atkinson, 2017)*. With continued research, the information could be used to approach unstructured technologies and formulate an artifact that could be used collectively by the healthcare field to continue their advancement in disease prediction.

The limitations of such research will be limited to the sample and selection size used. Ensuring the prediction has a high level of accuracy depends on the level of confidence in the analysis. Additionally, the nature of a patient's health records could limit those willing to allow access to their records to use such studies.

References and Citations

Belle, A., Thiagarajan, R., Soroushmehr, S. M. R., Navidi, F., Beard, D. A., & Najarian, K. (2015). Big Data Analytics in Healthcare. *BioMed Research International*, *2015*, 1–16. https://doi.org/10.1155/2015/370194

Sarmah, S. S. (2020). An Efficient IoT-Based Patient Monitoring and Heart Disease Prediction System Using Deep Learning Modified Neural Network. *IEEE Access*, *8*, 135784-.

Chae, S., Kwon, S., & Lee, D. (2018). Predicting Infectious Disease Using Deep Learning and Big Data. *International Journal of Environmental Research and Public Health*, *15*(8), 1596. https://doi.org/10.3390/ijerph15081596

Dhindsa, K., Bhandari, M., & Sonnadara, R. R. (2018). What's holding up the big data revolution in healthcare? *BMJ : British Medical Journal (Online)*, *363*. https://doi.org/10.1136/bmj.k5357

Khare, A., Jeon, M., Sethi, I. K., & Xu, B. (2017). Machine Learning Theory and Applications for Healthcare. *Journal of Healthcare Engineering*, *2017*, 1–2. https://doi.org/10.1155/2017/5263570

Martyushev-Poklad, A., Yankevich, D., & Petrova, M. (2022). Improving the Effectiveness of Healthcare: Diagnosis-Centered Care vs. Person-Centered Health Promotion, a Long Forgotten New Model. *Hypothesis and Theory*, *10*.

Dhanvijay, M., & Patil, S. (2019). Internet of Things: A survey of enabling technologies in healthcare and its applications. *ScienceDirect*, *153*, 113–131.

Almustafa, K. M. (2020). Prediction of heart disease and classifiers' sensitivity analysis. *BMC Bioinformatics*, *21*(1), 278. https://doi.org/10.1186/s12859-020-03626-y

Baker, S. B., Xiang, W., & Atkinson, I. (2017). Internet of Things for Smart Healthcare: Technologies, Challenges, and Opportunities. *IEEE Access*, *5*, 26521–26544. https://doi.org/10.1109/ACCESS.2017.2775180

Karahoca, A., Karahoca, D., & Aksoz, M. (2018). Examining intention to adopt to internet of things in healthcare technology products. *Kybernetes*, *47*(4), 742–770.

Bhattacharya, S., Pradhan, K., Bashar, M., Tripathi, S., Semwal, J., Marzo, R., Bhattacharya, S., & Singh, A. (2019). Artificial intelligence enabled healthcare: A hyper, hope or harm. *Journal of Family Medicine and Primary Care*, *8*(11).

Nguyen, T. L., & Do, T. T. (2019). *Artificial Intelligence in Healthcare: A New Technology Benefit for Both Patients and Doctors*. 1–15. https://doi.org/10.23919/PICMET.2019.8893884

Pavel, M., Jimison, H., Wactlar, H., Hayes, T., Barkis, W., Skapik, J., & Kaye, J. (2013). The Role of Technology and Engineering Models in Transforming Healthcare. *IEEE Reviews in Biomedical Engineering*, *6*, 156–177.

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. *BMJ*, n160. https://doi.org/10.1136/bmj.n160

Kitchenham, B., & Charters, S. (2017). *Guidelines for performing Systematic Literature Reviews in Software Engineering*. 1–66.

WHO Organization. (2019). WHO guideline Recommendations on Digital Interventions for Health System Strengthening. In *WHO guideline Recommendations on Digital Interventions for Health System Strengthening*. World Health Organization. https://www.ncbi.nlm.nih.gov/books/NBK541905/

Ahmed, M., Bogale, A., Tilahun, B., Kalayou, M., Klein, J., Mengiste, S., & Endehabtu, B. (2020). Intention to use electronic medical record and its predictors among health care providers at referral hospitals, north-West Ethiopia, 2019: Using the unified theory of acceptance and use technology 2 (UTAUT2) model. *BMC Medical Informatics and Decision Making*.

Sahoo, P. K., Mohapatra, S. K., & Wu, S.-L. (2016). Analyzing Healthcare Big Data With Prediction for Future Health Condition. *IEEE Access*, *4*, 9786–9799. https://doi.org/10.1109/ACCESS.2016.2647619

Basco, A., & Senthilkumar. (2017). *Real-time analysis of healthcare using big data analytics*. IOP Conf. Series: Materials Science and Engineering.

Mansour, R. F., Amraoui, A. E., Nouaouri, I., Diaz, V. G., Gupta, D., & Kumar, S. (2021). Artificial Intelligence and Internet of Things Enabled Disease Diagnosis Model for Smart Healthcare Systems. *IEEE Access*, *9*, 45137–45146. https://doi.org/10.1109/ACCESS.2021.3066365

Pasha, S. N., Ramesh, D., Mohmmad, S., Harshavardhan, A., & Shabana. (2020). Cardiovascular disease prediction using deep learning techniques. *IOP Conference Series: Materials Science and Engineering*, *981*(2), 022006. https://doi.org/10.1088/1757-899X/981/2/022006
Hill, N. R., Ayoubkhani, D., McEwan, P., Sugrue, D. M., Farooqui, U., Lister, S., Lumley, M., Bakhai, A., Cohen, A. T., O'Neill, M., Clifton, D., & Gordon, J. (2019). Predicting atrial fibrillation in primary care using machine learning. *PLOS ONE*, *14*(11), e0224582. https://doi.org/10.1371/journal.pone.0224582
Banaee, H., Ahmed, M., & Loutfi, A. (2013). Data Mining for Wearable Sensors in Health Monitoring Systems: A Review of Recent Trends and Challenges. *Sensors*, *13*(12), 17472–17500. https://doi.org/10.3390/s131217472
Gardašević, G., Katzis, K., Bajić, D., & Berbakov, L. (2020). Emerging Wireless Sensor Networks and Internet of Things Technologies—Foundations of Smart Healthcare. *Sensors*, *20*(13), 3619. https://doi.org/10.3390/s20133619
Ennafiri, M., & Mazri, T. (2020). *Internet of Things For Smart Healthcare: A Review on Potential IoT Based System and Technologies to Control Covid-19 Pandemic*. *XLIV-4-W3-2020*, 219–225. https://doi.org/10.5194/isprs-archives-XLIV-4-W3-2020-219-2020
Jo, T., Nho, K., & Saykin, A. J. (2019). Deep Learning in Alzheimer's Disease: Diagnostic Classification and Prognostic Prediction Using Neuroimaging Data. *Frontiers in Aging Neuroscience*, *11*, 220. https://doi.org/10.3389/fnagi.2019.00220
Marbury, D. (2018). Healthcare technology's future coming into focus. *Ophthalmology Times*, 3.
Ngiam, K. Y. (2019). Braving the new world of artificial intelligence. *Nature Medicine*, *25*, 12–13.
Gong, P., Zhang, C., & Chen, M. (2020). Editorial: Deep Learning for Toxicity and Disease Prediction. *Frontiers in Genetics*, *11*, 175. https://doi.org/10.3389/fgene.2020.00175
Chen, M. (2020). *Deep Learning with Application in Disease Prediction and Precipitation Forecasting* [Ph.D., State University of New York at Stony Brook]. https://www.proquest.com/docview/2429658795/abstract/30559AD0D90640EAPQ/1
Chen, M., Hao, Y., Hwang, K., Wang, L., & Wang, L. (2017). Disease Prediction by Machine Learning Over Big Data From Healthcare Communities. *IEEE Access*, *5*.
Harerimana, G., Jang, B., Kim, J. W., & Park, H. K. (2018). Health Big Data Analytics: A Technology Survey. *IEEE Access*, *6*.
Chui, K., Alhalabi, W., Pang, S., Pablos, P., Liu, R., & Zhao, M. (2017). Disease Diagnosis in Smart Healthcare: Innovation, Technologies, and Applications. *Sustainability*, *9*(12), 2309. https://doi.org/10.3390/su9122309
Dash, S., Shakyawar, S., Sharma, M., & Kaushik, S. (2019). Big data in healthcare: Management, analysis, and future prospects. *Journal of Big Data*.