Journal of Applied Disciplines

Volume 1 | Issue 1 Article 2

July 2023

How technology may be used for future disease predictions

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2023

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Abstract

Exasperated by the ongoing global pandemic, the healthcare system is grappling with the formidable challenges posed by proper and effective disease treatments. Nevertheless, amidst these growing difficulties, the healthcare field has witnessed significant technological advancements, offering promising avenues for disease prediction. Notably, a positive correlation exists between the utilization of technologies and their potential to serve as valuable tools for disease prediction. As our reliance on technological sophistication continues progressing, current research highlights numerous viable options to augment the healthcare sector. This review explores the current state of utilizing technologies and their potential to enhance healthcare, shedding light on their impact and future possibilities. By examining the existing literature, this study intends to provide a comprehensive overview of the diverse applications and benefits of technology in healthcare, offering insights into how technology can be harnessed to improve disease prediction and patient outcomes. Through analysis of the existing body of knowledge, this review aims to contribute to the ongoing discourse surrounding the integration of technology in healthcare, thereby informing future research and guiding policymakers and healthcare professionals in leveraging the full potential of technology to address the challenges faced by the healthcare system.

Keywords: Internet of Things (IoT), Internet of Medical Things (IoMT), Artificial Intelligence (AI), Machine Learning (ML)

1.0 Introduction

Our healthcare system has faced ongoing challenges 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 and 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 adequate diagnosis method. Current medical costs have continued to rise without the correct justification. Up to one-third of medical expenses are considered unnecessary, with only about half of care aligned to evidence-based treatments (Pavel et al., 2013). This is mainly because healthcare decisions are subjective, 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), 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 is 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 unknown, so prediction is not easy (Chae et al., 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, curating, and sharing data make it difficult to apply machine learning to large-scale healthcare (Dhindsa et al., 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.

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 showing gaps in the study are available to point to where a more in-depth analysis can begin.

2.0 Background

Since the increased technological advancements, Artificial Intelligence (AI) 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 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 improve 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 less 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' experience 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, a care provider could make more accurate recommendations (Pavel et al., 2013).

There have been several computer-aided methods that have been developed for disease predictions. APACHE III is a prognostic scoring system that predicts 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.

3.0 Research Methods

Due to its popularity and ties to healthcare, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework will be used throughout this paper. Systematic reviews and meta-analyses have become increasingly important in healthcare, with clinicians reading them to keep up with their specialties (Page et al., 2022). 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., 2022). In addition to using PRISMA, this paper follows the Kitchenham and Charters methodology by covering three main phases (planning, conducting, and reporting).

Specifying the research questions is a critical step in any SLR. Based on this, the following research questions are posed

R1. How have technologies been currently utilized in the healthcare field?

R2. Can technologies be an effective way to collect and filter patient data?

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

Per Kitchenham and Charter (2007), 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 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.

4.0 Conducting the Review

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 (Table I).

Table I. Keyword(s) used for search.

Deep Learning	Fog Computing	Artificial Intelligence
Internet of Medical Things (IoMT)	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)

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.

4.1 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, 2018*)* guide, the following classification scheme was developed (Table II).

Table II Classification Scheme

Machine Learning & Artificial Intelligence	Research shows how artificial intelligence gathers data from parties and shares it with healthcare professionals.
Big Data in Healthcare	Research shows how Big Data (unstructured data) is currently utilized in healthcare and the various methods used to collect data.
Disease Prediction & Improved Care	How has the data gathered been used to predict future disease?
Internet of Healthcare Things	How have current IoMT devices been used to collect patient data, and how it ties back into disease prediction?

4.2 Documenting the Search

Kitchenham and Charter's (2017) methods outline the necessity for documenting the search methods. This is necessary to allow the search to be replicated by other researchers. The criteria for selecting articles and creating a framework to classify the selected materials come from peer-reviewed journals. These databases cover most academic journals in English available and focus on the technology and healthcare field (Table III)

Table III Databases and journals used for research.

Database	*Journals Searched*	*Coverage*
IEEE	Computer Society	2005 - present
	Internet of Things Journal	2005 - present
	Biomedical Engineering	2005 - present
	Biomedical and Health Informatics	2005 - present
Academic Search Premier	International Journal of Environmental Research and Public Health	2005 - present
	Institute of Physics IOP Science	2005 - present
	Frontiers in Genetics	2005 - present
	Journals of Big Data	2005 - present
	Journal of the American Medical Information	2005 - present
PubMed	National Library of Medicine	2005 - present

The research area is 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 the present. 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 irrelevant 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 meets 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?

4.3 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 must be tied directly to the research questions.

5.0 Results

Shows in Figure 1, 1,065 papers were returned in the database searches with no additional records identified through other sources. After 173 duplicate records we removed, 892 records remained. Of the 892 records, an additional 837 documents were removed due to their lack of alignment with said classification scheme (Table III). What remained was 55 full-text articles for eligibility. A final level of exclusion removed 20 records for multiple reasons.

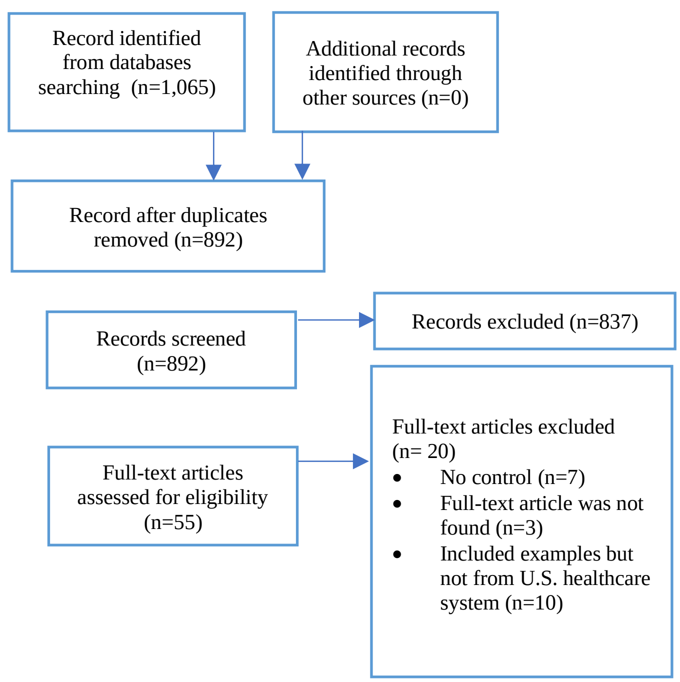

Figure I Flowchart of study selection.

What remained was 35 records included in this literature review that shared common themes in showing how technologies (beyond IoMT devices) had been used to aid in healthcare.

Results of Review

Multiple examples of technology being used in healthcare were shown to be prevalent. Due to this, sub-headings are used in this paper to organize the results in their respective categories. One common thread among the research is that they all use IoMT technologies.

Artificial Intelligence/Machine Learning

With inspirational technologies such as IoT and Artificial Intelligence (AI), healthcare services have improved. One such use of AI technology is in a proposed method called Crow Search Optimization algorithm-based Cascaded Long Short Term Memory (CSO-CLSTM). This AI advancement has shown 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 machine learning approach is currently used to identify nonlinear associate and complex interactions between variables without pre-specifying these relations in atrial fibrillation (Hill et al., 2019).

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 into analyzing the data collected by IoMT devices. Doctors typically don't analyze real-time steaming e-health data; data mining these historical records allows clinicians to examine conditions that could be common across subpopulations and regions to understand health trends (Chen et al., 2017). The more information a doctor has available in a searchable format, the more accurate the diagnosis.

Big Data Analytics (BDA)

Big Data Analytics (BDA) platforms best analyze the structure and unstructured data gathered from healthcare management systems (Sahoo et al., 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). Data mining devices (such as IoMT) have been shown to collect data to successfully predict and make informed decisions when considering continued time-series measurements for ongoing healthcare. (Banaee et al., 2013). With the continued reliance on wearable IoMT 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 real-time COVID-19 monitoring systems as an IoMT 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 et al., 2019).

Blockchain technologies for data distribution is an area that is growing in its usage in the healthcare sector (Marbury, 2018). Although used in cryptocurrency, Blockchain technologies have become popular in sharing large amounts of data with various healthcare providers by 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 and implementing Health 2.0's technologies (Software Defined Networks (SDN), Nanotechnologies, and Point-of-Care Devices (PoCD)) (Gong et al., 2020). Most research points to the need to offload the AI functionality outside of the IoMT devices to more reliable devices. It doesn't necessarily seem to be an issue with collecting data but how to share it with those most benefit from it. 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 only benefits a small group.

Disease Prediction & Improved Care

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 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 improve early detection ability.

An additional example is a piece of technology used called EarlySense. This technology continuously assesses heart and respiratory rates over one hundred times per minute. EarlySense patients achieved a 9% decrease in overall hospital stay. This ongoing monitoring isn't something clinicians can do and could be improved using IoMT technologies. (Nosta, 2018). Reduction in the length of hospital length is advantageous for the hospital also. The quicker turnaround time a hospital can have on a patient's visit, the more patients they can service, thus increasing their overall revenues. Hospital administrators know that the length of a hospital visit directly correlates to the general level of satisfaction a patient has. Patients feel when they are kept longer than necessary, it's frustrating and negatively impacts their experience. The length of stay directly impacts bed management, which lowers turnover and decreases revenue (Clarkson, 2021). Any hospital that wishes to maximize its revenues will take the necessary steps to implement technological advances to aid in its bottom line.

Discussion and Conclusion

Based on all the research completed up to this point, it's apparent that additional research into the field of IoMT would benefit the industry. Survey/research results could be used to identify the gaps in using 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 et al., 2019). This proposed research could show the validity of IoMT and how it could be advantageous in the future aggregation of data collected for potential disease predictions.

One area that had multiple occurrences in the research was the lack of technical horsepower; an IoMT device can handle a fine level of data filtration. This is where the concept of fog computing could be used in filtration. It's not feasible to expect IoMT devices to have a fine-grained level of data filtration so that 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 et al., 2017).

Additional areas where gaps have been seen are how to store the data to be easily assessable while maintaining integrity. 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. It commits based on analytic demands (Dash et al. 2019). 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 the usage of technologies for the betterment of patients.

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