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# Researching public health datasets in the era of deep learning: a systematic literature review

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## Abstract

**Objective:** Explore deep learning applications in predictive analytics for public health data, identify challenges and trends, and then understand the current landscape. **Materials and Methods:** A systematic literature review was conducted in June 2023 to search articles on public health data in the context of deep learning, published from the inception of medical and computer science databases through June 2023. The review focused on diverse datasets, abstracting applications, challenges, and advancements in deep learning. **Results:** 2004 articles were reviewed, identifying 14 disease categories.

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Observed trends include explainable-AI, patient embedding learning, and integrating different data sources and employing deep learning models in health informatics. Noted challenges were technical reproducibility and handling sensitive data. **Discussion:** There has been a notable surge in deep learning applications on public health data publications since 2015. Consistent deep learning applications and models continue to be applied across public health data. Despite the wide applications, a standard approach still does not exist for addressing the outstanding challenges and issues in this field. **Conclusion:** Guidelines are needed for applying deep learning and models in public health data to improve FAIRness, efficiency, transparency, comparability, and interoperability of research. Interdisciplinary collaboration among data scientists, public health experts, and policymakers is needed to harness the full potential of deep learning.

**Keywords**

public health datasets, deep learning applications, predictive modeling, EHR analysis, trends and challenges

## Introduction

The fusion of deep learning methodologies with extensive and heterogeneous health datasets has emerged as a powerful and trans-formative field, revolutionizing the way of analyzing, interpreting, and extracting insights from vast and complex healthcare data.[1] Public health datasets encompass a diverse range of information, including electronic health records, epidemiological data, images data[2]; where the traditional analytical approaches have limited capabilities to uncover hidden relationships and patterns within these datasets due data volume and complexity.[3]

Deep learning applications have helped medical professionals through several areas such as symptom monitoring, diseases and outbreak predictions, patients profiling, patients' disease history, predictive modeling, and decision support systems. Deep learning could revolutionize public health by providing insights and surveillance tools to prevent and treat diseases.

Health-related public data provides valuable resources for researchers. Wanga et al.[4] mentioned 28 of those health- related repositories such as OCHIN which is "a collaborative, member-based network of federally qualified health centers and similar organizations, which delivers primary health care to vulnerable populations".[5] It is the largest network of CHCs using a single instance of the Epic EHR.[6] It has more than 500 community health centers (CHCs) in its network and serves approximately 2.8 million patients.[7] High-dimensional EHR data provides a rich source of information for machine and deep learning algorithms, allowing them to capture complex patterns and relationships between different variables. Deep learning and high-dimensional EHR data have the potential to improve healthcare outcomes by enabling the development of more accurate and personalized predictions and decisions, leading to improved patient care and better population health management.

This systematic review aims to explore the scope and limits of cutting-edge deep learning techniques that researchers are using for predictive analytics in public health data and to review associated issues and trends, such as challenges, in this area of research. Specifically, in this review we tried to answer the following questions: (1) What are major deep learning and predictive modeling approaches discussed in public health research papers? (2) What are some of the significant research trends and associated issues in this area of research?

## Preliminary review of the literature

We conducted a preliminary SLR to learn about the general popular public health datasets that are available and used frequently in research papers. Based on this initial research, we focused on the three terms combined “public health datasets” in one source, Google Scholar. The initial search from Google Scholar for those three terms together retrieve around 750 results, excluding patents. We focus on two main aspects searching through those results:

- What are the main subjects discussed in those papers?
- What are the main public health datasets mentioned in those papers?

## *Preliminary SLR: Main subjects*

*Visualization.* Visualization is a large theme in surveyed research papers related to public health datasets. Some of the focused visualization subjects include: geospatial,[8–11] interactive data visualization,[12–15] customizable visualization,[16] and visualization libraries.[17] Research indicated that visualization is not as advanced in health applications as compared with other scientific disciplines despite its significant positive influence on better understanding data in those applications.[12]

While most of medical or health visualization focused on images (e.g.[10,18–21]), yet few research papers discussed text visualization, e.g. medical documents.[22]

*Health insurance issues and analysis.* Health information concerns from privacy perspectives span from personal, to health and also financial information about patients. Public and private health providers can have access to all those categories of sensitive information. There are few public insurance datasets such as:

- All-payer claims databases: (e.g. cited by:[23–27]).
- : CPS ASEC.[28–30]
- HealthCare.gov datasets.[31–33]
- Primary Care Reimbursement Service.[34,35]

*Public health datasets and predictive analytic.* Predictive analytic is a major tool for the evaluation and analysis of health datasets. Among all different public datasets and their focuses, machine learning and predictive analytics are on top of the researched subjects.

## *Preliminary SLR: popular public health datasets*

There are several public health datasets that are available online. The nature of variables and details in those datasets can vary from privacy and user information perspectives. Open data is a new public health model, where previously only reports or outputs in certain formats are provided in public, while raw data can be provided upon request.[36] The formats and structure for those datasets are not consistent due to several factors. Public health datasets may have to deal with different state and federal regulations specially in relation to privacy and sensitive information.

We include below a comprehensive list of some of the public health datasets that are frequently used in public health research. Most of the datasets are publicly available, but there are a few that may not be fully public or may have restrictions.

- US Census: General use popular important public dataset in US. It contains a lot of important information about people lives. Census data are used to distribute funds for government programs such as Medicaid, and for planning the locations of schools, roads, and other public facilities. Census data are also used to track population trends over time as well. In the preleiminary SLR, some papers reported using health-related data from US Census (e.g.[37]).

- OCHIN (Oregon Community Health Information Network) dataset (https://ochin.org/data-exchange). OCHIN is used in several health studies and publications and not fully publicly available.[38] OCHIN is a collaborative, member-based organization of federally qualified health centers and similar entities.
- The Uniform Hospital Discharge data set (UHDDS) with Restricted access.[39]
- The Minimum data set for long term care (MDS).
- The Health Plan Employer Data and Information Set (HEDIS) with Restricted access.
- Healthdata. gov which incorporates more than a century of US healthcare data.
- The World Health Organization.
- Data. gov which includes thousands of data sets which, among others, include health, public safety, and scientific research data sets.
- The Human Mortality Database (HMD).
- OpenFDA, launched by the U.S. Food and Drug Administration.
- Medicare. gov
- Canadian Community Health Survey (CCHS).
- National Health Interview Survey (NHIS).
- Mississippi Youth Risk Behavior Survey (YRBS).
- Behavioral Risk Factor Surveillance System (BRFSS).
- National Health and Nutrition Examination Survey (https://www.cdc.gov/nchs/nhanes/index.htm/).
- Medical MNIST (https://medmnist.com/).
- Medical imaging and MRICloud with Restricted access to specific research groups.[40]
- Open EEG (https://github.com/meagmohit/EEG-Datasets/).
- Ontario Incidence Study of Reported Child Abuse and Neglect-2003 (OIS 2003): (https://cwrp.ca).

## Searching strategy to retrieve studies

After completing the preliminary SLR process, we decided to focus on public health datasets in the era of deep learning. In this focused Systematic Literature Review (SLR), the guidelines were followed from References.[41,42] The research process is divided into three phases. In the first planning phase, the stages of defining research questions, developing, and validating review protocols are covered. In the second phase, identification and selection of relevant studies, data extraction, and the information synthesis process are covered; and in the third phase, writing and validating the review are reported.

### *Plan review*

*Review protocol.* The development and validation of the review protocol highlight the searching of related articles with the appropriate keywords and the literature sources.

*Searching Keywords.* To guarantee that the review closely covers Public Health dataset and relevant to deep learning and predictive modeling, we tried to limit our search to the most relevant search term. Thus, we started with the keywords, and then we went through the following steps:

- Extracting the major distinct terms from our research questions;
- Using different spellings of the terms;
- Updating our search terms with keywords from relevant papers.

We used the main alternatives and added “OR operator” and “AND operator” to get the maximum amount of directly relevant works in the literature as shown in (Table 1). This table outlines the alternative search keywords used to ensure comprehensive coverage of relevant literature in our systematic review. Each ID represents a distinct search query combination aimed to capture various studies related to public health datasets and deep learning techniques. For example, ID 1 queries include core terms related to public health data and the fundamental deep learning methods, ID 2 expands on ID 1 by including additional advanced deep learning methods to capture more recent advancements and specialized applications of deep learning in public health contexts, ID 3 queries further broadens the scope by incorporating even more specific deep learning techniques to cover a wide array of deep learning methodologies that may be applied in the analysis of public health data. Appendix A provides the specific search formulas used in each database

*Literature resources.* Primary review studies: PubMed, Web of Science, Scopus, and Springer databases were chosen for selection of relevant articles. These databases have maximum coverage of quality articles in our domain. We restricted our search to research articles published in English and in peer-reviewed journals or conferences available from the inception of each database through 2023.

## Conduct review

In this phase, we conducted the review according to the research questions, keywords, and protocols. This phase mostly emphasizes the inclusion and exclusion of articles, according to (Table 2).

**Table 1.** Searching keywords alternatives.

| ID | Keywords |
|---|---|
| 1 | (“Public health data” OR “public health dataset” OR “EHR” OR “electronic health record”) AND (“deep learning” OR “representation learning” OR “neural network” OR “convolutional neural network” OR “con- vNet” OR “CNN” OR “recurrent neural network” OR “RNN” OR “long short-term memory” OR “LSTM” OR “generative adversarial network” OR “GAN” OR “autoencoder” OR “restricted Boltzmann machine” OR “deep belief network” OR “DBN”) |
| 2 | (“Public health data” OR “public health dataset” OR “EHR” OR “electronic health record”) AND (“deep learning” OR “representation learning” OR “neural network” OR “convolutional neural network” OR “con- vNet” OR “CNN” OR “recurrent neural network” OR “RNN” OR “long short-term memory” OR “LSTM” OR “generative adversarial network” OR “GAN” OR “autoencoder” OR “restricted Boltzmann machine” OR “deep belief network” OR “DBN” OR “deep reinforcement learning” OR “DRL”) |
| 3 | (“Public health data” OR “public health dataset” OR “EHR” OR “electronic health record”) AND (“deep learning” OR “representation learning” OR “neural network” OR “convolutional neural network” OR “con- vNet” OR “CNN” OR “recurrent neural network” OR “RNN” OR “long short-term memory” OR “LSTM” OR “generative adversarial network” OR “GAN” OR “autoencoder” OR “AE” OR “restricted Boltzmann machine” OR “deep belief network” OR “DBN” OR “deep reinforcement learning” OR “DRL” OR “gated recurrent units” OR “GRU” OR “pre-trained model” OR “transfer learning” OR “graph neural network” OR “feed-forward neural network”) |

**Table 2.** (a) Inclusion criteria description and (b) exclusion criteria description.

| Category | Criteria |
|---|---|
| (a) Inclusion | • The research was relevant to public health datasets<br>• The research was directly related to the data<br>• The research was related to deep learning applications<br>• The research was conducted using deep learning techniques related to various data types<br>• For duplicate publications of the same study, the newest and most complete one was selected. This is recorded for only one study whose related work appeared two times<br>• The research is a journal article or a conference proceeding |
| (b) Exclusion | • Studies that were irrelevant to public health datasets and deep learning domain were skipped |

Generally, this study focused on peer-reviewed publications that was relevant to deep learning and directly related to the data, applied deep learning techniques used to analyze data available from public health datasets. Studies that were irrelevant to public health datasets and deep learning domain were skipped.

*Study selection.* As mentioned in section 2, we conducted a primary review of research articles using various databases, including PubMed, Web of Science, Scopus, and Springer. Our findings revealed that Scopus yielded the highest number of relevant articles among these databases. Specifically, approximately 45.80% of Springer's unique records, 59.16% of Web of Science's unique records, and 84.29% of PubMed's unique records were also included in Scopus. Consequently, we have chosen to focus our analysis primarily on Scopus results. The whole process of Scopus study selection is illustrated in (Figure 1). A total of 2545 articles appeared in the online search. By applying filtration with title, keyword, inclusion, and exclusion criteria, a total of 2534 papers were short-listed. Inclusion and exclusion criteria are defined in (Table 2). Among them, 530 articles were excluded; 200 articles were found irrelevant to deep learning, and 330 were found irrelevant to Public Health. At the end, 2004 articles are kept in the list after going through full reading. To ensure the quality of our selection, we assessed the remaining articles with a focus on identifying studies that are not only more pertinent and comprehensive but also address all the core research questions. These primary inquiries include whether the studies center around public health data and if they dig into the essential deep learning techniques, such as neural networks, CNNs, RNNs, LSTM, and GANs, particularly in the context of large datasets.

The article selection process involved three researchers: Authors "X", "B", and "C". The 2545 articles identified from the initial search were equally divided among the three researchers for screening. Each researcher independently reviewed their assigned articles based on predefined inclusion and exclusion criteria. To ensure consistency, a subset of 10% of the articles was randomly selected and reviewed by all three researchers, resulting in a Cohen's kappa statistic of 0.78, indicating substantial agreement. Authors "A" and "F" contributed to other essential tasks in the study but were not involved in the article screening process. Cohen's kappa statistic, a measure of inter-rater reliability, was calculated using the formula $\kappa = P_0 - Pe/1\text{-}Pe$, where $P_0$ is the observed proportion of agreement among raters and Pe is the expected proportion of agreement by chance. This confirming the reliability of the selection process. Collaborators "G" and "I" contributed to the data formatting process, ensuring that the data collected was in the appropriate formats for analysis and reporting.

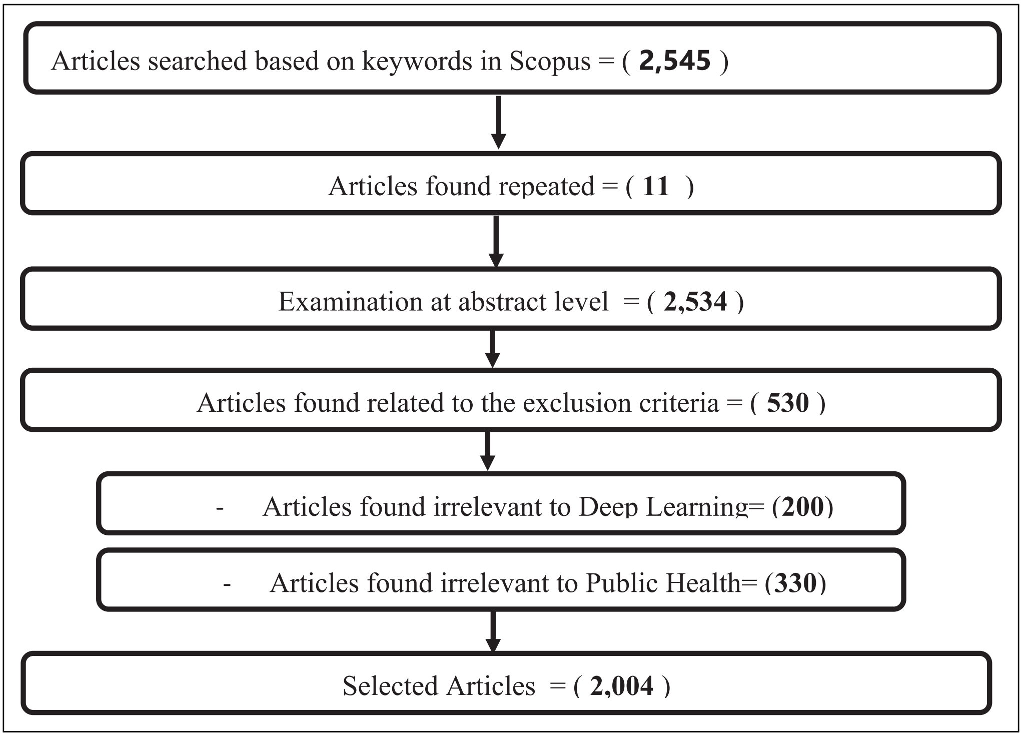



**Figure 1.** Study selection process.

*Report review.* At this stage, the extracted data were aggregated to answer the research questions. For our research questions, we used the narrative synthesis method. Accordingly, we used tables and charts to present our results. The guidelines of References[41] were closely followed in the reporting of results in the Statistical Analysis section below. The provided guidelines emphasize the importance of a thorough methods overview, calling for clear and detailed descriptions of research methods encompassing data collection, processing, and analysis to ensure reproducibility. Additionally, they stress the significance of presenting research results coherently through structured and organized formats, including visual aids like figures, tables, and graphs for improved clarity. Furthermore, the guidelines highlight the need for offering a comprehensive overview of how the research findings are applicable to real-world contexts and contribute to practical applications and services.

## Statistical analysis

In this section, we provide few stat figures and tables. (Figure 2) shows the years of publications for the selected papers. The Figure indicates the recent increase of interests in this field with a significant growth starting the year 2016. The same finding can be noticed observing the top 10 cited publications where they are between the years 2016-2019.

The top different disease categories are highlighted in (Figure 3) that used public health datasets and deep learning techniques.

The top different data formats or sources of data studied are presented in (Figure 4) that used public health datasets and deep learning techniques.

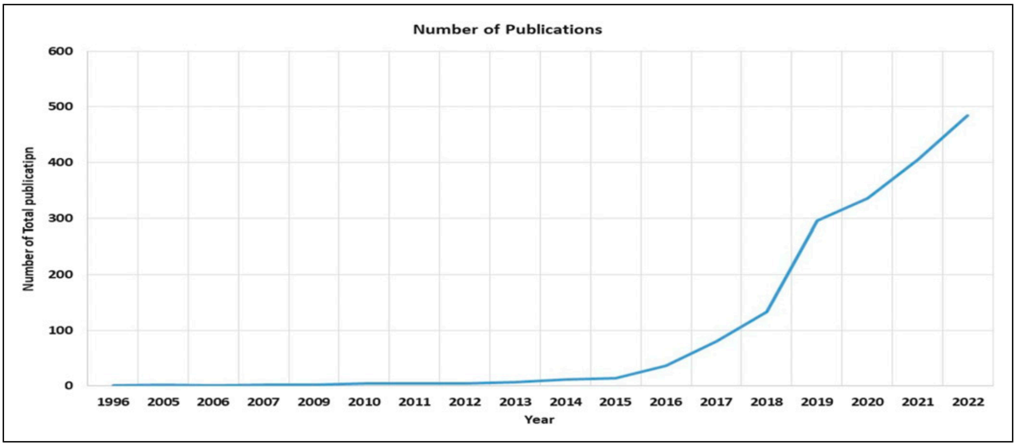



**Figure 2.** The Number of publications per year.

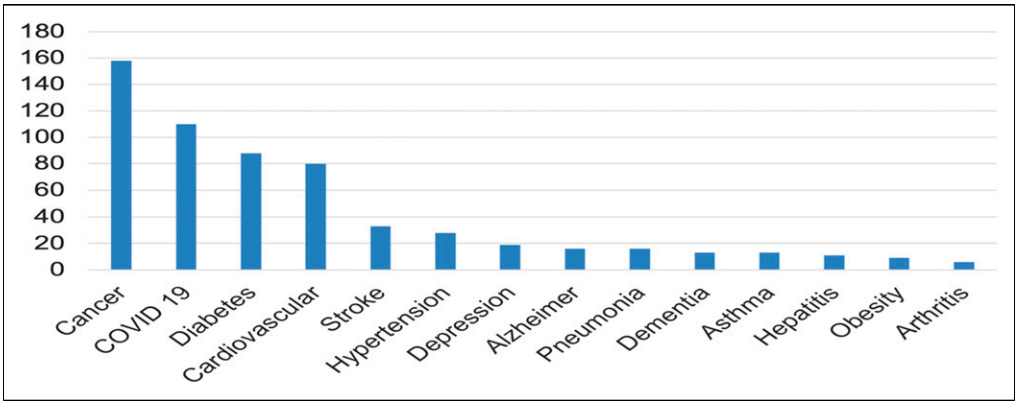



**Figure 3.** The Top Common Disease Categories Studied using Public Health Datasets.

(Tables 3 and 4) shows the distribution of our included publications based on their type. The overall included are about 2000 with roughly 1/4-th conference papers and 3/-4th journal articles.

(Table 5) shows for journal articles number of papers published in major publishers.

(Table 6) shows the different Deep learning types presented in the literature reviewed. Those are based on citing those types only within the "Abstract" section of the paper. While it captures a broad range of models, it is not exhaustive. Additional models may be identified in specific studies or emerging research.

(Table 7) shows the Top Researchers Names and Number of Publications per Researcher.

(Table 8) shows the top Journals and the Number of Publications shown in each Journal.

## Deep learning and health informatics

We noticed a research trend that started around a decade ago, employing deep learning models in health-related knowledge learning and prediction. Earlier in the statistics section, we showed that

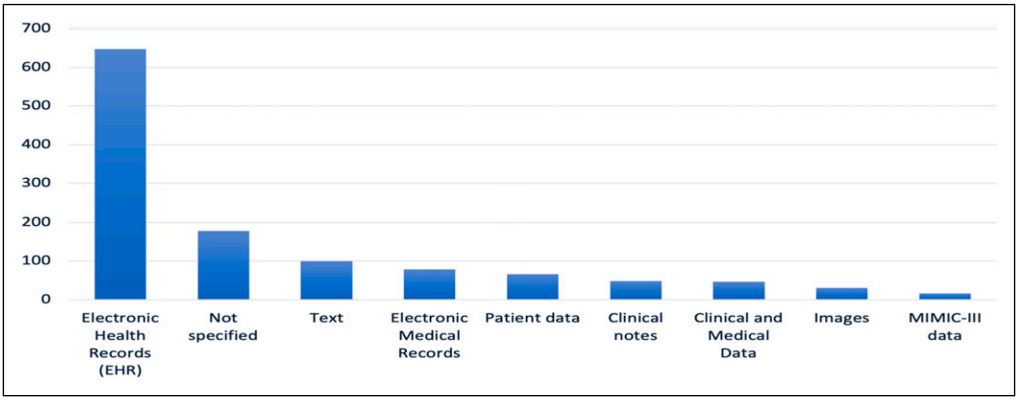



**Figure 4.** The top data formats or sources of data studied.

**Table 3.** Distribution of papers based on publication type. (Table 4) shows top 10 cited papers in our collected list. The list shows that most of the top cited papers focus on using deep learning approaches in health related data.

| Publication type | Number | Status |
|---|---|---|
| Journal articles | 1408 | Included |
| Book or book chapter | 91 | Excluded |
| Conference paper | 596 | Included |
| Conference review | 81 | Excluded |
| Review | 246 | Excluded |
| Others (note, erratum, editorial, short survey, letter) | 112 | Excluded |
| Total included | 2004 | |

**Table 4.** Top 10 cites articles.

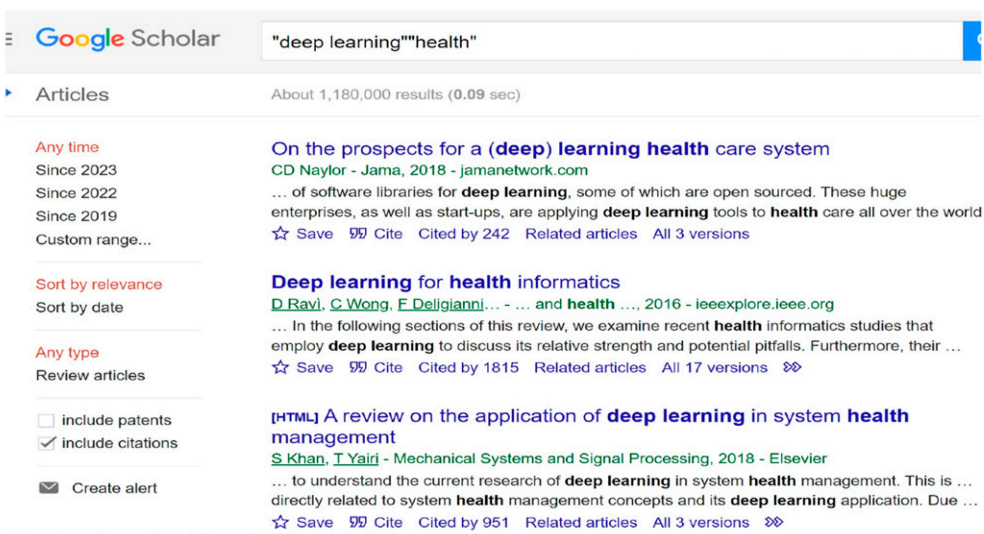
| Article | Year | Subject | Current citations no. (scopus) |
|---|---|---|---|
| 43 | 2018 | Deep learning for healthcare | 1153 |
| 44 | 2018 | Deep learning for healthcare | 1076 |
| 45 | 2018 | Deep learning in biology and medicine | 968 |
| 46 | 2016 | Deep patient | 864 |
| 47 | 2017 | Cardiovascular risk prediction | 626 |
| 48 | 2017 | Deep EHR | 557 |
| 49 | 2016 | Attention mechanisms and health care data | 536 |
| 50 | 2017 | RNN and heart failures detection | 458 |
| 51 | 2019 | Acute kidney injury prediction | 454 |
| 52 | 2017 | Graph-based attention and healthcare learning | 359 |

most of the top 10 cited papers in this review utilized deep learning models. This is not uncommon or surprising as deep learning has the similar hype in many other fields as well. (Figure 5) shows more than million candidate articles in Google Scholar that include the two keywords "Deep learning" and "Health". More than half of those are after 2015.

## Deep learning Models for health public data

Deep learning models (DLMs) or deep neural networks can be used to solve several urgent and important real-world health-related problems on large-scale datasets. The need of effective data analytics in health informatics for better decision making is an ongoing challenging issue.[53] Our analysis focuses on deep learning models that have been extensively validated and are widely adopted in current health data applications. Although newer architectures like transformers and large language models are gaining traction, their application in health informatics is still emerging and is therefore beyond the scope of this study. Our previous sections shows some of the popular DLMs in health informatics (e.g. LSTM, CNN, GAN, AE, RNN, GRU, GNN and DBN). We cover a summary of each one of those models in health informatics in the next sections.

*Long short-term memory networks: LSTM.* LSTM is a variant of RNN designed to alleviate problems related to long- term dependencies.[54] LSTMs are well-suited for processing sequences of data with long-range dependencies. They can capture information from earlier time steps and remember it for a more extended period, making them effective for tasks like natural language processing (NLP) and time series analysis.[55] LSTM can refer to the information of the previous unit when processing the information of this unit, but it does not refer to the information of the subsequent unit.[56] LSTM in health care research have been used to predicting life expectancy,[57] healthcare usage based on medical records,[58] and machine health monitoring.[59] LSTM networks' ability to handle long-range



Deep Learning and Health search on Google Scholar

**Figure 5.** Deep Learning and Health search on Google Scholar.

dependencies in health data makes them effective for modeling lifespan estimations. However, LSTMs can be computationally intensive and prone to overfitting if not properly used. Despite these challenges, their capacity to capture temporal dynamics and manage missing data proves advantageous in health applications like forecasting patient lifespans from historical records.

*Convolution neural networks: CNN.* CNN is an advanced version of DNNs which arranges its neurons in three basic dimensions. The main advantage of CNN is that it does both feature extraction and classification, automatically.[60–63] CNN is used in many image detection and classification in many domains and applications including health related image classification applications (e.g. medical images classification,[64,65] lung cancer,[66] Ultrasound images,[67] breast tumors,[68] skin cancer,[69] *tuberculosis*,[70] and many others.

*Generative adversarial networks: GAN.* GAN is an unsupervised learning method consisting of two neural networks that are competing with each other in trying to learn the pattern of its input by itself and generate new samples with similar characteristics to the real data. One key advantage of GAN is that the model is able to learn the underlying data distribution. Additionally, the existence of a discriminator enforces the generator in generating accurate results. GANs can also reduce the training data needed for training, which is suitable for medical imaging due to the shortage of data.[71] In health data GAN is used in many applications such as: ECG denoising,[72] chest X-ray images classification,[73] tomato leaf disease identification,[74] neuro imaging and clinical neuroscience.[75]

*Auto-encoders: AEs.* Autoencoders are unsupervised neural networks used for representing the structural data by data compression. They have been used for the purpose of reducing dimensionality and also detecting network anomalies in large datasets. Autoencoders benefit from the many technical advances made in the last years in the development of DNNS. One of the main advantages of autoencoders is their ability to learn quickly on unlabeled data.[76]

In health informatics, AEs are used to learn Cardiac-ICU and Neuro-ICU.[77] They are also used in medical imaging,[76] compressing patients features,[78] RNA target prediction,[79] detection of plants diseases,[80] and tumor identification and detection.[81–84]

*Recurrent neural networks: RNNs.* Recurrent neural networks are neural networks with directed cycles that are particularly suitable to process time series data.[85,86] They are designed to process sequences, and can remember or forget information from earlier steps when processing later steps in a sequence.[87] RNNs allow previous outputs to be used as inputs while hiding the state.[88] RNNs are used in health informatics in different examples or applications such as, future diagnosis of heart failure,[89,90] predicting health by suicide,[87] predicting hospital readmission of diabetic patients,[91] predicting HIV status,[92] and end-to-end classification of cell-cycle stages.[93]

*Gated Recurrent Units: GRU.* Gated Recurrent Units are special variants of LSTMs that merge the forget and input gates into a single update gate resulting in a simpler more efficient model than standard LSTM models.[94] GRUs do not incorporate memory cells, they have reset gates instead. These reset gates allow the hidden state to leave the unimportant information and thus, focusing on the quality of content.[95] In health informatics, GRUs are used in life estimation,[96] patient case similarity evaluation,[97] flu forecasting,[98] clinical event prediction,[99] stroke volume estimation,[100] prediction of Parkinson's disease,[101] patients trajectory prediction,[102] predicting blood pressure,[103] and human emotions recognition.[104]

*Graph Neural Networks: GNN.* Graph neural networks (GNNs) are models for representation of learning graphs, they are built upon the multi- layer perceptrons (MLP) architecture with additional message passing layers to allow features to flow a cross nodes.[105] They are increasingly becoming popular in various fields such as computer vision, computational biology and chemistry, where data are naturally explained by graphs.[106] Graph Neural Networks are used in health informatic research and applications such as: classification of mammograms,[107] estimating the state of epidemics spreading,[108–110] identification of providers with similar risk profiles in healthcare claims,[111] virus-human protein-protein interaction prediction,[112] modelling the bioactivities of ligands targeting orphan G protein-coupled receptors,[113] drug-target affinity prediction,[114,115] and prediction of circRNA-miRNA association.[116]

*Deep belief networks: DBN.* Deep belief nets are probabilistic generative models that are composed of multiple layers of stochastic, latent variables.[117] The main advantages of deep belief networks are their efficient learning algorithm, their ability to extract high dimensional features and to represent them in low dimensions, as well as their associative memory ability.[118] Deep belief nets are used in health informatics research and applications such as: seizure detection,[119] heart failure prediction,[120] detecting Neuro-degenerative Disease from MRIs,[121] emotion recognition,[122] and the classification of malaria-infected and uninfected images.[123]

## Deep learning applications in health public data

Applying Deep learning (DL) techniques in health public data has revolutionized how vast amounts of healthcare information are analyzed and interpreted in many health applications.[124] These techniques contribute to several applications that help in assessing population health trends, optimizing resource allocation, and enhancing public health strategies.[125] In this section, we outline the most crucial applications where the Deep Learning (DL) approaches are utilized and elucidate how Deep Learning (DL) approaches contribute to the enhancement of these applications and we discuss how the DL techniques hold immense promise for reshaping healthcare in public health datasets.

*Disease prediction.* Deep learning applications in the health public provide invaluable tools for accurate disease prediction, offering unprecedented insights into early detection, improving prevention strategies, and disease progressive assessment. With the development of DL techniques, the accuracy of medical disease prediction is continuously improved.[126] Several works reviewed the deep learning algorithms for disease prediction as.[127] In[127], Yu et al. showed the use of Structured data algorithms and Unstructured data algorithms to predict several types of disease. The DL techniques are extensively used for Chronic Disease prediction and for Epidemic Outbreak Prediction. The application of deep learning in infectious disease prediction has proven the efficiency in the surveillance of outbreaks.

*Drug discovery.* Drug discovery research generally aims to identify molecules with therapeutic effects against specific diseases The primary objective of drug discovery research is typically to identify molecules with therapeutic effects targeted at specific diseases.[128] DL techniques have emerged as a powerful tool being used in all stages of drug discovery and development. Several research utilized DL techniques in Deep learning in drug discovery.[129] For instance, In[130], Bai et al. proposed a tool called MolAICal that employs a two-component approach to design 3D drugs: the first component utilizes deep learning (DL) and a genetic algorithm trained on FDA-approved drugs, and the second component integrates molecular docking with a DL. Popova et al.[131] designed a deep reinforcement learning-based approach called ReLeaSE utilized for drug design. ReLeaSE integrates two deep neural networks (DNN), known as generative and predictive. The generative model was used to produce new compounds, and the predictive model was used to predict the properties of the compound.[131] The SLR in[129] presented the integration between the recent DL technologies and several drug discovery applications.

*Image analysis.* Medical image analysis plays a crucial role in healthcare that enhances early and accurate diagnosis and treatment planning and monitoring. DL techniques have revolutionized medical image analysis, offering unparalleled capabilities in interpreting imaging data and improving diagnostic decision-making. DL techniques are used for several medical image types and utilized in several disease diagnostic processes. Suzuki et al.[132] overviewed the area of deep learning in medical imaging and included the deep learning effects in the medical imaging analysis field, the focus of this overview is two models: a massive-training artificial neural network (MTANN) and a convolutional neural network (CNN) their applications to medical imaging. Several systematic reviews have already discussed the current approaches of DL in Medical image analysis as.[133,134] Other research focuses on using medical images and DL to study specific diseases, for example, the research in[135] determined the types of medical images utilized in the classification of COVID-19 and explored the employed methodologies in the COVID-19 classification tasks.

*Health monitoring.* The utilization of public datasets with deep learning techniques in health monitoring provides many applications with powerful tools for advancing personalized healthcare solutions.[136] The public health datasets, are comprised of diverse sources and kinds of data such as electronic health records and population health statistics that provide a comprehensive foundation of information for the health monitoring systems.[137,138] Deep learning techniques with their capabilities in handling large and complex datasets, bring unparalleled analytical prowess to extract meaningful insights from the available public health data.[139,140] By utilizing deep learning techniques, researchers can develop predictive models for health monitoring offering a nuanced understanding of health dynamics.[141] combining the accessibility of public data with the analytical power of deep learning holds significant potential to enhance the precision of health monitoring which contributes to early disease detection, supports the development of more targeted health monitoring systems, and provides effective healthcare interventions on a population scale. Sujith et al. in[136] presented a review of the smart health monitoring frameworks that utilized deep learning and machine learning techniques and algorithms for enhancing the handling of the healthcare data generated in Smart health monitoring.

*Medical research.* The availability of many public datasets and the strength of DL techniques fosters a collective approach to problem- solving in medical research.[142] This collaborative paradigm accelerates the discovery, leading to breakthroughs in disease understanding, drug development, and personalized medicine. The utilization of deep learning in public datasets marks a paradigm shift in medical research, where open access to data enhances medical innovation,[143] and drives advancements that have the potential to revolutionize healthcare practices and outcomes.[144]

## *Common disease categories and techniques studied*

In this paper, different disease categories studied are discussed. The most common disease categories studied are presented in (Table 9). The top common disease categories studied include

Hepatitis, Cardiovascular, Cancer, Stroke, Pneumonia, Diabetes, Alzheimer, Dementia, Obesity, Asthma, Hypertension, Arthritis, COVID-19, and Depression. The most common techniques used among these disease categories include Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Bi-directional Long Short-Term Memory (BiLSTM), Deep Neural Network (DNN), Perceptron Neural Network Autoencoder Networks, BERT (Bidirectional Encoder Representations from Transformers) Deep Auto-encoder Artificial Neural Network, Longitudinal Deep Learning Model, MLP (Multilayer Perceptron), and Transfer Learning.

## Research trends and challenges: EXAMPLES

One of the promising research trends in the scope of this paper is obviously to use deep learning algorithms to improve the accuracy of data analysis tasks. Another trend that we discussed already is the usage of different deep learning models and settings in health information data analysis.

We cite examples of research trends in health informatics datasets utilizing machine and deep learning methods.

### *The integration of different data sources or types*

In (Figure 4), data formats or sources of data are presented. Many recent research publications integrate data from different sources and types. So far, those are the different types of data used :

- Electronic Health Records Structured data
- Images
- Text (unstructured)
- Biological sequences
- ECG, EEG, MEG, etc signals
- Patient, clinical and medical data

In the last couple of decades the amount of data used in data analytic research increased rapidly. Additionally, there was a significant increase in the usage of unstructured data or text that is coming from several input sources such as: web-based contents, and documents, patients and medical records, and so on. Such spectrum of data is not only different in terms of those types mentioned earlier, but also in many other aspects. For example, how you deal with combining data from social networks that may have a lot of misinformation with data from hospitals, clinics and medical doctors?.

In addition, the presence of a significant quantity of data in various unspecified formats or originating from diverse sources in reviewed studies necessitates adherence to the principles of FAIRness in open and responsible research. This concept emphasizes the importance of data being Findable, Accessible, Interoperable, and Reusable, ensuring that research data management is conducted efficiently and effectively.

### *Deep learning research and reproducibility issues*

The issue of reproducibility is an ongoing problem in deep learning research in general. Many research papers present models, settings and discuss results and accuracy, however, with no solid public data about these details such results can be hardly verifies.

Technical reproducibility refers to the ability to reproduce a paper's results precisely as presented in the paper under the same condition.[145,146] Reproducibility is also critical for deep learning research, whose goal is to develop algorithms to reliably solve complex tasks at scale.[147] Reproducibility is an essential metric when assessing for possible clinical deployments of evaluated algorithms. of any algorithm.

## *Explainable-AI*

Explainable-AI is a rapidly emerging research area that focuses on annotating model's decisions as well as decision- making characteristics.[148,149] It is used to describe an AI model, its expected impact and potential biases and helps characterize model accuracy, fairness and transparency.[150] Explanations serve as a bridge between humans and AI systems.[151] The EU's guidelines on AI robustness and explainability[152] emphasize three key elements for the proper utilization of AI: transparency, reliability, and safeguarding of individual data. There are many popular frameworks of explainable AI including SHAP, LIME, MUSE, PDP, CE, etc. In health data Explainable-AI is important to interpret results and utilize their findings. Explainable AI is critical in health informatics helps avoid practical consequences.[153,154] It can also improve fairness and remove bias in decision making.[155] "Positional SHAP" (PoSHAP),[156] is proposed to interpret models trained from biological sequences by exploiting SHAP to generate positional model interpretations.

## *Patient embedding learning*

Patient embedding learning has several potential applications in healthcare, including:

- Predictive modeling: Patient embeddings can be used as input features in predictive models, allowing for more accurate predictions of patient outcomes, such as hospital readmission or disease progression.
- Improved patient clustering: Patient embeddings can be used to cluster patients into subpopulations with similar medical histories and demographics, improving population health management and reducing health disparities.
- Personalized medicine: Patient embeddings can be used to predict the likelihood of a patient responding to a specific treatment, allowing for the development of more personalized treatment plans.

## *Imbalanced data*

Handling of imbalanced health-related public data poses a considerable challenge for machine learning and deep learning approaches.[157] This imbalance data can impact model training, where the algorithm may prioritize the majority class. To overcome this challenge, employing machine learning and deep learning techniques in health public dataset should explore several imbalance handling strategies,[158] such as oversampling the minority class,[159] or utilizing techniques like Synthetic Minority Over-sampling Technique (SMOTE).[160,161]

Deep learning techniques offer a promising approach for handling imbalanced health datasets.[162] As examples, Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) excel in handling and capturing spatial and temporal dependencies in medical data.[163,164] Moreover, transfer learning Techniques where pre-trained deep learning models are fine-tuned for specific health challenges, can be particularly advantageous in scenarios with limited imbalanced labeled data.[165]

### Data ownership

Health data ownership and privacy concern are debated issues in the context of healthcare systems.[166] The current use of Big Data in healthcare faces challenges due to a lack of rules that manage data ownership and responsibilities.[167] These challenges arise when considering the collaborative and constructed nature of clinical data.[168] In[169] et al suggested discussing the use of Blockchain as shown in[170] to offer a new way to empower patients to control their data while ensuring secure and confidential data sharing through encrypted transactions.[168] However, despite Blockchain techniques' potential benefits in enhancing security and privacy, the widespread adoption of blockchain for healthcare data transfer and storage is still pending.[171]

## Discussions, limitations of the study and recommendations for future work

In conclusion, this systematic literature review delves into the dynamic landscape of public health research within the era of deep learning. The synthesis of existing studies has provided a comprehensive overview of the applications, challenges, and advancements in utilizing deep learning methodologies for the analysis of diverse datasets in public health contexts. The findings underscore the potential of deep learning to revolutionize the way we approach and address public health issues, offering innovative solutions for data-driven decision-making.

Throughout the review, common themes such as predictive modeling, disease surveillance, and risk assessment have emerged as focal points of deep learning applications in public health. However, the review also highlights challenges such as data privacy concerns, interpretability of models, and the need for standardized methodologies. These challenges underscore the importance of a thoughtful and ethical integration of deep learning into public health research.

As the field continues to evolve, future research should focus on addressing the identified challenges, exploring novel applications, and fostering interdisciplinary collaboration between data scientists, public health experts, and policymakers. By doing so, we can harness the full potential of deep learning to advance our understanding of public health phenomena, ultimately contributing to more effective strategies for disease prevention, health promotion, and healthcare delivery. This review serves as a valuable resource for researchers, practitioners, and policymakers navigating the intersection of public health and deep learning, providing a roadmap for future investigations in this rapidly evolving field.

There are a few limitations of this review to consider. We were unable to review all of the initial results due to resource constraints. We conducted a primary review of research articles using various databases, including PubMed, Web of Science, Scopus, and Springer. Our findings revealed that Scopus yielded the highest number of relevant articles among these databases. Therefore, our screening process could be considered a convenience sample which optimizes for recent research and highly visible research based on citation frequency. A future review could take the time to review all initial search results rather than adopting our visibility approach.

## Conclusions

The employment of Deep Learning Models in public health settings continually proves to play a transforming role that can advance multiple areas particularly those of disease prediction, surveillance and risk assessment. Despite the challenges highlighted in this study, Deep learning methods hold promising future in improving healthcare and disease prevention. This study serves as a helpful resource for future research to address these challenges and work as a guideline for further study in this field.

## Author contribution

Rand Obeidat, Izzat Alsmadi, and Qanita Bani Baker: These three researchers were responsible for the initial screening of the 2,545 articles identified from the initial search. Each researcher independently reviewed their assigned articles based on predefined inclusion and exclusion criteria. Aseel Al-Njadat and Sriram Srinivasan: These authors contributed to other essential tasks as analyzing, reporting and writing of the paper in the study but were not involved in the article screening process. Godswill Ashong and Ifeanyi Osigwe: These authors contributed to the data formatting process, ensuring that the data collected was in the appropriate formats for analysis and reporting.

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# Appendix A

## *Detailed search formulas and criteria*

This appendix provides the specific search formulas used in each database (i.e. ID 1 in Table 1) to ensure the retrieval of relevant literature on the application of deep learning in public health data.

## *PubMed*

To conduct a comprehensive search in PubMed, the following steps were taken. First, we navigated to the PubMed Web site. The search formula used was for ID 1 as follows:

("Public Health Data" [Title/Abstract] OR "Public Health Dataset" [Title/Abstract] OR "EHR" [Title/Abstract] OR "electronic health record" [Title/Abstract]) AND ("deep learning" [Title/Abstract] OR "representation learning" [Title/Abstract] OR "neural network" [Title/Abstract] OR "convolutional neural network" [Title/Abstract] OR "ConvNet" [Title/Abstract] OR "CNN" [Title/Abstract] OR "recurrent neural network" [Title/Abstract] OR "RNN" [Title/Abstract] OR "long short-term memory" [Title/Abstract] OR "LSTM" [Title/Abstract] OR "generative adversarial network" [Title/Abstract] OR "GAN" [Title/Abstract] OR "autoencoder" [Title/Abstract] OR "restricted boltzmann machine" [Title/Abstract] OR "deep belief network" [Title/Abstract] OR "DBN" [Title/Abstract])

## *Web of Science*

We accessed the Web of Science database. The initial search formula for ID 1 was:

TS=("Public Health Data" OR "Public Health Dataset" OR "EHR" OR "electronic health record") AND TS=("deep learning" OR "representation learning" OR "neural network" OR "convolutional neural network" OR "ConvNet" OR "CNN" OR "recurrent neural network" OR "RNN" OR "long short-term memory" OR "LSTM" OR "generative adversarial network" OR "GAN" OR "autoencoder" OR "restricted boltzmann machine" OR "deep belief network" OR "DBN")

## *Scopus*

In Scopus, the search was conducted using the following detailed ID 1 formula:

TITLE-ABS-KEY ((“Public Health Data” OR “Public Health Dataset” OR “EHR” OR “electronic health record”) AND (“deep learning” OR “representation learning” OR “neural network” OR “convolutional neural network” OR “ConvNet” OR “CNN” OR “recurrent neural network” OR “RNN” OR “long short-term memory” OR “LSTM” OR “generative adversarial network” OR “GAN” OR “autoencoder” OR “restricted boltzmann machine” OR “deep belief network” OR “DBN”))

### *Springer*

For Springer, the search was performed using the following ID 1 search formula:

(“Public Health Data” OR “Public Health Dataset” OR “EHR” OR “electronic health record”) AND (“deep learning” OR “representation learning” OR “neural network” OR “convolutional neural network” OR “ConvNet” OR “CNN” OR “recurrent neural network” OR “RNN” OR “long short-term memory” OR “LSTM” OR “generative adversarial network” OR “GAN” OR “autoencoder” OR “restricted boltzmann machine” OR “deep belief network” OR “DBN”)

## Appendix B

Appendix Table A1

**Table A1.** Top publishers This table lists the top publishers and their respective article counts.

| Publisher | Count |
| --- | --- |
| IEEE | 644 |
| Elsevier | 200 |
| Springer | 137 |
| ACM | 148 |

Appendix Table A2

**Table A2.** Deep Learning Models This table shows the count of various deep learning models used in the reviewed articles This table shows the count of various deep learning models used in the reviewed articles.

| Type | Count |
| --- | --- |
| LSTM | 224 |
| CNN | 174 |
| GAN | 150 |
| AE | 148 |
| RNN | 139 |
| GRU | 46 |
| GNN | 21 |
| DBN | 11 |

Appendix Table A3

**Table A3.** Top researchers names and number of publications per researcher This table lists the top researchers and the number of publications attributed to each.

| Researcher name | Number of occurrence |
|---|---|
| Sun, jimeng (9737233900) | 9737233900′ occurs 26 times |
| Wang, fei (56177292700) | 56177292700′ occurs 23 times |
| Xiao, cao (57199799682) | 57199799682′ occurs 22 times |
| Xu, Hua (55493876700) | 55493876700′ occurs 17 times |
| Liu, Hongfang (7409753328) | 7409753328′ occurs 16 times |
| Jiang, Xiaoqian (24479530900) | 24479530900′ occurs 15 times |
| Glicksberg, Benjamin S. (55845627200) | 55845627200′ occurs 15 times |
| Tang, Buzhou (35115621400) | 35115621400′ occurs 15 times |
| Ma, fenglong (57052032200) | 57052032200′ occurs 14 times |
| Qian, Buyue (36601594000) | 36601594000′ occurs 13 times |

Appendix Table A4

**Table A4.** Top Journals and the Number of Publications shown in each Journal This table lists the top journals and the number of publications in each journal.

| Journal name | Number of occurrence |
|---|---|
| 'Journal of Biomedical informatics' | Occurs 116 times |
| 'Lecture notes in computer science' | Occurs 73 times |
| 'BMC medical informatics and decision making' | Occurs 73 times |
| 'Journal of the American medical informatics association' | Occurs 68 times |
| 'JMIR medical informatics' | Occurs 61 times |
| 'IEEE journal of Biomedical and health informatics' | Occurs 56 times |
| 'Artificial intelligence in medicine' | Occurs 48 times |
| 'PLoS one' | Occurs 41 times |
| 'Studies in health technology and informatics' | Occurs 37 times |
| 'Scientific reports' | Occurs 37 times |

## Appendix Table A5

**Table A5.** Summary of common disease categories and techniques studied This table summarizes the common disease categories and the techniques used in the studies.

| Disease category | Common techniques | Samples of studies' references |
| --- | --- | --- |
| Cancer | Recurrent neural network, convolutional neural network | 63,105,172–180 |
| COVID-19/Corona virus | Convolutional neural network, Multilayer perceptron, transfer learning | 140,181–188 |
| Diabetes | Convolutional neural network, long short term memory networks (LSTM) | 189–196 |
| Cardiovascular | Convolutional neural network, long short term memory networks (LSTM), bidirectional long short-term memory (BiLSTM) | 197–203 |
| Stroke | Recurrent neural network (RNN), convolutional neural network (CNN), deep neural network (DNN), perceptron neural network | 204–208 |
| Hypertension | Convolutional neural network (CNN), long short-term memory (LSTM), bidirectional long short-term memory (BiLSTM), Autoencoder networks | 209–211 |
| Alzheimer | Convolutional neural network (CNN), long short-term memory, BERT, deep Auto-encoder | 212–215 |
| Depression | Artificial neural network, deep neural network | 216–218 |
| Dementia | Neural networks, recurrent neural networks | 219,220 |
| Pneumonia | Recurrent neural network, BiLSTM, deep neural network | 204,221–223 |
| Asthma | Recurrent neural network, long short-term memory, BiLSTM | 224,225 |
| Obesity | Recurrent neural network, long short-term memory, BiLSTM | 226,227 |
| Hepatitis | Artificial neural network | 228–230 |
| Arthritis | Convolutional neural network, longitudinal deep learning model | 231,232 |