big data and cognitive computing

Review

A Review of Artificial Intelligence, Big Data, and Blockchain Technology Applications in Medicine and Global Health

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Abstract: Artificial intelligence (AI) programs are applied to methods such as diagnostic procedures, treatment protocol development, patient monitoring, drug development, personalized medicine in healthcare, and outbreak predictions in global health, as in the case of the current COVID-19 pandemic. Machine learning (ML) is a field of AI that allows computers to learn and improve without being explicitly programmed. ML algorithms can also analyze large amounts of data called Big data through electronic health records for disease prevention and diagnosis. Wearable medical devices are used to continuously monitor an individual's health status and store it in cloud computing. In the context of a newly published study, the potential benefits of sophisticated data analytics and machine learning are discussed in this review. We have conducted a literature search in all the popular databases such as Web of Science, Scopus, MEDLINE/PubMed and Google Scholar search engines. This paper describes the utilization of concepts underlying ML, big data, blockchain technology and their importance in medicine, healthcare, public health surveillance, case estimations in COVID-19 pandemic and other epidemics. The review also goes through the possible consequences and difficulties for medical practitioners and health technologists in designing futuristic models to improve the quality and well-being of human lives.

Keywords: big data; blockchain; machine learning; artificial intelligence; healthcare; Alzheimer's disease; health technology; COVID-19; cancers; internet of things

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Citation: M., S.; Chattu, V.K. A Review of Artificial Intelligence, Big Data, and Blockchain Technology Applications in Medicine and Global Health. *Big Data Cogn. Comput.* **2021**, *5*, 41. https://doi.org/10.3390/bdcc5030041

Academic Editor: Min Chen

Received: 26 May 2021
Accepted: 27 August 2021
Published: 6 September 2021

1. Introduction

Big data, as the term implies, refers to huge volumes of data that are challenging to manage with standard software or web-based systems. By the end of 2020, 44 trillion GB of data was accumulated, and Google processes 40,000 search inquiries per second. Every day, 3.46 million searches are made, totaling 1.2 trillion each year. There is more storage capacity, processing capability, and analytical power than previously available. Despite the fact that there are numerous definitions for big data, Douglas Laney's is the most common and widely recognized. Laney highlighted that (big) data was growing in three dimensions: volume, velocity, and variety (the three "V's"). The 'huge' component of big data refers to its size. The term "big data" encompasses not just volume but also velocity and diversity. Velocity denotes the pace or rate at which data is collected and made available for further processing. Transaction-level data, video, audio, text, or log files are among the several forms of structured and disorganized data that every company or system may gather. These three 'Vs' have become the industry standard for defining big data [1]. In recent years, the term "big data" has gained a lot of traction throughout the world. Almost every research area, whether in industry or academia, generates and analyzes big data for various objectives. The administration of this massive pile of data, which may be both structured and disorganized, is the most difficult endeavor. Implementing artificial intelligence (AI) algorithms and new fusion techniques would make sense with such a vast volume of data. Indeed, using machine learning (ML) approaches such as neural networks and other AI algorithms to achieve automated decision-making would be a huge accomplishment. Machine learning is the study of computer programs that learn through inference and patterns rather than being explicitly programmed with algorithms and statistical models. In the recent decade, the area of machine learning has seen tremendous advancements [2]. Data, the backbone of every model, are the most important components of machine learning: the more relevant the data, the more precise the forecasts. Following the data, we must choose an algorithm depending on the problem to make more accurate forecasts.

Patients can use blockchain technology to define access rules for their medical data, such as permitting specific researchers to access parts of their data temporarily for a period of time. Patients can link to other hospitals and have their medical data collected automatically using blockchain technology. Because of its transparency, it is a secure method for storing and exchanging information [3]. Blockchain offers a wide range of healthcare applications, including mobile health apps, monitoring equipment, electronic medical records for sharing and storing, clinical trial data, and cloud storage of insurance information. Because anybody wishing to modify a block once it has been added to the chain would have to refigure the altered block and all following blocks, which would take an impossibly large amount of computing power, blockchain is stable.

Furthermore, because the data are kept in several copies on various nodes, blockchain is safe as there is no defined centralized structure for a bad user to attack. Blockchain is suitable for healthcare data management because of these features [4]. It's seen to be a promising technique for securely transmitting health information. However, it is unclear if blockchain is the answer to all of the problems associated with extremely sensitive data. The usefulness of blockchain technology to the healthcare sector has been questioned. Given blockchain's recent development, governments may wish to investigate possible situations in which blockchain may be used in the healthcare sector and analyze the obstacles connected with the industry's traditionalism. When building and implementing blockchain solutions for healthcare necessitates a thorough evaluation of the trade-offs [5]. In this context, we want to talk about how to use the principles that underpin machine learning, big data, and blockchain technology, as well as their relevance in medicine, healthcare, and public health.

2. Materials and Methods

For this review, we have done a comprehensive literature search in popular databases such as Scopus, MEDLINE/PubMed, and Web of Science. The keywords for the search included "blockchain" OR "machine learning," OR "artificial intelligence" OR "big data" AND ("medicine" OR "public health" OR "hospital"). Grey literature, such as reports from organizations and websites of authentic tech companies, was also accessed to gather the required information. All the relevant full texts were assessed, and data were extracted. The applications of these emerging technologies such as blockchain, machine learning, and artificial intelligence in the health domain such as hospitals, healthcare, and public health were summarized and presented in various sections. The major findings are classified into various subsections and described in the results. The thematic areas identified for discussion included ML and its applications in healthcare; blockchain technology and its application in healthcare; AI and big data analytics in healthcare; personalized health using ML over big data and the internet of things (IoT). The application of these innovative and novel technologies in various medical conditions (cardiovascular diseases, Alzheimer's disease, Parkinson's disease, cancers, and COVID-19) and global health (disease prediction, surveillance, data collection, etc.) are discussed in-depth with highlighting the advantages and challenges.

3. Results

The review findings from the published literature are summarized under various broad subsections with detailed summaries, classifications, and applications of various technologies in healthcare and public health domains.

3.1. Types of Machine Learning Applications

The various achievements of ML and its applications in hospitals, healthcare settings and in public health domains are summarized below (Table 1).

Table 1. Different types of machine learning applications in healthcare and global health.

Sl. No	Applications	Examples	Technology
1	Medical Imaging Diagnosis	The goal of skin image analysis is to find skin cancer	Computer vision using deep learning
2	Smart Health Records	OCR recognition is based on machine learning and document categorization techniques that employ vector machines	Handwriting detection technique based on Google Cloud Vision API or Matlab machine learning
3	Identifying Diseases and Diagnosis	Therapeutic treatments in oncology	Watson Genomics is a product from IBM that combines cognitive computing with genome-based tumor sequencing
4	Crowdsourced Data Collection	IBM, in conjunction with Medtronic, to develop a platform that can understand, collect, and real-time exchange diabetes and insulin data	Apple's Research Kit gives consumers access to interactive programs that employ machine learning to cure Asperger's syndrome and Parkinson's illness
5	Drug Discovery and Manufacturing	Biomarker discovery or validation	Deep Genomics uses artificial intelligence, especially deep learning, to help decipher the genome's meaning
6	Better Radiotherapy	Medical image analysis	DeepMind Health, a division of Google, is assisting UCLH researchers in the development of algorithms that can distinguish between healthy and malignant cells
7	Tools for Risk Identification	El Camino Hospital researchers developed a method for forecasting patient falls by combining EHRs, nurse call data, and bed alarm data	Anomaly detection systems can anticipate catastrophic consequences, including strokes, heart attacks, and sepsis
8	Outbreak Prediction	Networks can aid in the interpretation of this data and the prediction of severe infectious disease epidemics, such as malaria	BlueDot is a specialized tool for tracking epidemics
9	Personalized Medicine	Based on patients' clinical history and accessible genetic information, evaluate the danger to the patients	Improved medical technology to spot genetic mutations
10	Natural Language Processing	Review management and sentiment analysis	NLP-enabled systems that detect and categorize words and phrases using algorithms

Source: Flat World Solutions. Top 10 Applications of Machine Learning in Healthcare [6].

3.2. Blockchain Technology in Healthcare

In the healthcare business, the use of blockchain technology is experiencing a conceptual transformation. It has contributed considerable value to data management operations by improving efficiency, access control, technical innovation, privacy protection, and security. The findings show that the current restrictions are largely related to model performance as well as implementation limits and costs [7]. The name "blockchain" refers to how BC maintains transaction data, which is organized into "blocks" that are connected together to form a "chain." As the number of transactions rises, so does the length of the chain. The attention you receive is recorded in a personal ledger since each entry is saved as a block on a chain. The data or information component, the hash, and the preceding hash are the three primary parts of a block. A peer-to-peer network, cascaded encryption, distributed database, transparency with pseudonymity, and irreversible records are all features of blockchain. Drug development, clinical trials, medical data management, and security are some of blockchain's uses [8].

Classification of Blockchain Applications

Public, private, and consortium blockchains are the three primary varieties. Permissionless blockchains are those in which anybody may join the network and view and write to the ledger. Bitcoin and Litecoin are two examples. Private blockchains are permissioned blockchains that prevent users from joining the network and reading or writing to the ledger without permission. Hyperledge and Multichain are two examples. Alexandra Cernian et al. [9] presented PatientDataChain, a blockchain-based solution built on a decentralized healthcare infrastructure which integrates a layer of trust in the healthcare value chain. The information obtained is entered into a unified personal health records (PHR) system, in which the patient owns his or her data and links, various healthcare providers. PatientDataChain's decentralized nature, which is based on blockchain technology, allowed it to take advantage of the right context to develop a new and better data-sharing and exchange system that is safe, adaptable, and dependable. This method improves data security and privacy while also allowing secure access to PHR. This system also provides patients and clinicians with an immutable log of medical records, which enhances patients' travels along the health value chain. Challenges of blockchain include:

- Integration concerns and initial cost;
- Identity, security, and privacy;
- Standardization;
- Cultural adoption;
- Uncertain regulatory and compliance status.

The blockchain reduces the dangers of data being kept centrally by storing it across its network. Its network is devoid of centralized sources of vulnerability that may be exploited by computer hackers. Everyone is aware of the security issues that plague the internet today. To secure our identity and assets online, we all rely on the "username/password" approach. Encryption technology is used in blockchain security solutions. The so-called public and private "keys" serve as the foundation for this. A user's address on the blockchain is represented by a "public key" (a lengthy, randomly generated string of integers). Bitcoins transferred over the network are traced back to that address. The "private key" functions similarly to a password, granting access to the owner's Bitcoin or other digital assets.

A prototype model was proposed by Dara Tith et al. [10], which uses a purpose-based access control scheme; it is implemented by a blockchain system using Hyperledger Fabric. All metadata of patient records, consents, and data access are written immutably on the blockchain and shared among participant organizations. A blockchain chain code that performs business logic managing patient consent was also created. The system has high reliability and availability, transparency, and traceability, which are common features of the blockchain system. Transparency and traceability are considered especially important in dealing with patient consent to ensure that patient data is shared properly.

3.3. Artificial Intelligence and Big Data Analytics Tools and Techniques

The capacity of a digital computer or a computer-controlled robot to accomplish activities typically performed by intelligent individuals is referred to as artificial intelligence (AI). The term refers to a project aiming at developing systems with humanlike cognitive skills, such as the capacity to reason, detect meaning, generalize, and learn from previous experiences. AI methods include machine learning, pattern recognition, neural networks, expert systems, and fuzzy logic. Many AI models are statistically sound, and they train using nonlinear optimization techniques [11]. Cost reduction in medical treatments, elimination of illness-related risk factors, disease prediction, improved preventative care, and medication efficiency analysis are just a few of the big data uses in healthcare. Big data analytics (BDA) is a term that refers to the tools and procedures that are used to turn large amounts of data into meaningful information for analysis. Many firms use BDA to bring together IT specialists, business experts, and data scientists to obtain deeper insights into a company's operations and steer it in the right direction. Thus, the companies are able provide their customers with a competitive advantage by offering effective solutions. The creation of BDA is due to the unanticipated huge rise of yearly data. Nowadays, billions and trillions of data transactions happen over a day or sometimes in an hour [12]. Big data analytics tools help enterprises and companies manage big volumes of data generated by different processes. There are thousands of big data tools that can help you save time, money and provide valuable business insights. The following Table 2 illustrates some of the tools available with their pros and cons.

Table 2. Listing of available big data tools with their advantages and disadvantages.

S. No	Big Data Analytics Tools	Advantages	Disadvantages
1	"Xplenty" is a cloud-based platform for integrating, processing, and preparing data for analytics.	Elasticity and scalability	There is just one billing option: yearly billing
2	"Apache Cassandra" is a distributed NoSQL database management system that is free and open-source. It is built to handle enormous amounts of data.	No single point of failure	It necessitates extra troubleshooting and maintenance work
3	"MongoDB" is a document-oriented, NoSQL database	Supports a variety of platforms and technologies	Limited analytics.
4	Apache "Hadoop" is a software framework for handling large data and clustered file systems	For R&D reasons, this is quite beneficial	Due to its 3× data redundancy, it is possible to run out of storage space
5	"Datawrapper" is a device-friendly open-source data visualization tool	Works great on any device, whether it's a phone, a tablet, or a computer	Limited color palettes
6	"Rapidminer" is a cross-platform solution that combines machine learning and predictive analytics in a single environment	Excellent customer service and technical assistance	The quality of online data services has to be enhanced
7	"Tableau" is a business intelligence and analytics software application	It comes with a slew of useful features and is lightning fast	Formatting controls could be improved
8	"KNIME" is an open-source program that stands for Konstanz Information	It works nicely with various languages and technologies	MinerIt is possible to enhance data handling capabilities
9	Apache "Storm" is a distributed stream processing system that runs on several platforms	Extremely quick and fault-tolerant	Difficult to learn and use
10	"CDH" (Cloudera Distribution for Hadoop) is aimed at enterprise-class Hadoop implementations	High security and governance	Multiple installation methods are suggested, which seems perplexing

3.4. Mobile Health

Mobile health (mhealth) is a rapidly growing area of the digital health industry that uses mobile technology like smartphones, tablets, and wearables to provide healthcare support, delivery, and intervention. While any mobile devices that send data are considered mhealth, cell phones are presently the most common platform for mhealth delivery [13]. Z.F. Khan and S.R Alotaibi developed a system that includes three key components: (1) medical data collected from patients via mobile phones and telemonitoring devices, (2) an AI and big data analytics platform, and (3) output to a mobile care monitor. The combined AI and big data platform handle the entire process of evaluating a large volume of data received from multiple sources in various forms. These are coupled to create the impression of facilitating real-time decision-making. Several analytics tools, including data mining and AI, are used for the analysis of patient's collected data. These big data analytical techniques may be used to find abnormalities by evaluating a large quantity of data from a variety of datasets and sources, including biological signals, physiological sensing data, genetic data, and biomedical imaging. The AI-based engine is made up of a stream analysis module and an AI-based report management tool. These examine the results of the big data analysis engine's queries. The technique enhances the overall performance of mhealth since AI and big data analytics are included. [14].

3.5. Personalized Health Using Machine Learning over Big Data and IoT

Personalized health (PH) is a modern approach to patient-oriented treatment that requires advancements in the normal healthcare system. Patient information collected from electronic health records (EHR), wearable and mobile devices, the IoT, web-based information systems, and social media is the main objective of this new advancement. PH applies AI techniques to the collected information set to enhance the technique of sickness progression, patient self-management, prediction of sickness, and clinical involvement. During this view, methods of machine learning are commonly used to build analytical models. Such concepts are implemented in entirely separate patient management frameworks and health call support networks. Such models examine mainly the information obtained from detector systems and multiple databases to spot the patient's behavioral habits and health conditions. ML uncovers hidden insights in the IoT data, allowing for faster, more automatic responses and better decision-making [15]. The IoT generates enormous amounts of data from millions of devices. ML is fueled by data which are used to obtain insight. ML identifies patterns in prior behavior and builds models to predict future behavior and occurrences. By absorbing pictures, videos, and sounds, machine learning for IoT may be used to forecast future trends, identify anomalies, and augment intelligence. IoT technology greatly assists medical professionals and patients in the most modern healthcare application environments. Since its application to healthcare, machine learning, artificial intelligence, and big data have made physicians' jobs considerably simpler in determining the core cause of disease and forecasting its severity utilizing contemporary algorithms.

Ed-daoudy and Maalmi demonstrated a data processing and monitoring application that combined Kafka with Spark streaming. This application will analyze and store real-time data from connected devices for real-time analytics. To begin, Kafka producers generate a continuous stream of data messages that are collected by Kafka streaming. A topic that offers a name to the numerous illnesses is modeled by a stream that comes in the Kafka streaming. They are forwarded to the Spark streaming program, which performs real-time processing. Spark streaming gets numerous health characteristics via Kafka streaming and uses machine learning to forecast health status using the decision tree model, which is stored in NoSQL Cassandra [16]. Shama Siddiqui et al. suggested the integration of music therapy with body area network (BAN) and ANN-enabled IoT architecture to give instant support to patients by automating music treatment. The suggested architecture includes utilizing BAN to monitor patients' bodily data, ANN to categorize the condition, and playing the most suitable style of music via the patient's portable device. In addition, the ANN will use music analytics to iteratively enhance the process of automated music treatment, such as the type and length of music played, as well as its influence on patient body metrics. Healthcare practitioners and academics alike have been paying close attention to the use of BAN in healthcare applications.

BAN has been shown in several trials to greatly improve the quality of life and life expectancy of patients by providing remote monitoring capabilities [17]. Ahmed S. Salama et al. proposed a new model based on cloud IOT that can be used to forecast chronic kidney diseases (CKD) in smart cities. Stakeholders utilize a range of devices such as PCs, laptops, smartphones, tablets, digital sensors etc. to submit a wide range of medical readings and requests to get various medical services, such as CKD diagnosis. The cloud broker's job is to communicate with the cloud service and transmit and receive requests (tasks). IoT endpoints transmit large amounts of medical data to clouds over the internet in order to set up a massive medical database for better CKD prediction. Logistic regression (LR) and neural networks are both used in a hybrid machine learning model (NN). The LR method is used to identify key variables that impact CKD. The neural network (NN) is utilized to predict CKD. The experimental findings reveal thirteen (13) key variables out of twenty-four (24) that influence CKD, with the hybrid intelligent model with a higher prediction of CKD with a 97.8% accuracy rate [18].

Zafer Al-Makhadmeh and Amr Tolba suggested a heart illness detection system based on IoT medical devices and the higher-order Boltzmann deep belief neural network (HOBDBNN). A sensor device is placed on the human body to gather IoT medical data. The data is gathered and transferred over the gateway before being stored on a cloud server. The cloud is utilized to access heart disease data, which is subsequently processed in three steps: (1) heart data preprocessing, (2) feature extraction, and (3) heart disease prediction. The feature selection phase is ignored throughout this approach because the system's purpose is to predict heart disease by processing or analyzing more data and features. By evaluating such characteristics and employing excellent training and classification methods, the developed system effectively predicts heart disease. The testing findings demonstrate that the suggested technique analyses large data and detects aberrant cardiac patterns with 99.03 percent accuracy in the shortest period (8.5 s) [19]. C.B. Sivaparthipan et al. hypothesized the importance of robotics in Parkinson's disease (PD) and their interaction with big data analytics. The suggested approach includes collecting data from big data from the healthcare business using mobile phones and recognizing the gait performance of PD patients. The robot must be preprogramed with enough data to recognize the symptoms of all conditions or diseases. The robot activities are carried out once the path has been defined since it is necessary to identify obstacles, safe zones, and dangerous zones.

Furthermore, it is reliant on training data, and any errors in the data might result in significant damage to the system during processing. Both the robots and the user utilize a laser range finder to assess and study the path for walker movements. Furthermore, the laser range scanner is designed for use with a road condition analyzer, primarily to detect obstacles. Finally, the piecewise linear Gaussian dynamic time warp (GDTW) ML method is used to detect the freezing and festinating gaits. The advantage of this approach is that it may be used for both illness analysis and physical treatment, although physical treatment is the most effective treatment for Parkinson's disease [20].

4. Discussion

The healthcare industry has traditionally been an early user of technological innovations and has reaped significant benefits. Machine learning, a subset of AI, is being used in a variety of health-related fields, including the development of novel medical treatments, the processing of patient data and records, and the treatment of chronic diseases. It boosted the application of deep learning and machine learning in medicine. The term "deep learning" (DL) refers to a branch of ML, which is itself a branch of AI, and it employs layered architecture to evaluate data algorithmically. ML is a type of computer programming that uses an algorithm to apply statistical operations to inputs to turn them into outputs with little human intervention. Although machine learning models improve over time, they still need to be regulated and steered to some extent. On the other hand, a deep learning model can use neural networks to determine if a prediction is correct or not [21]. Various ML algorithms are used for disease prediction for decades; we aim to compile ML algorithms' prediction ability in heart disease and Alzheimer's disease in the following sections.

4.1. Heart Disease Prediction

Heart disease, also known as cardiovascular disease, is an illness that mostly affects the elderly and is caused by problems with the heart and blood vessels. Symptoms of this condition include high blood pressure, arterial hardening, chest pain or angina, heart attacks (cardiac arrest), and strokes. Cardiovascular diseases are a group of conditions that occur when the heart and blood vessels do not work properly due to fatty deposits or increased risk of blood clots [22]. Mohammad Shafenoor Amin et al. demonstrated a heart disease prediction system using a FS and data mining approach. Models were created utilizing a variety of characteristics, and seven classification approaches, including (1) k-NN, (2) naive Bayes (NB), (3) decision tree (DT), (4) logistic regression (LR), (5) neural network, (6) support vector machine (SVM), and (7) Vote (a hybrid methodology with LR and NB). Finally, the best prediction model was created using the nine significant attributes and the Vote technique, giving better accuracy. The dataset applied in this research was collected from the UCI machine learning repository [23]. Cleveland, Hungary, Switzerland, and the VA Long Beach are among the four databases [24]. Senthilkumar Mohan et al. presented a unique approach for identifying relevant characteristics using machine learning techniques, which improves the accuracy of cardiovascular disease prediction. naive Bayes, logistic regression (LR), generalized linear model, deep learning, decision tree, RF, gradient-boosted trees (GBT), and support vector machine (SVM) were among the approaches utilized. Among them, the hybrid random forest with linear model (HRFLM) method was utilized to combine the features of random forest (RF) and linear method (LM), resulting in improved accuracy [25].

Archana Singh and Rakesh Kumar proposed a machine-learning-based approach for predicting heart disease. Different ML algorithms used were k-nearest neighbor, decision tree, linear regression, and support vector machine (SVM). It was concluded that KNN is the best among them with 87% accuracy [26]. Amin Ul Haq et al. demonstrated a machine-learning-based diagnostic technique for heart disease prediction using a heart disease dataset. Three feature selection techniques and six machine learning algorithms were utilized in this hybrid intelligent system architecture. Relief feature selection algorithm, minimal-redundancy maximal-relevance feature selection algorithm, and least absolute shrinkage and selection operator were the feature selection methods used. The six machine learning methods used were logistic regression, KNN, ANN, SVM, NB, and DT, while the performance measures of the seven classifiers were classified as accuracy, specificity, sensitivity, Matthews' correlation coefficient, and execution time. When the FS algorithm chose the classifiers' logistic regression, the accuracy was 89 percent [27]. By using data science, Saba Bashir et al. presented a prediction model for cardiac disease in medicine. FS was used to apply several data mining techniques such as decision trees, logistic regression, logistic regression SVM, naive Bayes, and random forest. Logistic regression SVM provided the highest level of accuracy [28]. Krittanawong, Chayakrit, et al. presented a model in which patient data is stored on centralized systems, which might be difficult to access and incompatible with other stakeholders in the healthcare system. Separate proprietary servers are used by consumer devices. Smart contracts begin as patient-owned data components in the blockchain architecture, and they serve as the foundation for a safe and transparent information flow. Individual data components can be turned on or off for various stakeholders by the data owner (usually a patient). Smart contracts and artificial intelligence (AI) tools can interact, and AI tools can also be blockchain-enabled. These analytical tools, databases, and clinical trials are not housed in a single location but rather dispersed. Incentives might flow based on data ownership, data relevance to each process, or value contributed by a provider, healthcare institution, or consumer firm. Regulatory supervision will have to change as the models evolve [29].

4.2. Alzheimer's Disease Prediction

Alzheimer's disease (AD) is a neurologic condition in which the brain shrinks (atrophy) and brain cells die. Alzheimer's disease is the most prevalent form of dementia, which is defined as a progressive loss of cognitive, behavioral, and social abilities that impair a person's capacity to operate independently. Forgetting recent events or discussions is one of the first indications of Alzheimer's disease. A person with Alzheimer's disease will acquire significant memory impairment and lose the capacity to carry out daily duties as the disease advances. Taeho Jo et al. proposed utilizing neuroimaging data to classify and predict Alzheimer's disease. Deep learning methods continue to improve performance and appear to offer promise for employing multimodal neuroimaging data to diagnose Alzheimer's disease. Hybrid techniques, which combine standard machine learning methods for diagnostic classification with deep learning approaches for feature extraction, performed better and might be a suitable option for dealing with limited data. An autoencoder (AE) was used to decode the original picture values, making them comparable to the original image, which was then used as input, allowing the restricted neuroimaging data to be successfully used. The accuracy for AD categorization was 98.8%, and for predicting conversion from moderate cognitive impairment (MCI), a prior stage of AD, it was 83.7 percent [30]. Ankita Sharma et al. suggested a Hadoop-based big data system for identifying early diagnostic indicators of Alzheimer's disease by combining noninvasive magnetic resonance imaging (MRI), MR spectroscopy (MRS), and neuropsychological test outcomes. (1) Data normalization, (2) data management, (3) data storage, and (4) data processing were the four primary components of the suggested framework. Quality checks, feature extraction, selection, and decision integration are all part of data processing [31]. Weiming Lin et al. presented a CNN-based MRI image analysis for the prediction of Alzheimer's disease from MCI.

The MRI data were split into two pathways, one for extracting CNN-based image features and the other for extracting FreeSurfer-based image features. CNN has trained on the AD/NC (normal controls) picture patches in the left path and then is used to extract CNN-based features from MCI images in the right path. FreeSurfer-based characteristics were computed in the proper direction using FreeSurfer software. These characteristics were concatenated as a features vector and given to an extreme learning machine as a classifier after being further mined using dimension reduction and sparse feature selection via PCA and Lasso, respectively [32]. More morphological information from MRI scans, such as cortical volume, surface area, cortical thickness average, and standard deviation of thickness in each region of interest, was mined using the FreeSurfer (version 4.3) [33–35]. The extreme learning machine (ELM) is a novel learning method for feed-forward neural networks with a single hidden layer. While maintaining a decent balance between sensitivity and specificity, the suggested approach beats others in terms of accuracy and AUC [36].

Alexander Kautzky et al. developed a prediction model that supports a unique diagnostic factor for Alzheimer's disease than the clinical presentation, allowing early detection of characteristic alterations even before symptoms appear. The ABC score for Alzheimer's disease, which is based on a composite score for Ab-peptides, neurofibrillary tangles, and neuritic plaques released by the National Institute on Aging—Alzheimer's Association (NIAA), was predicted from structural MRI data using random forest (RF). At least two years before death, MRI scans were conducted. Nested cross-validation was used to make the prediction (CV). In 77 percent of instances, the ML algorithms RF and SVM were used to create a model that correctly predicted AD neuropathological change [37]. Ibra-him Almubark et al. suggested research utilizing patient neuropsychological and machine learning approaches to identify Alzheimer's disease early. Dataset 1 consisted of the results of nine standard neuropsychological tests (including general cognitive assessments, learning, and memory, language, and activities of daily living); Dataset 2 consisted of the responses and reaction time from a 5.5-min spatial attention task (cognitive), and Dataset 3 consisted of the results of Datasets 1 and 2. Each dataset includes 28 patients with mild Alzheimer's disease (AD) or moderate cognitive impairment (MCI) and 50 cognitively normal older people (control group). On all three datasets, the feature selection method PCA was used, and the number of principal components picked for Datasets 1, 2 and 3 were 5, 24 and 25, respectively. Support vector machine (SVM), random forest (RF), gradient boosting (GB), and AdaBoost (AB) classifiers were then employed for classification. The models performed better with Dataset 1 than Dataset 2 using the identical machine learning technique. Standard neuropsychological tests, they argued, are a better tool for detecting and classifying AD issues than this spatial attention cognitive task [38]. Pilozzi, Alexander, and Xudong Huang proposed a sentiment analysis based on the NLP model, which is used to detect the need for and assist the implementation of anti-stigma initiatives aimed at reducing the public stigma associated with Alzheimer's disease (AD) and other dementia sufferers. A chatbot/AI companion would help Alzheimer's sufferers live independently while reducing social isolation and loneliness, both of which aggravate self-stigma. Because information security is a major concern for the general public, and especially for those who have sensitive health information that they'd prefer to keep private, enhanced information security, such as that provided by decentralized databases like a blockchain-based service, could be extremely useful in combating the stigma associated with AD [39] (Table 3).

Table 3. List of various machine learning algorithms used for disease prediction.

Sl.No	Author (Year) Reference No.	ML Algorithms	Parameters Evaluated	Efficiency (%)
1	Mohammad Shafenoor Amin et al. (2018) [23]	Vote with naive Bayes (NB) and logistic regression (LR)	Accuracy, precision, F-measure	Accuracy—87.41%
2	Senthilkumar Mohan et al. (2019) [25]	Random forest with linear model	Accuracy, classification error, Pprecision, F-measure, sensitivity, specificity	Accuracy—88.4%
3	Archana Singh & Rakesh Kumar (2020) [26]	K-nearest neighbor	Accuracy	Accuracy—87%
4	Amin Ul Haq et al. (2018) [27]	Logistic regression	Accuracy, MCC, AUC, processing time, sensitivity, specificity	Accuracy—89%
5	Saba Bashir et al. (2019) [28]	Logistic regression SVM	Accuracy	Accuracy—84.85%
6	Taeho Jo et al. (2019) [30]	Autoencoder (SAE), recurrent neural network (RNN)	Accuracy	Accuracy—98.8%; accuracy—96.0%
7	Ankita Sharma et al. (2019) [31]	Principle component analysis (PCA)	Sensitivity, specificity	Sensitivity—92%; specificity—94%
8	Weiming Lin et al. (2018) [32]	Convolutional neural network (CNN)	Accuracy, sensitivity, specificity, AUC	Accuracy—79.9%; AUC—86.1%
9	Alexander Kautzky et al. (2020) [37]	Random forest, support vector machines	Accuracy, sensitivity, specificity	Accuracy—77%
10	Ibrahim Almubark et al. (2019) [38]	Random forest (RF), support vector machine (SVM), gradient boosting (GB), and AdaBoost (AB) classifier	Sensitivity, specificity, accuracy	Accuracy—91.08%; accuracy—89.67%

4.3. Bioinspired Algorithms Used in Healthcare

Bioinspired computer optimization algorithms are a novel method for developing new and resilient competitive strategies that are based on the ideas and inspiration of nature's biological evolution [40]. In recent years, bioinspired optimization algorithms have gained popularity in machine learning as a means of finding the best solutions to complicated problems in science and engineering. Organizations in the healthcare industry are struggling to come up with innovative methods to reduce healthcare use and expenditures while increasing quality and results. Individual behavior cannot be predicted by predictive models intended to anticipate global use for a healthcare institution. Massive volumes of healthcare data, on the other hand, are available in databases and may be utilized to explore patterns and, as a result, knowledge discovery. The variety and complexity of healthcare data necessitate careful consideration of statistical approaches. Healthcare data is multivariate, making analysis both challenging and intriguing. Bioinspired algorithms are extremely beneficial in illness research, prediction, and diagnosis. In the following sections, we discuss the use and prediction abilities of bioinspired algorithms in cancer, Parkinson's disease, and the recently discovered COVID-19 disease (Table 4).

Table 4. List of some important disease prediction models based on bioinspired algorithms.

Sl.No	Author (Year) Reference No	Database Used	Bioinspired Algorithms	Measured Parameters
1.	Rania M. Ghoniem (2020) [41]	Radiopaedia and LiTS (Liver tumor segmentation challenge) dataset	Artificial bee colony optimization (ABC) algorithm	Specificity, F1-score, accuracy, and computational time
2.	V. R. Elgin Christo et al. (2019) [42]	Wisconsin Diagnostic Breast Cancer (WDBC) dataset and hepatitis dataset	Lion optimization algorithm, differential evolution, and glowworm swarm optimization	Accuracy, precision, sensitivity, and specificity
3.	M. Supriya &A. J. Deepa (2020) [43]	Wisconsin Breast Cancer Database (WBCD)	Gray wolf optimization (GWO) algorithm, modified dragonfly algorithm (MDF)	Accuracy, precision, recall
4.	Moolchand Sharma et al. (2019) [44]	UCI Dataset of Wisconsin Diagnostic Breast Cancer	Particle swarm optimisation, artificial bee colony optimization, ant colony optimization, firefly algorithm	Accuracy
5.	Dinesh Valluru & I.Jasmine Selvakumari Jeya (2019) [45]	Lung CT images from ELCAP Public Lung Image Database	Gray wolf optimization	Accuracy
6.	Rodrigo Olivares et al. (2020) [46]	Parkinson's disease audio dataset taken from UCI Machine Learning Repository	Bat algorithm	Accuracy, loss
7.	Prerna Sharma et al. (2018) [47]	Real-time Parkinson handwritten and speech dataset	Modified gray wolf optimization (MGWO)	Accuracy, detection rate, false alarm rate
8.	Somayeh Hessam et al. (2019) [48]	Parkinson disease dataset from UCI repository	Biogeography-based optimization (BBO)	Accuracy, rate of error (RMSE) convergence
9.	Akram Pasha, and. Latha P. H (2020) [49]	Parkinson disease dataset from UCI repository	Genetic algorithm and binary particle swarm optimization	Accuracy, precision, recall, F-score

Table 4. *Cont.*

Sl.No	Author (Year) Reference No	Database Used	Bioinspired Algorithms	Measured Parameters
10.	Prerna Sharma et al. (2019) [50]	Parkinson disease dataset from UCI repository	Antlion optimization (ALO) algorithm	Accuracy, computational time
11.	Eghbal Hosseini et al. (2020) [51]	Benchmark functions of well-known optimization problems	COVID-19 optimizer algorithm (CVA)	Mean, standard deviation
12.	Mohamed Abdel-basset et al. (2020) [52]	Images of the COVID-19 chest may be seen on GitHub.	Improved marine predators algorithm (IMPA)	Signal-to-noise ratio (SNR), standard deviation, peak signal-to-noise ratio (PSNR), universal quality index (UQI), structured similarity index metric (SSIM),
13.	Aytaç Altan, and Seçkin Karasu (2020) [53]	2905 real raw chest X-ray image dataset	Chaotic salp swarm algorithm (CSSA)	Accuracy, sensitivity, specificity, and time consumption
14.	Mohammed A. A. Al-qaness et al. (2020) [54]	COVID-19 confirmed cases in China from 21 January to 18 February 2020	Salp swarm algorithm (SSA), flower pollination algorithm (FPA)	Mean absolute percentage error (MAPE), mean absolute error (MAE), root mean squared relative error (RMSRE), root mean squared relative error (RMSRE), coefficient of determination (R2), CPU time
15.	Sally Elghamrawy & Aboul Ella Hassanien (2020) [55]	617 CT scans chest images collected from different resources	Whale optimization algorithm (WOA)	Accuracy, F-score, G-mean, and the area under the ROC curve (AUC)

4.4. Cancer Diagnosis

Cancer is one of the deadly diseases caused by aberrant cell division. The bioinspired algorithm plays an important role in detecting and diagnosing different types of cancer early, such as liver, breast, lung, prostate, skin, etc., thereby reducing the mortality rate. Rania M. Ghoniem suggested a new bioinspired deep learning technique for improving liver cancer prediction outcomes. To begin, a new hybrid segmentation method called SegNet-UNet-ABC was proposed for extracting liver lesions from CT images utilizing SegNet, UNet, and artificial bee colony optimization (ABC). In this case, the ABC method was utilized to enhance the performance of liver lesion segmentation by tuning the hyperparameters of the SegNet and UNet deep learning architectures. Second, a suggested hybrid LeNet-5/ABC algorithm was presented; this approach employs CNN's LeNet-5 architecture as a feature extractor and classifier, as opposed to prior research on liver cancer diagnosis that uses standard feature-based classification methods. ABC is a meta-heuristics algorithm inspired by nature, namely the behavior of honeybees in search of a high-quality food source. It's used to solve optimization problems and discover the best solutions [41]. V. R. Elgin Christo et al. developed a clinical diagnostic that classifies breast cancer tumors using bioinspired algorithms for feature selection and a gradient descendent backpropagation neural network. The suggested framework is made up of three subsystems: preprocessing, feature selection, and classification. The missing value imputation step and the normalizing phase make up the preprocessing subsystem. The feature selection subsystem chooses the best collection of features from which to construct the classifier model. The wrapper approach is used to choose features in this study, and it is based on the following algorithms: glowworm swarm optimization, differential evolution, and lion optimization algorithm with AdaBoostSVM accuracy. In training and testing the system, the classification subsystem employs gradient descent with momentum and a variable learning rate neural network classifier. In predicting breast cancer tumors, the algorithm had a classification accuracy of 98.734 percent [42].

A breast cancer prediction system (BCPS) using optimized artificial neural networks was proposed by Supriya et al. (OANN). The unprocessed BC data are first entered into this system in this way. Second, by employing Hadoop MapReduce, the repetitive data from huge data storage are removed. The data are preprocessed using replacing missing attributes (RMA) and normalized in the third stage. In the subsequent step, the features are picked to use the modified dragonfly (MDF) method, which picks a minimal subset of the original features set. The chosen characteristics are then used to classify the data. It categorizes the characteristics by using an optimized artificial neural network (OANN). The gray wolf optimization (GWO) is used to optimize the weight values of ANNs. The K-fold cross validation (KFCV) is the final stage of the planned work's implementation [43]. Moolchand Sharma et al. published a paper that analyses several bioinspired algorithms with different machine learning classifiers, including artificial bee colony optimization, particle swarm optimization, ant colony optimization, and firefly method. Decision trees, linear support vector machines, K-nearest neighbor, and random forest classifiers are among the classifiers utilized. Particle swarm optimization gives the highest results with random forest classifiers (96.45%) among these four bioinspired techniques [44]. Dinesh Valluru and I. Jasmine Selvakumari Jeya proposed an optimum support vector machine (SVM) for lung image classification, in which SVM parameters are improved, and features are selected using a modified gray wolf optimization method and genetic algorithm (GWO-GA). The GWO algorithm is based on the leadership hierarchy's hunting method. Grey wolves are top-level predators that generally reside in packs of 5 to 12 wolves. The suggested approach has a 93.54 percent classification accuracy [45]. Kumar, Rajesh, et al. presented a multimodel strategy for diagnosing early-stage cancer from CT scan data that incorporates deep learning and blockchain technology. The major goal of integrating blockchain and deep neural networks is for the model to accept input data from each patient in the distributed network and identify a specific health problem of the patient using a low-dose CT scan or speculating on radiology images. On the blockchain distributed network, a deep neural network model analyzes the report photos that contain information on the cancer nodules performed for a patient. In addition, deep learning models need a considerable number of resources, such as computer power, to train the model. To train the model, the blockchain is mined. The lung cancer diagnosis output will be published on the blockchain through a shared blockchain network, which will address the problem of computing resources. The smart contract allows hospitals to share data, allowing the deep neural network to learn from a large quantity of data from various patient cases in order to detect cancer signs and better describe the region of interest in terms of tissue characteristics [56].

4.5. Parkinson's Disease Diagnosis

Parkinson's disease is a movement disorder that affects the neurological system. The symptoms emerge gradually, and the first signs may be a barely detectable tremor in only one hand. Tremors are frequent and are often accompanied by stiffness or decreased mobility. Rodrigo Olivares et al. proposed an improved extreme learning machine (ELM) based on the bat algorithm, which improves the ML technique's training phase approach to increase accuracy while lowering or maintaining loss in the learning phase. The bat algorithm is used to compute the parameter values to determine the best achievable configuration for the ELM, which is a feed-forward neural network. The bat algorithm is a swarm intelligence optimization approach based on the echolocation function of bats, which helps them to avoid obstacles while flying and find food or refuge. The Parkinson's disease (PD) categorization method has a maximum accuracy of 96.74 percent [46]. Prerna Sharma et al. presented the modified gray wolf optimization (MGWO) model, which is based on the standard gray wolf optimizer (GWO), which is a feature selection search method. The hunt-down behavior of wolves inspired GWO, a meta-heuristic algorithm. The accuracy of the selected characteristics was predicted using the K-nearest neighbor, random forest, and decision tree algorithms. The modified gray wolf optimization (MGWO) technique takes a collection of features as input and outputs a reduced subset of characteristics that improves the model's performance. Voice PD, sound recordings, and Parkinson's HandPD are among the datasets used (spiral and meander). The identification of Parkinson's disease is estimated to be 94% accurate [47]. Somayeh Hessam et al. [48] proposed a hybrid method for detecting Parkinson's disease (PD) using biomedical voice measures. By combining a multilayer perceptron neural network (MLP) with biogeography-based optimization, a hybrid method was created (BBO). Biogeography, the science of biological organisms connected to their geographical dispersion across time and space, inspired the core notion of the biogeography-based optimization algorithm. The BBO algorithm was developed to help ecosystems reach a stable state while accounting for a variety of species (including predators, prey, and others) as well as the effects of migration and mutation. BBO has been hired to find the best MLP settings and improve forecast accuracy [57].

In order to create effective ML classifiers to classify PD, Akram Pasha and P H. Latha developed a bioinspired feature selection technique to pick the best subset of features from the PD data set. For classification, the study used 11 machine learning (ML) classifiers: logistic regression (LR), radial basis function support vector machine (rSVM), Gaussian naive Bayes (GNB), linear support vector machine (lSVM), Ada Boost (AB), Gaussian process classifier (GPC), k-nearest neighbor (kNN), decision tree (DT), random forest (RF), multilayer perceptron (MLP) and quadratic discriminant analysis (QDA) for classifying, coupled with two bioinspired algorithms such as genetic algorithm (GA) and binary particle swarm optimization (BPSO) for feature selection. The two bioinspired algorithms attain a maximum accuracy of between 89.0 and 90.07 percent [49]. Sharma and Rishabh Jain et al. created the antlion optimization (ALO) method, which is used to diagnose Parkinson's disease patients at an early stage. The method decreases the number of characteristics (symptoms) necessary for illness diagnosis. The antlion optimization (ALO) method is a new metaheuristic approach for determining the best distributed generation (DG) size. ALO is based on the ant lion's distinct hutting habit. The ALO algorithm is based on the natural hunting mechanism of antlions. The random wander of ants, construction of traps, trapping of ants in traps, collection of prey, and rebuilding of traps are the five key phases of prey hunting. Random forest, KNN, and decision tree algorithms with full features and reduced features using ALO are the ML classifiers used in this study [50].

4.6. COVID-19 Disease Prediction

According to the World Health Organization, coronavirus disease (COVID-19) is an infectious disease caused by a newly discovered coronavirus. The majority of those infected with the COVID-19 virus will experience either mild to moderate respiratory symptoms who can recover without medical help. The elderly and those with underlying medical disorders such as cardiovascular diseases, diabetes mellitus, chronic lung diseases, and cancers are more likely to develop serious illnesses. The COVID-19 virus is primarily transmitted through droplets of saliva or nasal discharge when an infected person coughs or sneezes; hence, respiratory etiquette is very important. Eghbal Hosseini et al. proposed a unique COVID-19 optimizer algorithm (CVA) that covers virtually all viable areas of optimization problems and reduces the number of COVID-19 afflicted nations, slowing the epidemic's progress. Coronavirus has spread fast in nature due to its strong transmission behavior and the speed of the R-value (first estimations of reinfection average were 2–3 other people) within each nation, followed by further outbreaks. The suggested CVA algorithm was influenced by these outbreaks and export processes in producing its initial solutions and population imitating COVID-19 spreading characteristics. Some confirmed instances (CVA solutions) may not expand in a specific region or export to other nations during the COVID-19 spread. This is due to the fact that those cases (CVA solutions) have recovered or have already gone away. In the following population, these solutions are eliminated from the feasible list, and the algorithm searches for the remaining best answers. The CVA then starts the process of disseminating the best ideas to the rest of the population. When compared to the volcano eruption algorithm (VEA), gray wolf optimizer (GWO), particle swarm optimization (PSO), and genetic algorithm (GA), the CVA approach outperforms them by up to 15%, 37%, 53% and 59%, respectively [51]. Basset et al. developed a hybrid COVID-19 detection model for X-ray image segmentation based on an improved marine predators' algorithm (IMPA). The RDR approach improves the IMPA's performance by allowing it to achieve better solutions in fewer iterations. RDR works by identifying particles that haven't found better solutions in a certain number of iterations and then directing them to the best solutions. The marine predators' algorithm (MPA) is a nature-inspired optimization approach that follows the laws that naturally control optimal foraging strategy and encounter rate policy in marine environments. The performance of IMPA was compared to five state-of-the-art algorithms: equilibrium optimizer (EO), Harris hawk algorithm (HHA), whale optimization algorithm (WOA), sine cosine algorithm (SCA), and salp swarm algorithms (SSA) on nine chest X-ray images with threshold levels between 10 and 100 [52].

To detect the patient infected with coronavirus pneumonia from X-ray pictures, Aytaç Altan and Seçkin Karasu proposed a hybrid model comprising of two-dimensional (2D) curvelet transformation, chaotic salp swarm algorithm (CSSA), and deep learning approach. The 2D curvelet transform is performed to pictures collected from the patient's chest X-ray radiographs, and a feature matrix is generated using the resulting coefficients to increase the performance of the deep learning model EfficientNet-B0, which is known to have a low computation cost. To ensure that the model is resilient, the coefficients in the feature matrix were improved using the CSSA, which has a quick processing time. One of the newest search methods, chaos optimization, has the goal of converting variables from chaos to solution space. The avoidance of local minima and the quick convergence rate are the major reasons for utilizing the chaos optimization technique [53]. Mohammed A. A. Al-Qaness et al. suggested a model that uses the salp swarm method to create an improved adaptive neuro-fuzzy inference system (ANFIS) (SSA). It's a forecasting algorithm that uses previously confirmed COVID-19 cases in China to predict and forecast the number of confirmed cases in the next 10 days [52]. Yang introduced the flower pollination algorithm in 2012 [54], which is an optimization approach. It mimics pollinators transferring pollen from blooms in nature. The two forms of pollination are used in this algorithm (i.e., self-pollination and cross-pollination). Pollination happens without pollinators in self-pollination, whereas pollens are transferred between plants in cross-pollination. Self-pollination is referred to as local pollination, whereas cross-pollination is referred to as global pollination. Seyedali Mirjalili presented SSA as an optimization approach in 2017. It mimics the salps' natural behavior [58]. The salp chain is the name for this type of activity. SSA's mathematical model begins by dividing its population into two groups: leaders and followers. The front salp is the leader, while the other salps are the followers. To prevent being stuck at the local optima, SSA is used to enhance FPA [59]. Sally Elghamrawy and Aboul Ella Hassanien [55] proposed an AI-inspired model for COVID-19 diagnosis and patient response to treatment prediction (AIMDP). Convolutional neural networks (CNNs) are a deep learning method used by the diagnosis model to segment data. The prediction model is used to forecast a patient's capacity to respond to therapy based on a variety of parameters, including age, infection stage, respiratory failure, multiorgan failure, and treatment regimens. The whale optimization algorithm (WOA) is used by PM to choose the most receptive candidates. Eyedali Mirjalili presented the WOA, one of the most recent nature-inspired metaheuristic algorithms, in 2016. WOA mimics humpback whales' social behavior when seeking prey. The spiral bubble-net feeding strategy is used by humpback whales to pursue a group of krill (prey) that are near to the surface by spinning around them in a decreasing circle and generating bubbles along a '9'-shaped route [60]. Fusco, Antonio, et al. wanted to prove that blockchain can be used in healthcare and provide a trace route for COVID19-compliant clinical practice. The integration of blockchain and artificial intelligence technologies allows for the construction of a generalizable prediction system that might help to control pandemic danger on national territory. To highlight potential and limitations, a strength, weakness, opportunity, and threat (SWOT) analysis of the implementation of a blockchain-based prediction model in healthcare and severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infection was conducted. Blockchain has the potential to play a key role in the future of digital healthcare, especially in improving COVID19-safe clinical practice [61]. The following table illustrates a survey on different bioinspired algorithms applied in disease prediction models.

4.7. Trends in Global Health

Emerging technologies in healthcare include information technology, nanotechnology/nanomedicine, biotechnology, cloud computing, internet of things, augmented/virtual reality, GPS, RFID, voice search, chatbots, social media, blockchain, personalized medicine, biometrics, electronic health records, wearable computing devices, drones, robotics, and artificial intelligence [62]. These technologies are utilized in the discovery of novel medications and treatments, as well as improving healthcare outcomes and lowering healthcare costs and waste. Combining diagnosis and treatment always helps to improve healthcare outcomes. For example, ASBRU is a component of the ASGAARD project, which is developing a collection of task-specific problem-solving methodologies for the design, implementation, and evaluation of treatment programs. The name of an ASBRU plan identifies its five components: preferences, intents, conditions, consequences, and a planning body (layout) that defines the activities to be performed. ASBRU enables a clinical protocol to be represented in a computer processable format. It also allows doctors to adapt the procedure to the patient's condition. As a result, the medical community accepts standards and computer support more readily [63]. In addition, theranostics is a new discipline in which diagnostics and targeted therapy are combined to provide a patient-specific treatment plan. Theranostics is frequently conducted in nuclear medicine clinical practice with the same molecule tagged with two distinct radionuclides, one for imaging and the other for treatment [64]. Value-based healthcare is a kind of healthcare delivery in which hospitals and clinicians are compensated based on patient health results. Providers are paid for helping patients improve their health, minimize the impacts and incidence of chronic illness, and live better lives in an evidence-based manner under value-based care agreements. Two examples are accountable care organizations (ACOs) and medical homes. The Centers for Medicare & Medicaid Services (CMS) created ACOs to deliver high-quality medical care to Medicare participants. Doctors, hospitals, and other healthcare providers collaborate as a networked team to offer the best-coordinated care at the lowest feasible cost in an ACO. Each team member is responsible for his or her own risk and reward, with incentives to enhance automobile access. This is in contrast to fee-for-service healthcare, in which individual doctors are rewarded for ordering more tests and procedures and managing more patients, regardless of patient results [65]. A patient-centered medical home (PCMH) is a care paradigm that addresses a patient's various health, behavioral, and social requirements. PCMH aims to change the way primary care is organized and delivered by introducing new delivery models based on five principles: accessible care, coordinated care, quality care, complete care, and patient-centered care [66]. The following figure (Figure 1) depicts the different trends in global healthcare.

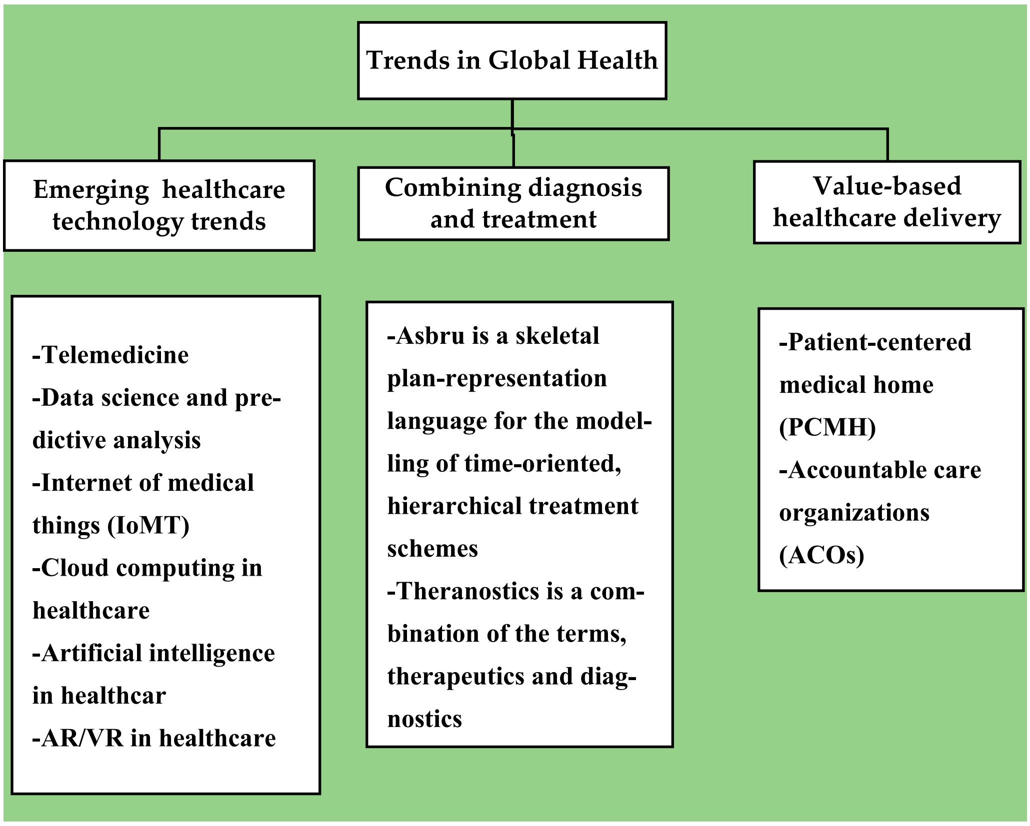

Figure 1. Different Trends in Global health.

5. Conclusions

The big data approach to healthcare delivery could be a game changer, enabling the development of machine learning systems of care and more accurate individual management to improve population health. Artificial intelligence is rapidly advancing and is already being utilized to aid and improve healthcare in a number of high-income nations. AI has a lot of potential for enhancing healthcare delivery in low-resource areas. These technological advances such as AI, ML and big data analytics provide new opportunities for medicine and public health to advance health equity by analyzing complex, multilayered and multimodal data and design impactful solutions. More research and financing are needed to improve its acceptance in these circumstances. However, the issues of equity should not be ignored in the public health interventions. This paper reviews and presents relevant ML/AL research, big data analytics and blockchain technology applications in various health conditions, surveillance and epidemic management using medical data that has been conducted in recent years. Medical data research is still in its infancy, and many challenges have to be tackled. Big data storage, mining, analysis, and related research are necessary to properly harness the intense patterns in massive data, as public health involves many dimensions of individual, environmental, and societal factors.

Author Contributions: Conceptualization, S.M. and V.K.C.; methodology, V.K.C.; software, S.M.; validation, S.M. and V.K.C.; formal analysis, S.M.; investigation, S.M. and V.K.C.; resources, S.M.; data curation, S.M.; writing—S.M.; writing—review and editing, V.K.C.; supervision, V.K.C.; project administration, V.K.C. Both the authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author (V.K.C.).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Dash, S.; Shakyawar, S.K.; Sharma, M.; Sandeep, K. Big data in healthcare: Management, analysis and future prospects. *J. Big Data* **2019**, *6*, 1–25. [CrossRef]
2. Anirudh, V.K. What Is Machine Learning: Definition, Types, Applications and Examples. 13 December 2019. Available online: https://www.toolbox.com/tech/artificial-intelligence/tech-101/what-is-machine-learning-definition-types-applications-and-examples/ (accessed on 24 December 2020).
3. Yoon, H.-J. Blockchain Technology and Healthcare. *Health Inform. Res.* **2019**, *25*, 59–60. [CrossRef]
4. Chen, H.S.; Jarrell, J.T.; Carpenter, K.A.; Cohen, D.S.; Huang, X. Blockchain in Healthcare: A Patient-Centered Model. *Biomed. J. Sci. Tech. Res.* **2019**, *20*, of15017.
5. Clohessy, T.; Hasselgren, A.; El-Gazzar, R.; Stendal, K. Blockchain in Health Care: Hope or Hype? *J. Med. Internet Res.* **2020**, *22*, e17199. [CrossRef]
6. Flatworld Solutions. Top 10 Applications of Machine Learning in Healthcare. Available online: https://www.flatworldsolutions.com/healthcare/articles/top-10-applications-of-machine-learning-in-healthcare.php (accessed on 2 January 2021).
7. Tandon, A.; Dhir, A.; Islam, N.; Mäntymäki, M. Blockchain in healthcare: A systematic literature review, synthesizing framework and future research agenda. *Comput. Ind.* **2020**, *122*, 103290. [CrossRef]
8. Sadiku, M.N.O.; Eze, K.G.; Musa, S.M. Block chain Technology in Healthcare. *Int. J. Adv. Sci. Res. Eng.* **2018**, *4*, 154–159. [CrossRef]
9. Cernian, A.; Tiganoaia, B.; Sacala, I.; Pavel, A.; Iftemi, A. Patient Data Chain: A Block-chain-Based Approach to Integrate Personal Health Records. *Sensors* **2020**, *20*, 6538. [CrossRef]
10. Tith, D.; Lee, J.S.; Suzuki, H.; Wijesundara, W.M.A.B.; Taira, N.; Obi, T.; Ohyama, N. Patient consent management by a purpose-based consent model for electronic health record based on blockchain technology. *Healthc. Inform. Res.* **2020**, *26*, 265–273. [CrossRef]
11. Benke, K.; Benke, G. Artificial intelligence and big data in public health. *Int. J. Environ. Res. Public Health* **2018**, *15*, 2796. [CrossRef]
12. Kaur, P.; Sharma, M.; Mittal, M. Big Data and Machine Learning Based Secure Healthcare Framework. *Procedia Comput. Sci.* **2018**, *132*, 1049–1059. [CrossRef]
13. Milward, J. What Is Mobile Health? 20 May 2019. Available online: https://www.addiction-ssa.org/knowledge-hub/what-is-mobile-health (accessed on 23 January 2021).
14. Khan, Z.F.; Alotaibi, S.R. Applications of Artificial Intelligence and Big Data Analytics in m-Health: A Healthcare System Perspective. *J. Health Eng.* **2020**, *2020*, 1–15. [CrossRef]
15. Nafis, M.T.; Urooj, A.; Biswas, S.S. Recent Machine Learning and Internet of Things (IoT) Applications for Personalized Healthcare: Issues and Challenges. In *Sustainable and Energy Efficient Computing Paradigms for Society*; Ahad, M., Paiva, S., Zafar, S., Eds.; EAI/Springer Innovations in Communication and Computing: Cham, Switzerland, 2021; pp. 119–126. [CrossRef]
16. Ed-daoudy, A.; Maalmi, K. A new Internet of Things architecture for real-time prediction of various diseases using machine learning on big data environment. *J. Big Data* **2019**, *6*, 1–25. [CrossRef]
17. Siddiqui, S.; Nesbitt, R.; Shakir, M.Z.; Khan, A.A.; Khan, A.A.; Khan, K.K.; Ramzan, N. Artificial Neural Network (ANN) Enabled Internet of Things (IoT) Architecture for Music Therapy. *Electronics* **2020**, *9*, 2019. [CrossRef]
18. Abdelaziz, A.; Salama, A.S.; Riad, A.M.; Mahmoud, A.N. A machine learning model for predicting of chronic kidney disease based internet of things and cloud computing in smart cities. In *Security in Smart Cities: Models, Applications, and Challenges*; Springer: Cham, Switzerland, 2019; pp. 93–114.
19. Almakhadmeh, Z.; Tolba, A. Utilizing IoT wearable medical device for heart disease prediction using higher order Boltzmann model: A classification approach. *Measurement* **2019**, *147*, 106815. [CrossRef]
20. Sivaparthipan, C.; Muthu, B.A.; Manogaran, G.; Maram, B.; Sundarasekar, R.; Krishnamoorthy, S.; Hsu, C.; Chandran, K. Innovative and efficient method of robotics for helping the Parkinson's disease patient using IoT in big data analytics. *Trans. Emerg. Telecommun. Technol.* **2019**, *31*, e3838. [CrossRef]
21. Grossfield's, B. Deep Learning VS. Machine Learning: A Simple Way to Learn the Difference. 23 January 2020. Available online: https://www.zendesk.com/blog/machine-learning-and-deep-learning (accessed on 30 January 2021).
22. What Is Heart Disease? Heart Disease (for Kids)—Nemours Kidshealth. Available online: https://kidshealth.org/en/kids/heart-disease.html (accessed on 31 July 2021).
23. Amin, M.S.; Chiam, Y.K.; Varathan, K.D. Identification of significant features and data mining techniques in predicting heart disease. *Telemat. Inform.* **2018**, *36*, 82–93. [CrossRef]
24. Dua, D.; Karra Taniskidou, E. UCI Machine Learning Repository. Master's Thesis, School of Information and Computer Science, University of California, Irvine, CA, USA, 2017.
25. Mohan, S.; Thirumalai, C.; Srivastava, G. Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques. *IEEE Access* **2019**, *7*, 81542–81554. [CrossRef]
26. Archana, S.; Kumar, R. Heart disease prediction using machine learning algorithms. In Proceedings of the 2020 International Conference on Electrical and Electronics Engineering (ICE3), Fargo, ND, USA, 14–15 February 2020; pp. 452–457.

27. Haq, A.U.; Li, J.P.; Memon, M.H.; Nazir, S.; Sun, R. A Hybrid Intelligent System Framework for the Prediction of Heart Disease Using Machine Learning Algorithms. *Mob. Inf. Syst.* **2018**, *2018*, 1–21. [CrossRef]
28. Saba, B.; Khan, Z.S.; Khan, F.H.; Anjum, A.; Bashir, K. Improving heart disease prediction using feature selection approaches. In Proceedings of the 2019 16th International Bhurban Conference on Applied Sciences and Technology (IBCAST), Islamabad, Pakistan, 8–12 January 2019; pp. 619–623.
29. Krittanawong, C.; Rogers, A.J.; Aydar, M.; Choi, E.; Johnson, K.W.; Wang, Z.; Narayan, S.M. Integrating blockchain technology with artificial intelligence for cardiovascular medicine. *Nat. Rev. Cardiol.* **2019**, *17*, 1–3. [CrossRef]
30. Jo, T.; Nho, K.; Saykin, A.J. Deep learning in Alzheimer's disease: Diagnostic classification and prognostic prediction using neuroimaging data. *Front. Aging Neurosci.* **2019**, *11*, 220. [CrossRef]
31. Sharma, A.; Shukla, D.; Goel, T.; Mandal, P.K. BHARAT: An Integrated Big Data Analytic Model for Early Diagnostic Biomarker of Alzheimer's Disease. *Front. Neurol.* **2019**, *10*, 9. [CrossRef]
32. Lin, W.; Tong, T.; Gao, Q.; Guo, D.; Du, X.; Yang, Y.; Guo, G.; Xiao, M.; Du, M.; Qu, X.; et al. Convolutional neural networks-based MRI image analysis for the Alzheimer's disease prediction from mild cognitive impairment. *Front. Neurosci.* **2018**, *12*, 777. [CrossRef]
33. Fischl, B.; Dale, A.M. Measuring the thickness of the human cerebral cortex from magnetic resonance images. *Proc. Natl. Acad. Sci. USA* **2000**, *97*, 11050–11055. [CrossRef]
34. Fischl, B.; Van Der Kouwe, A.; Destrieux, C.; Halgren, E.; Ségonne, F.; Salat, D.H.; Busa, E.; Seidman, L.J.; Goldstein, J.; Kennedy, D.; et al. Automatically Parcellating the Human Cerebral Cortex. *Cereb. Cortex* **2004**, *14*, 11–22. [CrossRef]
35. Desikan, R.S.; Ségonne, F.; Fischl, B.; Quinn, B.T.; Dickerson, B.C.; Blacker, D.; Buckner, R.L.; Dale, A.M.; Maguire, R.P.; Hyman, B.T.; et al. An automated labeling system for subdividing the human cerebral cortex on MRI scans into gyral based regions of interest. *Neuroimage* **2006**, *31*, 968–980. [CrossRef] [PubMed]
36. Han, X.; Jovicich, J.; Salat, D.; van der Kouwe, A.; Quinn, B.; Czanner, S.; Busa, E.; Pacheco, J.; Albert, M.; Killiany, R.; et al. Reliability of MRI-derived measurements of human cerebral cortical thickness: The effects of field strength, scanner upgrade and manufacturer. *NeuroImage* **2006**, *32*, 180–194. [CrossRef] [PubMed]
37. Kautzky, A.; Seiger, R.; Hahn, A.; Fischer, P.; Krampla, W.; Kasper, S.; Kovacs, G.G.; Lanzenberger, R. Prediction of autopsy verified neuropathological change of Alzheimer's disease using machine learning and MRI. *Front. Aging Neurosci.* **2018**, *10*, 406. [CrossRef] [PubMed]
38. Almubark, I.; Chang, L.-C.; Nguyen, T.; Turner, R.S.; Jiang, X. Early Detection of Alzheimer's Disease Using Patient Neuropsychological and Cognitive Data and Machine Learning Techniques. In Proceedings of the 2019 IEEE International Conference on Big Data (Big Data), Los Angeles, CA, USA, 9–12 December 2019; pp. 5971–5973. [CrossRef]
39. Pilozzi, A.; Huang, X. Overcoming Alzheimer's Disease Stigma by Leveraging Artificial Intelligence and Blockchain Technologies. *Brain Sci.* **2020**, *10*, 183. [CrossRef]
40. Darwish, A. Bio-inspired computing: Algorithms review, deep analysis, and the scope of applications. *Futur. Comput. Inform. J.* **2018**, *3*, 231–246. [CrossRef]
41. Ghoniem, R.M. A Novel Bio-Inspired Deep Learning Approach for Liver Cancer Diagnosis. *Information* **2020**, *11*, 80. [CrossRef]
42. Elgin Christo, V.R.; Khanna Nehemiah, H.; Minu, B.; Kannan, A. Correlation-Based Ensemble Feature Se-lection Using Bioinspired Algorithms and Classification Using Backpropagation Neural Network. *Comput. Math. Methods Med.* **2019**, 1–17. [CrossRef]
43. Supriya, M.; Deepa, A.J. A novel approach for breast cancer prediction using optimized ANN classifier based on big data environment. *Heal. Care Manag. Sci.* **2019**, *23*, 414–426. [CrossRef]
44. Sharma, M.; Gupta, S.; Sharma, P.; Gupta, D. Bio-inspired algorithms for diagnosis of breast cancer. *Int. J. Innov. Comput. Appl.* **2019**, *10*, 164–174. [CrossRef]
45. Valluru, D.; Jeya, I.J.S. IoT with cloud based lung cancer diagnosis model using optimal support vector machine. *Health Care Manag. Sci.* **2020**, *23*, 670–679. [CrossRef] [PubMed]
46. Olivares, R.; Munoz, R.; Soto, R.; Crawford, B.; Cárdenas, D.; Ponce, A.; Taramasco, C. An Optimized Brain-Based Algorithm for Classifying Parkinson's Disease. *Appl. Sci.* **2020**, *10*, 1827. [CrossRef]
47. Sharma, P.; Sundaram, S.; Sharma, M.; Sharma, A.; Gupta, D. Diagnosis of Parkinson's disease using modified grey wolf optimization. *Cogn. Syst. Res.* **2018**, *54*, 100–115. [CrossRef]
48. Hessam, S.; Vahdat, S.; Asl, I.M.; Kazemipoor, M.; Aghaei, A.; Shamshirband, S.; Rabczuk, T. Parkinson's Disease Detection Using Biogeography-Based Optimization. *Comput. Mater. Contin.* **2019**, *61*, 11–26. [CrossRef]
49. Pasha, A.; Latha, P.H. Bio-inspired dimensionality reduction for Parkinson's disease (PD) classification. *Health Inf. Sci. Syst.* **2020**, *8*, 13–22. [CrossRef] [PubMed]
50. Sharma, P.; Jain, R.; Sharma, M.; Gupta, D. Parkinson's diagnosis using ant-lion optimisation algorithm. *Int. J. Innov. Comput. Appl.* **2019**, *10*, 138–146. [CrossRef]
51. Hosseini, E.; Ghafoor, K.Z.; Sadiq, A.S.; Guizani, M.; Emrouznejad, A. COVID-19 Optimizer Algorithm, Modeling and Controlling of Coronavirus Distribution Process. *IEEE J. Biomed. Health Inform.* **2020**, *24*, 2765–2775. [CrossRef] [PubMed]
52. Abdel-Basset, M.; Mohamed, R.; Elhoseny, M.; Chakrabortty, R.K.; Ryan, M. A Hybrid COVID-19 Detection Model Using an Improved Marine Predators Algorithm and a Ranking-Based Diversity Reduction Strategy. *IEEE Access* **2020**, *8*, 79521–79540. [CrossRef]

53. Altan, A.; Karasu, S. Recognition of COVID-19 disease from X-ray images by hybrid model consisting of 2D curvelet transform, chaotic salp swarm algorithm and deep learning technique. *Chaos Solitons Fractals* **2020**, *140*, 110071. [CrossRef]
54. Al-Qaness, M.A.; Ewees, A.A.; Fan, H.; Abd El Aziz, M. Optimization method for fore-casting confirmed cases of COVID-19 in China. *J. Clin. Med.* **2020**, *9*, 674. [CrossRef]
55. ELGhamrawy, S.M. Diagnosis and Prediction Model for COVID19 Patients Response to Treatment based on Convolutional Neural Networks and Whale Optimization Algorithm Using CT Images. *MedRxiv* **2020**, 1–23. [CrossRef]
56. Kumar, R.; Wang, W.; Kumar, J.; Yang, T.; Khan, A.; Ali, W.; Ali, I. An Integration of blockchain and AI for secure data sharing and detection of CT images for the hospitals. *Comput. Med. Imaging Graph.* **2020**, *87*, 101812. [CrossRef] [PubMed]
57. Simon, D. Biogeography-based optimization. *IEEE Trans. Evol. Comput.* **2008**, *12*, 702–713. [CrossRef]
58. Yang, X.S. Flower pollination algorithm for global optimization. In Proceedings of the International Conference on Unconventional Computing and Natural Computation, Orléans, France, 3–7 September 2012; pp. 240–249.
59. Mirjalili, S.; Gandomi, A.H.; Mirjalili, S.Z.; Saremi, S.; Faris, H.; Mirjalili, S.M. Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems. *Adv. Eng. Softw.* **2017**, *114*, 163–191. [CrossRef]
60. Mirjalili, S.; Lewis, A. The whale optimization algorithm. *Adv. Eng. Softw.* **2016**, *95*, 51–67. [CrossRef]
61. Fusco, A.; Dicuonzo, G.; Dell'Atti, V.; Tatullo, M. Blockchain in healthcare: Insights on COVID-19. *Int. J. Environ. Res. Public Health* **2020**, *17*, 7167. [CrossRef]
62. Sadiku, M.N.; Akhare, Y.P.; Musa, S.M. Emerging technologies in healthcare: A tutorial. *Int. J. Adv. Sci. Res. Eng. (IJASRE)* **2019**, *5*, 199–204. [CrossRef]
63. Seyfang, A.; Miksch, S.; Marcos, M. Combining diagnosis and treatment using ASBRU. *Int. J. Med. Inform.* **2002**, *68*, 49–57. [CrossRef]
64. Filippi, L.; Chiaravalloti, A.; Schillaci, O.; Cianni, R.; Bagni, O. Theranostic approaches in nuclear medicine: Current status and future prospects. *Expert Rev. Med. Devices* **2020**, *17*, 331–343. [CrossRef] [PubMed]
65. NEJM Catalyst. What is Value-Based Healthcare? 1 January 2017. Available online: https://catalyst.nejm.org/doi/full/10.1056/CAT.17.0558 (accessed on 31 July 2021).
66. Jolles, M.P.; Lengnick-Hall RMittman, B.S. Core functions and forms of complex health interventions: A patient-centered medical home illustration. *J. Gen. Intern. Med.* **2019**, *34*, 1032–1038. [CrossRef] [PubMed]