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The applications of machine learning techniques in medical data processing based on distributed computing and the Internet of Things

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A R T I C L E I N F O

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Deep learning
Distributed computing

A B S T R A C T

Medical data processing has grown into a prominent topic in the latest decades with the primary goal of maintaining patient data via new information technologies, including the *Internet of Things* (IoT) and sensor technologies, which generate patient indexes in hospital data networks. Innovations like distributed computing, *Machine Learning* (ML), blockchain, chatbots, wearables, and pattern recognition can adequately enable the collection and processing of medical data for decision-making in the healthcare era. Particularly, to assist experts in the disease diagnostic process, distributed computing is beneficial by digesting huge volumes of data swiftly and producing personalized smart suggestions. On the other side, the current globe is confronting an outbreak of COVID-19, so an early diagnosis technique is crucial to lowering the fatality rate. ML systems are beneficial in aiding radiologists in examining the incredible amount of medical images. Nevertheless, they demand a huge quantity of training data that must be unified for processing. Hence, developing *Deep Learning* (DL) confronts multiple issues, such as conventional data collection, quality assurance, knowledge exchange, privacy preservation, administrative laws, and ethical considerations. In this research, we intend to convey an inclusive analysis of the most recent studies in distributed computing platform applications based on five categorized platforms, including cloud computing, edge, fog, IoT, and hybrid platforms. So, we evaluated 27 articles regarding the usage of the proposed framework, deployed methods, and applications, noting the advantages, drawbacks, and the applied dataset and screening the security mechanism and the presence of the *Transfer Learning* (TL) method. As a result, it was proved that most recent research (about 43%) used the IoT platform as the environment for the proposed architecture, and most of the studies (about 46%) were done in 2021. In addition, the most popular utilized DL algorithm was the *Convolutional Neural Network* (CNN), with a percentage of 19.4%. Hence, despite how technology changes, delivering appropriate therapy for patients is the primary aim of healthcare-associated departments. Therefore, further studies are recommended to develop more functional architectures based on DL and distributed environments and better evaluate the present healthcare data analysis models.

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1. Introduction

Health and medicine are receiving tremendous attention worldwide, and many new techniques and scientific reports are being implemented [1–3]. In recent decades, distributed computing, signal processing, and healthcare have been the main topics of utmost interest [4–6]. These two subjects have been integrated, and researchers have already been developing methods to seek beneficial novel trends in data supplied by medical equipment and utilized in training courses and examinations [7,8]. The results of medical measurements, experiments, and inspections would ultimately be incorporated into models using novel methods [9,10]. The aim of healthcare systems, which is to restore patients' health, involves the application of effective medical data enabling evidence-based intervention [11–13]. Due to records management, compliance and regulatory obligations, and patient care, the healthcare industry produces a lot of data [14,15]. Also, the current tendency is for these massive volumes of data to be rapidly digitalized and assembled with data gathered from individual and mobility devices [16–18]. In terms of patient information, treatment options, pharmaceutical details, or other aspects of healthcare, everything must be done fast, correctly, and, in some situations, transparently enough to meet severe industry rules [19,20]. Medical data processing is one of the essential duties of *Healthcare Providers* (HCP) [21]. Computerized physician order input apps featuring decision support fields prevent excess medical faults using integrated memory help [22]. These automated notification alarm signals allow suitable and prompt response that provides better and more efficient healthcare coverage [23]. The design principles of computer technologies must follow pre-stated rules and principles to preserve secrecy [24]. So, user-friendly technology provides the effective and timely transmission of healthcare data for excellent patient care fulfilling the demands of the individuals and the institution [25].

Gathering data without any distortion is costly and time-consuming [26]. A vast volume of medical data is now available because of recording devices and technological advancements. These medical records are chaotic and must be eliminated to obtain an accurate diagnosis [27]. The use of Information Technologies (IT) for medicine, including *Artificial Intelligence* (AI), has recently increased; meanwhile, all versions of such systems are inadequate, lacking actual data, particularly register-based models [27]. In general, AI has already been acknowledged as a valuable strategy for assistance in various medical concepts, including the diagnosis of diseases, management and remote monitoring of patients, and effective treatment options [28–30]. *Machine Learning* (ML) is one of the most frequently employed AI methodologies, corresponding to the intelligence revealed by computers [31]. *Deep Learning* (DL) is an improved and scalable ML extension that aids in enhancing the design and use of learning algorithms [32–34]. DL, a subtype of ML, has been used frequently to build intricate models using enormous amounts of data and in a streamlined setting [35,36]. The cloud platform has gradually become one of the most popular topics in computer science [37]. *High-Performance Computing* (HPC), virtualization, and utility computing are some of the various research fields that cloud computing is centered on [38]. Also, edge computing provides the capacity to deal with concerns, including reaction time, power consumption, bandwidth cost reduction, data security, and privacy [39]. Plus, fog computing covers the accompanying topics by presenting elastic services and resources to target customers at the network's edge, while cloud computing focuses on distributing resources over the core network [40]. Besides, *Quality of Service* (QoS) is required to support the operation of any healthcare system by aiding in the efficient and successful management of work procedures [41]. So, tasks would be disrupted if QoS is not implemented appropriately [42]. As a result, previous studies have stated that innovative ML techniques combined with powerful distributed cloud computing platforms assist in the exploration of healthcare and medical big data [43–45].

Medical data processing components, such as image processing methods, drug discovery, *Facial Emotion Recognition* (FER), survival analysis, forecasting, and so on, have earned great interest in the healthcare setting. As a result, these components were also appropriate for healthcare and medical research. However, there is no comprehensive study of the utilization of distributed computing systems in medical processing. This study concentrates on prioritizing the advancements, recognition, and classification of healthcare challenges, including cancers or epidemic situations such as COVID-19, healthcare data processing, and medical image processing methods to address medical issues, and so on, to present a comprehensive description of the modern devices supplied to use these innovations. Consistent with previous reviews on many medical data processing applications recently produced for identifying and treating various disorders, this study makes a substantial contribution by targeting the most promising field of research. This study employs a *Systematic Literature Review* (SLR) [46,47] to identify, analyze, and combine results from relevant investigations. We also classify medical data processing platforms used for healthcare delivery into five categories: *Internet of Things* (IoT), cloud, edge, fog, and hybrid platforms. Hybrid platforms integrate some platforms like IoT, edge, fog, *Internet of Drones* (IoD), or *Internet of Vehicles* (IoV). We evaluated numerous features such as benefits, challenges, datasets, usage, methods, and security for each classification associated with medical data processing methods. This paper describes the methodologies and implementations of data processing in the outlet of healthcare. We have also looked over future scopes, in particular, highlighting all of the gaps that need to be handled. In general, the expenditures of the present paper are:

- Providing a thorough analysis of the most current innovations in medical data processing;
- Proposing a systematic review of the available platforms for medical data processing;
- Providing a summary of the most basic ML/DL-based methodologies in medical data processing;
- Presenting a summary of distributed computing methods for healthcare data analysis by classifying them based on practical characteristics of the techniques;
- Evaluating each method that is associated with numerous aspects such as advantages, challenges, databases, implementations, privacy, and security matters;
- Outlining the vital aspects where the preceding strategies may be improved soon.

The study's layout is defined by the classifications mentioned below. The following section discusses the principles of distributed computing and the terminology of applied platforms in medical data processing. The relevant reviews are presented in Section 3. The research methodologies for study materials and inclusion criteria are discussed in Section 4. The classifications of the selected articles are explained in Section 5. The results and comparisons, explaining platforms, methods, dataset, privacy, and security with a comprehensive analysis of the results, are presented in Section 6. Section 7 discusses the topics and difficulties that are still unresolved. Finally, a brief conclusion of the study with recommendations for further research is provided in Section 8. Table 1 illustrates the abbreviation applied within this paper.

2. Terminologies and fundamental concepts

This section addresses the primary concepts of data processing techniques in the healthcare era regarding the association with platforms of ML and distributed computing.

2.1. Machine learning and deep learning methods

Integrating AI in the medical sector has been an increasingly prominent topic [48]. ML is a subtype of AI, defined as a branch of science focusing on how computers learn from data [49,50]. It emerges at the

Table 1
Abbreviation table.

Abbreviation	Definition	Abbreviation	Definition	Abbreviation	Definition
ADE	Adverse Drug Effect	FDA	Federated Deep Learning	MLPs	Multilayer Perceptrons
AI	Artificial Intelligence	FER	Facial Emotion Recognition	MSE	Mean Squared Error
ANN	Artificial Neural Network	FL	Federated Learning	NFV	Network Function Virtualization
AUC	Area Under Curve	FIS	Fuzzy Inference System	NLP	Natural Language Processing
BERT	Bidirectional Encoder Representations from Transformers	GANs	Generative Adversarial Networks	NN	Neural Network
CAD	Computer Aided Diagnosis	HCP	Health-Care Provider	QoS	Quality of Service
CDSS	Clinical Decision Support Systems	HEM	Hybrid Ensemble Model	RBFNs	Radial Basis Function Networks
COVID-19	Coronavirus Disease 2019	HIoT	Healthcare Internet of Things	RBMs	Restricted Boltzmann Machines
CNNs	Convolutional Neural Networks	HPC	High-Performance Computing	RL	Reinforcement Learning
CKD	Chronic Kidney Disease	ICT	Information and Communication Technologies	RNNs	Recurrent Neural Networks
CPS	Cyber-Physical Systems	ICU	Intensive Care Unit	ROC	Receiver Operating Characteristic
CVS	Cross-Validation Score	IJP	Inkjet-Printed	RQs	Research Questions
CTA	CT-Angiography	IoMT	Internet of Medical Things	SDCA	Summation Discriminant Correlation Analysis
DBNs	Deep Belief Networks	IoT	Internet of Things	SDN	Software-Defined Network
DDTL	Distant Domain Transfer Learning	IoV	Internet of Vehicles	SLA	Selective Learning Algorithm
DFF	Distant Feature Fusion	IT	Information Technologies	SLR	Systematic Literature Review
DICOM	Digital Imaging and Communications in Medicine	LDP	Local Differentially Private	SOMs	Self-Organizing Maps
DWT-PCA	Discrete Wavelet Transform and Principal Component Analysis	LSTMs	Long Short-Term Memory Networks	SVM	Support Vector Machine
DL	Deep Learning	MAS	Multi-Agent System	TL	Transfer Learning
EA	Epileptiform Activity	MEC	Mobile Edge Computing	US	Ultra-Sound
EDA	Exploratory Data Analysis	ML	Machine Learning	WHO	World Health Organization

intersection of statistics, which aims to discover connections between data, and computer science, emphasizing efficient computing processes [51]. It is possible to establish complicated relationships utilizing ML that could be difficult to represent using an equation [52]. For instance, *Neural Networks* (NN) similarly show the data on the function of the human brain by integrating a vast number of neurons [53]. This allows ML systems to address the issue similarly to one used by a physician, achieving justified outcomes by investigating the facts. One of the key components of ML is the requirement to supply the algorithm with a large amount of data to progress on the investigation. There are diverse groups of patients followed retrospectively, but they generally contain hundreds or a few thousands of individuals. However, ML systems could deal with massive datasets [54]. Breakthroughs in DL and ML will aid in making healthcare decisions but will not displace the physician entirely. With the assistance of ML, the introduction of patient records optimized the outcomes of statistical regression significantly, providing a perspective for individualized therapy. Human mistakes in healthcare are connected with significant financial losses, most of which can be eliminated with the assistance of ML and DL. Previous studies reported reduced mortality rate and lower hospitalization in an *Intensive Care Unit* (ICU) after treatments were administered in an ML model [55].

When designed, assessed, and distributed correctly, DL approaches can aid in acquiring, interpreting, and combining healthcare information from diverse sources and bringing it to our fingertips—as if we had an experienced subspecialist to rely on for every patient and medical circumstance. Also, DL could aid in remote monitoring and analysis of patients, leading the data collection that can be forwarded to a healthcare facility. Perhaps ML algorithms can assist in discovering novel and subtle data trends that could influence patient care [56]. So, ML is applied in several contexts, such as deepfake detection, image classification, spam detection, multimedia concept retrieval, video recommendation, and text mining.

Among numerous AI techniques, DL is extremely widely implemented in these apps. The unforeseen expansion in data collection capabilities and the significant advancements made in hardware advances, such as *High-Performance Computing* (HPC), are the fundamental causes of the ongoing birth of new research in deep learning and distributed learning [57]. Also, the effectiveness of DL in several pattern recognition chores has created enthusiasm and a strong perception that DL will bring revolutionary advances in healthcare. With the development of DL in many ML applications in recent years, there are high expectations that DL can bring advancements in *Computer Aided Diagnosis* (CAD) performance and the prevalent use of DL-based CAD or AI in various procedures in patient care [58]. It is essential to express the emerging prominence of ML approaches in incorporating health data [59].

2.2. Medical data processing in general

In recent decades, QoS and computation of data processing connected to healthcare have become a major task in numerous research disciplines, for example, ML, AI, and DL utilizing medical data and processing records stored in medical centers [60,61]. The three primary data streams from clinical trials, records connected to medical research, and organizational information procedures drive the collection of data ledgers. Medical data acquisition and pre-processing design setting is a significant priority in healthcare [62,63]. Assessing and analyzing this recorded information for computer-based executives helps, and the emergence of real-time platforms is now a major trend in the latest smart healthcare. Medical data analysis has progressed rapidly due to improvements in ML and AI technology [64]. The healthcare industry creates a vast quantity of data in the event of record-keeping, regulatory compliance, and patient care [65]. The current tendency is for these large volumes of data to be progressively integrated and combined with information obtained from individual and mobility sensors. Efficient data processing and investigation may discover hidden insights for improving patient care, especially with large datasets. They can further properly estimate a patient's health condition if the data is obtained from outside medical clinics. The findings might also be applied to better, less expensive real-time healthcare [9].

In addition, the government and authorized healthcare centers are primarily responsible for data collection. Knowledge application, which is the purpose and motivating factor behind data processing, has become largely involved in clinical management and treatment program termination. Categorization, clustering, association rules, and regression are just a few of the data mining technologies easily accessible. Researchers can only make a decision and build a prediction model after carefully considering the dataset. In understanding the performance of the model, experts must perform certain tests on it. Furthermore, the patterns and data discovered must be examined and improved. Consequently, data processing is an ongoing dynamic process that needs corrective input. Only in this manner will we be able to get a comparatively superior knowledge model [66].

2.3. What is distributed computing?

Cloud computing is the strategy of storing and processing data using a network of remote computers on the Internet or, rather, a personal computer or local server. Also, IoT is a platform in which objects are implanted with a network connection, enabling them to collect and share data without the need for human interaction [67–70]. Moreover, edge and fog platforms are novel storage and data analysis paradigms providing an extra layer of processing capability between the cloud and a device, such as a medical sensor. The additional layer is close to the data source. Such structures reduce the amount of data that must be transported to and received from cloud-based servers and increase the accessibility of data that must be acted upon within milliseconds of collection. To the degree that specific projects call for speedy data analysis, fog can help emerge paradigms in healthcare data analysis and remote medical monitoring, such as processing massive data and privacy-conscious distributed learning systems [71]. In addition to data collection, an edge medical device serves as a gateway to a network or the Internet. The edge computing paradigm shifts network service administration from central nodes (known as the core) to the opposite extreme, which is the sensor component, rather than to nodes. Fog and edge are beneficial when the aim is immediate data processing following the instantaneous creation of a rules-based command. These two designs may enable medical sensor data to be placed quickly, resulting in efficient conclusions. The following are three possible obstacles for distributed data analysis using edge or fog platforms with limited computational power: (1) converting medical data from multiple sources to a popular architecture while also protecting privacy if data are to be shared; (2) attempting to balance abstract data to allow for restricted storage device against lesser abstraction to allow for productivity; and (3) recognizing inaccurate data from separated deficient sensors or wireless transmitters [39,72]. In the next section, we will briefly analyze the relevant reviews on this topic, mostly regarding the use of IoT and the *Internet of Medical Things* (IoMT) in healthcare data, DL applications in patient care, and virtual patient monitoring.

3. Relevant reviews

In the previous section, we discussed concepts of distributed computing, ML, and DL with applications of them deployed in medical data processing. In this section, we will have a brief review of the related works in this field. Generally, ML and, specifically, DL techniques dominate medical image and data analysis. In a related study, Sarhan et al. [73] provided an overview of ML techniques recommended for diagnosing, classification, and segmentation of multiple lesions in ophthalmic diseases, primarily diabetic retinopathy, age-related macular degeneration, and glaucoma, as well as a brief description of public datasets and issues associated upon each pathology and the strategy development. Color fundus imaging and optical coherence tomography were identified as the most frequently utilized imaging modalities.

Also, Kaur and Kaur [74] presented a comprehensive understanding of DL and its implications in healthcare obtained during the last decade. They focused on the DL image processing capabilities used to defeat COVID-19 and an in-depth analysis of the recent structure built using this technology. Moreover et al. [57] evaluated the methodologies associated with the study of the head and brain from the fetal Ultra-Sound (US) perspective. The investigated methods are further classified into five broad groups depending on their basic theoretical approach, as described in Global intensity-based, learning-based, deformable, registration, and active shape models. Also, the best image-processing approaches for analyzing the head and brain were determined. The assessment of the reviewed methods enabled the identification of the essential techniques for each sector, their benefits, and the ongoing value of the investigation.

Kashani et al. [75] intended to identify systematically and taxonomically categorize *Healthcare Internet of Things* (HIoT) research to provide an extensive comparison with the existing publications' limits and potentials by providing a comprehensive overview of the latest studies in HIoT that concentrate on applied methodologies, methods, and tools. The reviewed articles were classified into five categories: communication-based, security-based, resource-based, application-based, and sensor-based. The advantages and drawbacks of the proposed techniques and a complete comparison of assessment procedures, tools, and metrics were also discussed. In addition, Gatouillat et al. [76] provided a detailed literature evaluation of the current efforts focused on strengthening the IoMT via the application of formal approaches supplied by the *Cyber-Physical Systems* (CPS) community by explaining the realistic use of the democratization of medical supplies for both healthcare professionals and patients. They also tried to propose undiscovered research pathways and possible developments to address unknown research difficulties. The domain of IoMT-based systems and IoMT devices was investigated from a multi-layer perspective.

Also, Mbunge et al. [77] discussed the dynamic sensory web in the major trends, competencies, innovations, apparent issues, and ethical concerns, as well as emerging technologies, including AI, IoT, IoMT, big data, and cloud, which are critical in the progression and integration of sensory emotive Web in virtual healthcare. They provided a summary of the expansion of the WWW in healthcare, emphasizing capacities and technology even while explaining security and ethical concerns. Finally, they presented a variety of solutions to the limitations and ethical concerns.

Ben-Israel et al. [78] aimed to discover the use of AI methods in clinical settings and their capacity to build upon the tremendous human intellect that has brought medicine to where it is now. They emphasized the present status of ML studies in clinical medicine by characterizing the target patient demographics, types of employed data, and the existence or absence of DL techniques. Also, Heidari et al. [79] concentrated on emphasizing the achievements, recognition, and identification of DL and medical image processing approaches to combat the COVID-19 pandemic, mortality forecast, predicting health equipment, and so on by creating an SLR to explore, interpret, and integrate data from comparable research. In their study, the DL techniques applied in COVID-19 were divided into seven basic separate categories. Several features like benefits, difficulties, database, utilizations, safety, and TL for each classification and approach using DL methods were reviewed in this study.

This survey paper distinguishes itself from previous studies by comprehensively analyzing distributed computing systems in medical data processing. It explores the utilization of various platforms such as IoT, cloud, edge, fog, and hybrid platforms and evaluates them based on practical characteristics. The survey also emphasizes the integration of ML/DL methodologies in medical data processing and provides a systematic review of the available techniques. It evaluates each methodology from different perspectives, including advantages, challenges, implementations, and privacy/security considerations. Additionally, the paper identifies gaps and limitations in existing strategies, highlighting areas for future improvements. Overall, this survey provides a valuable resource for researchers and practitioners in the field, offering a comprehensive overview and identifying avenues for further research and development. A summary of relevant reviews is provided in Table 2. In the next section, we are going to discuss research methodologies thoroughly.

4. Research methodology

In the previous section, we provided a summary of the related reviews of DL-based techniques in medical data processing. In this section,

Table 2
Summary of related works.

Researchers	Idea	Scope	Advantages	Challenges
Sarhan et al. [73]	Reviewing most recent impactful papers about ML methods in Ophthalmology.	Data processing	Pointing to limitations and strengths	The papers published before 2015 were not included
Kaur and Kaur [74]	Illustrating the concept of DL techniques using medical imaging.	Image processing using DL	Introducing some issues and confrontations to control the health crisis and outbreaks	Future works are not thoroughly discussed.
Torres et al. [80]	Reviewing the state-of-the-art of image-based approaches to assess fetal head/brain in the US.	Image processing methods	It was the first review that thoroughly investigated the fetal head and brain in the US.	Future works are not thoroughly discussed.
Kashani et al. [75]	Attempting to establish, compare, and categorize available data in HIoT systems.	IoT in healthcare	The results are presented in great detail.	Future works are not thoroughly discussed.
Gatouillat et al. [76]	Describing the progression of IoMT actions over time.	IoMT	Mentioned potential research paths and issues of relevance	There are still some unexplained challenges
Mbunge et al. [77]	Discussing emotive sensory Web in virtual healthcare.	Virtual healthcare	Outlined capabilities and innovations, privacy, and ethical aspects	The procedure for selecting articles is not obvious
Ben-Israel et al. [78]	Highlighting the current status of ML research in clinical practice.	ML on patient care	The results are presented in great detail.	The procedure for selecting articles is not obvious.
Heidari et al. [79]	Reviewing the DL apps created for the diagnosis and cure of COVID-19 disease.	DL	The results are presented in great detail	No solution was recommended for ethical and technological issues

we will give the details of the methodologies employed in this study. Also, the SLR approach is used in this section to clarify how medical data processing is done [81]. The SLR is a critical review and investigation of all studies on a specified subject. This section concludes a thorough examination of the performance of each distributed computing platform in the analysis of medical data. Following that, we examine the validity of the study selection approaches. The study topics and selection criteria are covered in detail in the following subsections, along with the search process.

4.1. Formalization of questions

The basic targets of this research are to categorize, distinguish, and assess all related articles discovered in medical data processing methodologies. To meet the above-stated objectives, the elements and features of the approaches can be thoroughly studied utilizing an SLR. An additional goal of SLR is to understand the significant concerns and problems facing this industry. A few Research Questions (RQs) that have been formulated are as follows:

ü **RQ 1**: What are the main issues and unanswered questions that need to be resolved in this area?

The answers to this issue will be offered in Section 5, and the unresolved issues will be presented in Section 7.

ü **RQ 2**: What steps should we take to find the article and choose the best data processing techniques for the healthcare setting?

This is addressed in Sections 6 and 7.

ü **RQ 3**: How can distributed computing mechanisms be classified in medical healthcare? What are some of their examples?

The response to this issue is found in Section 6.

ü **RQ 4**: What techniques are employed by the researchers to conduct their study?

This question is answered in Sections 5.1 to 5.5.

4.2. The selection procedure for articles

The technique used to find and choose the papers for this investigation consists of the following five steps. This method is shown in Fig. 1. Table 3 displays the search phrases and keywords used to index the articles in the first phase. These publications are the results of a search of widely used electronic databases. Applied electronic databases include Scopus, IEEE Explore, Springer Link, Google Scholar, Elsevier, Nature, JMIR, Soft Computing, and Computer Communications. Moreover, journals, conference papers, books, chapters, notes, technical studies, and special issues are excluded. Stage 1 yielded 1608 papers. The publisher's distribution is illustrated in Fig. 2.

In stage 2, duplicated papers are omitted. Next, in stage 3, based on the inclusion criteria, the selection of articles is continued, with which

Table 3
Search terms and keywords.

S#	Search Terms and Keywords
S1	"Medical data processing" or "Healthcare data processing"
S2	"Medical data processing" or "Medical data analysis"
S3	"Machine learning" or "Deep learning"
S4	"Medical data processing" and "Cloud computing"
S5	"Medical data processing" and "Internet of things"
S6	"Medical data processing" and "Edge computing"
S7	"Medical data processing" and "Fog computing"
S8	"Medical data processing" and "Hybrid techniques"

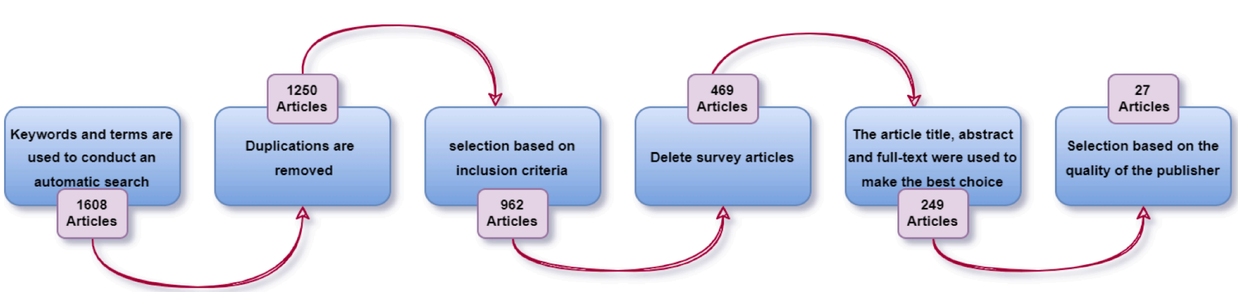

Fig. 1. The stages of the search procedure and article selection.

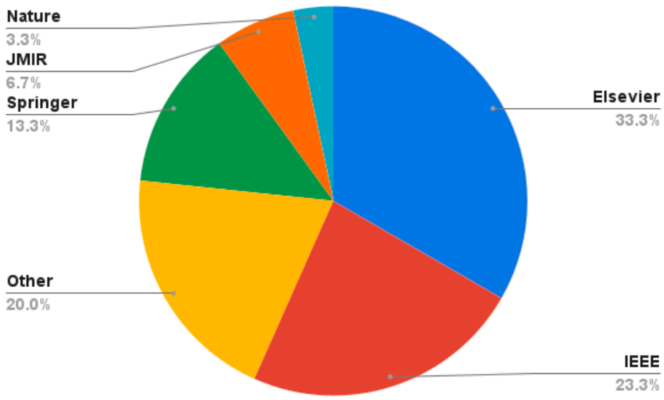

Fig. 2. The distribution of papers based on the publisher.

962 papers remain. The distribution of papers regarding the type is represented in Fig. 4. Stage 4 eliminates the review articles; of the remaining 962 items in Stage 2, 493 (or 51.2%) were review papers. IEEE and Elsevier collectively publish 34% of all scientific articles. BioMed and IEEE publish 18.8% of all review papers. There are now 469 articles remaining, and Fig. 3 shows how they are distributed by publication and article kind at this time. Stage 5 involved reviewing the papers' titles and abstracts. At this stage, 249 publications have been selected for further study, with the distribution of the papers depending on the publisher shown in Fig. 4. The papers' methodology, evaluation, discussion, and conclusion have also been examined to verify their relevance to the research. The remaining publications in Table 4 were reviewed and examined using 27 papers that satisfied the high requirements. In Fig. 5, the distribution of the chosen articles by their publishers is also depicted. Elsevier and Springer publish most selected articles (36%, 13 articles). The lowest number is related to The Optical Society, Frontiers Media S.A., Academic Press Inc., Alexandria University, and Tech Science Press (18%, 5 articles). The year with the most papers published (46%) is 2021, whereas the year with the fewest articles published (11%) is 2019. In Fig. 6, the journals that publish the publications are shown. Journal of Medical Internet Research, IEEE IoT Journal, and Informatics in Medicine Unlocked publish the most articles (22%, 6 articles).

Fig. 3. The criteria for selecting papers to be included in the process.

5. Medical data processing methods

In Section 4, we talked about the methodologies of this study based on the SLR method. This part will review the techniques applied in medical data processing for healthcare delivery as classified into five categories: IoT, cloud, fog, edge, and hybrid methods. Moreover, we take a brief review of some articles published recently for each of the platforms. Fig. 7 illustrates the taxonomy of medical data processing methods.

5.1. Cloud computing

For a variety of applications, cloud computing as a network approach provides diversity, reliability, adaptability, inclusivity, flexibility, intention, unpredictability, scalability, dynamic nature, quick service structure, lower capital costs, distribution, and resource pooling [109–111]. Cloud computing allows content providers to get internet access for sharing flexible computer resources [112]. Additionally, it offers various features for processing data on a widespread, decentralized basis [113]. A cloud environment can offer clients a variety of services and computational resources, including databases, networking, storage, and applications. [114]. While giving excellent cooperation opportunities, it offers the organization, businesses, and individuals considerable financial benefits. So, the cloud-based platform helps the medical and healthcare groups by facilitating equal access to clinical information. [115].

In a relevant study, Lee et al. [82] created a DL-based *Natural Language Processing* (NLP) algorithm for medical specialty categorization by gathering data that adequately represented patients' symptoms in a real-world context. They built several DL-based NLP systems, compared their results, and then chose the best model for an AI chatbot that was deployed on Google Cloud. First of all, data collection and sanitation were done, and an *Exploratory Data Analysis* (EDA) was conducted to uncover the interpretable aspects of the data before creating the DL–based NLP models. Four different *Long Short-Term Memory* (LSTM) frameworks with or without recognition, with or without a pre-trained FastText embedding layer, and bidirectional encoder ideas from NLP transformers were trained and evaluated using a randomly chosen test data set. Precision, recall, F1-score, and *Area Under Curve* (AUC) were utilized to assess the models' performance. An AI chatbot was created to make it simple for patients to use this specialty referral system. The AI chatbot was made using the "Alpha" open-source framework.

In another study, Egger et al. [83] introduced Studierfenster, a client-server platform for (bio-) medical image analysis that is also free and open-source. It has several features, including the ability to display medical data in popular web browsers. Other features include calculating standard medical scores, manually outlining structures in medical images slice by slice, placing landmarks in medical imaging data, visualizing medical data in *Virtual Reality* (VR), reconstructing faces, and registering medical data for *Augmented Reality* (AR). *Convolutional Neural Network* (CNN)-based automated cranial implant design, *Generative Adversarial Network* (GAN)-based in-painting of aortic dissections, and CNN-based automatic aortic landmark recognition in *CT-Angiography* (CTA) pictures are more advanced features. To assess Studierfenster's accessibility and practical functions, a user study was conducted with medical and non-medical professionals in medical image processing. A mean of 6.3 out of 7.0 potential points was obtained from participants who were asked to rate their overall opinion of Studierfenster in an ISO standard (ISO—Norm) questionnaire.

Besides, Stirling et al. [84] created a minimally invasive *Electroencephalography* (EEG) recording device which is implanted under the scalp. An ML algorithm guided the identification of Epileptiform Activity (EA) developed to identify significant EEG signals and predict the chance of a seizure hourly. The approach comprised a *Random Forest* (RF) regressor with a Logistic Regression (LR) classifier. The system's ability to identify five participants' Interictal *Epileptiform Activity* (EA)

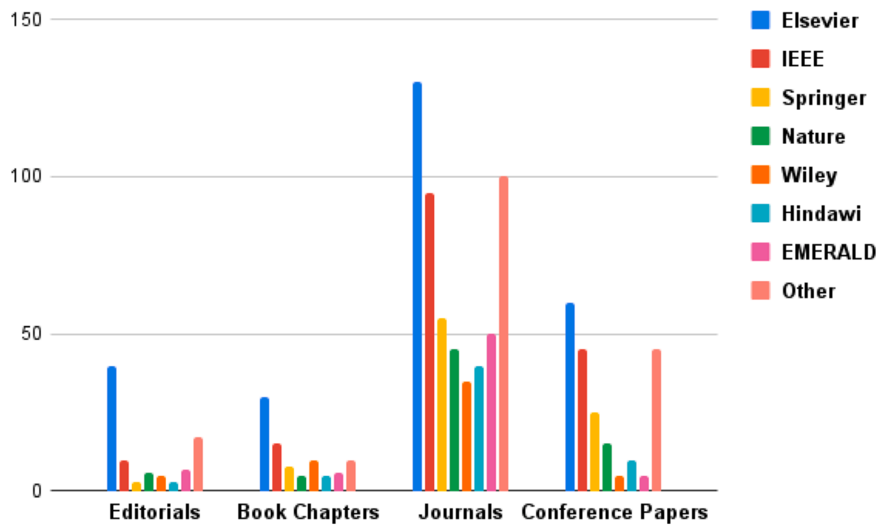

Fig. 4. Overview of the type of publisher in the reviewed papers.

Table 4
Details of the selected articles (updated on March 15, 2023).

Publisher	Author	Citation	JCR	Scopus	Journal Name	H-index
Journal of Medical Internet Research	Lee et al. [82]	2	Q1	Q1	**Journal of Medical Internet Research**	142
Springer New York	Egger et al. [83]	0	Q1	Q1	**Journal of Digital Imaging**	58
Frontiers Media S.A.	Stirling et al. [84]	5	Q2	Q2	**Frontiers in Neurology**	67
Institute of Electrical and Electronics Engineers Inc.	Aazam et al. [85]	1	Q1	Q1	**IEEE Transactions on Sustainable Computing**	21
Springer Netherlands	Liu et al. [86]	0	Q2	Q2	**Journal of Supercomputing**	68
Institute of Electrical and Electronics Engineers Inc.	Ma and Pang [87]	22	Q2	Q1	**IEEE Access**	158
Institute of Electrical and Electronics Engineers Inc.	Niu et al. [88]	11	Q1	Q1	**IEEE Journal of Biomedical and Health Informatics**	125
Elsevier Ltd.	Połap et al. [89]	24	Q2	Q2	**Journal of Information Security and Applications**	40
Springer London	Khan et al. [90]	13	Q1	Q1	**Neural Computing and Applications**	80
Institute of Electrical and Electronics Engineers Inc.	Mahawaga Arachchige et al. [91]	38	Q1	Q1	**IEEE Internet of Things Journal**	97
Springer Verlag	Mansour and Althobaiti [92]	0	Q2	Q2	**Soft Computing**	90
Nature	Warnat—Herresthal et al. [93]	31	Q1	Q1	**Nature Publishing Group**	1226
Institute of Electrical and Electronics Engineers Inc.	Kong et al. [94]	16	Q1	Q1	**IEEE Internet of Things Journal**	97
Alexandria University	Yang et al. [95]	2	Q1	Q1	**AEJ - Alexandria Engineering Journal**	58
Elsevier BV	Rahman et al. [96]	0	Q2	Q2	**Smart Health**	9
Tech Science Press	Khan et al. [97]	14	Q2	Q1	**Computers, Materials and Continua**	40
Academic Press Inc.	Manocha et al. [98]	4	Q1	Q1	**Journal of Biomedical Informatics**	103
Public Library of Science	Shukla et al. [99]	28	Q1	Q1	**PLoS ONE**	332
Elsevier	Horng et al. [100]	0	Q1	Q1	**Computer Communications**	105
Elsevier BV	Mohamed Akram et al. [101]	0	Q2	Q1	**Biomedical Signal Processing and Control**	84
Elsevier Ltd.	Singh et al. [102]	2	–	Q2	**Informatics in Medicine Unlocked**	32
Elsevier Ltd.	Fan et al. [103]	35	Q1	Q1	**Information Processing and Management**	101
Elsevier	Arabi and Zaidi [104]	17	Q1	Q1	**Medical Image Analysis**	135
The Optical Society	Yuan et al. [105]	12	Q1	Q1	**Biomedical Optics Express**	86
Elsevier Ireland Ltd	Al-Saffar and Yildirim [106]	11	Q1	Q1	**Computer Methods and Programs in Biomedicine**	102
Elsevier Ltd.	Momenzadeh et al. [107]	0	–	Q2	**Informatics in Medicine Unlocked**	32
Springer Netherlands	Seba and Benifa [108]	0	Q3	Q2	**Wireless Personal Communications**	65

and seizures was discussed. EA is characterized as both interictal and ictal epileptic activity, including electrographic episodes and interictal discharges. Additionally, the recordings were evaluated qualitatively in contrast to a reference-standard 7-day ambulatory video-EEG monitoring. The potential for seizure forecasting using sub-scalp EEG was also shown through a case study that acted as a proof-of-concept for how cycles may be produced from event detection systems in the EEG and how these cycles may be used to estimate epileptic episodes. The ability of a sub-scalp device to precisely record ultra-long-term EEG (>12 months) and identify focal seizure activity was successfully shown in the end. All five subjects handled the device well, and there were no major adverse effects, indicating that a discreet, minimally invasive device might be used to monitor EA over an extended period continuously.

Aazam, Islam [64] provided a three-tier cloud-fog-IoT framework, a

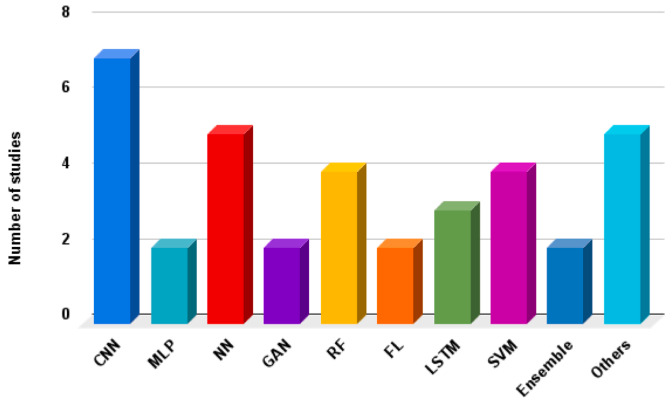

Fig. 5. The publisher`s distribution of the selected papers.

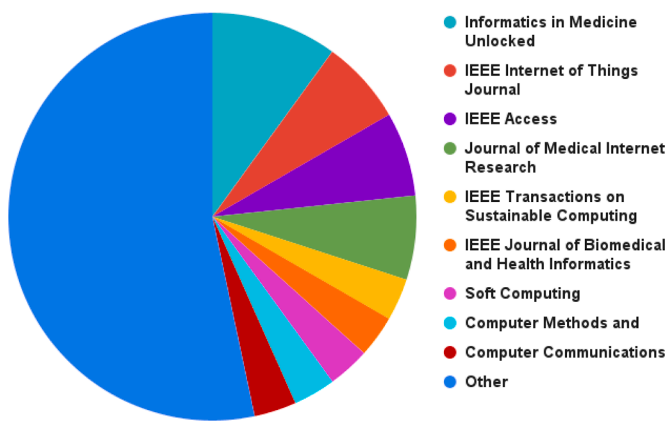

Fig. 6. Journal-based distribution of the chosen articles.

term created as the CoT model, and a task offloading mathematical system for managing incoming tasks from an underlying IoT and selecting whether to offload to fog, a cloud, or cooperatively to fog-cloud. As a proof-of-concept, the CoT architecture was constructed based on datasets suited for IoT in general and DL approaches in particular. The architecture of the model was assessed by taking into consideration computational workloads for different applications in IoT linked to medical, multimedia, location-based, and text, and by utilizing actual datasets, based on three scenarios: fog-only (F), cloud-only (C), and fog-cloud (F/C) computing referred primarily from hereon as (F/FC/C). Their research examined the factors that may impact the performance and power of F/C/FC settings. The outcome indicated how much a variable might affect the speed and power usage, the drawbacks, and what might aid in reducing these parameters.

Additionally, to utilize distributed parallel classification methods in hospital intelligent guidance, Liu et al. [86] developed the *Parallel Random Forest* (PRF) classification technique. The main usage of the proposed model was for the detection and classifying colon cancer. The model was designed based on the Apache Spark cloud computing and with the *Bilayer Parallel Training-CNN* (BPT-CNN) platform application. An *Adaptive Domain Density Peak Clustering* (ADDPC) method was put forth in light of sparse cluster loss in data sets with variable density distribution. Additionally, a case study evaluation of the model's performance was conducted. The outcomes showed that a distributed cloud computing platform-based PRF algorithm might independently construct data-parallel tasks, maximizing the cost and efficiency of data communication.

Finally, Ma and Pang [87] systematically evaluated the drawbacks of the present convolution *Neural Network* (NN) algorithm and sports medical data to develop the CNN algorithm-based on the resampling approach with a self-adjusting function. To analyze vast volumes of data more properly, they also innovatively presented the supplementary model tensor convolution self-coding NN framework to realize the analysis of multi-dimensional input of sports medicine. Therefore, a cloud-based fusion hardware-in-the-loop simulation model was developed to advance the creation of an intelligent healthcare data platform for sports medicine. This model underwent analysis and research to provide technical support and experience for the actual cloud-based fusion hardware-in-the-loop system.

Cloud computing is a versatile and advantageous network approach used in various applications. It provides benefits such as diversity, reliability, adaptability, flexibility, and scalability while reducing capital costs. By offering access to flexible computer resources and decentralized data processing, cloud computing enables content providers to share information and services effectively. In the medical and healthcare sector, cloud-based platforms facilitate equal access to clinical information and provide financial benefits. Several studies have demonstrated the practicality and benefits of cloud computing in different domains. For example, researchers developed a DL-based NLP algorithm for medical specialty categorization and deployed it on Google Cloud. Another study introduced a free and open-source platform for (bio-) medical image analysis, which received positive ratings in a user study. A machine learning-guided minimally invasive EEG recording device was created to predict seizures accurately. Additionally, researchers proposed a three-tier cloud-fog-IoT framework for task offloading management and developed a Parallel Random Forest classification technique for colon cancer detection. They also evaluated the drawbacks of existing convolutional neural network algorithms and proposed a cloud-based fusion hardware-in-the-loop model for intelligent healthcare data processing in sports medicine. These advancements highlight the potential of cloud computing in revolutionizing medical data processing. The cloud platforms and their characteristics are covered in Table 5 for medical data processing.

5.2. IoT platform

The IoT is a constantly growing ecosystem that combines hardware, apps, items, and computational devices for data collection, transfer, and communication. The IoT offers a smooth platform to enable

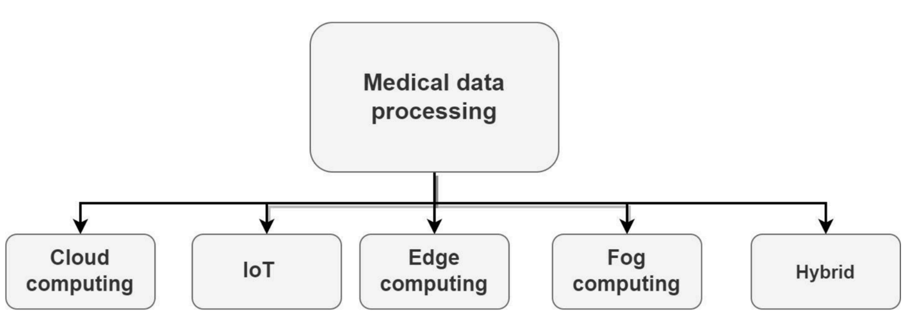

Fig. 7. The proposed medical data processing taxonomy separated five distinct methods.

Table 5
The methods, properties, and features of cloud computing platforms in medical data processing.

Researchers	Idea	Advantages	Challenges	Security?	Dataset	Using TL?	Method	Usage?
Lee et al. [82]	Developing an AI chatbot with the based NLP models.	-High accessibility -Easy-to-use application -Low delay	-High complexity	No	A Korean web-based platform called HiDoc	No	LSTM	Giving medical advice in the COVID-19 pandemic
Egger et al. [83]	Introducing a framework for medical image analysis.	-High accuracy -Can be extended to other fields of research	-High energy consumption	No	Digital Imaging and Communications in Medicine	No	CNN +GAN	Image analysis
Stirling et al. [84]	Presenting a DL method for seizure detection.	-High sensitivity	-Significant false positives	No	ACTRN 12619001587190	No	RF+LR	Identification of seizure activity
Aazam et al. [85]	Providing an implementation of the three-tier CoT architecture.	-High scalability, -Low energy consumption,	-High delay	No	IoT jobs/tuples	No	DNN	Handling of incoming tasks
Liu et al. [86]	Establishing a reliable medical data management system.	-High accuracy, -High robustness, -Low delay,	-High complexity -No solution for the defects.	No	UCI (UC Irvine ML Repository)	No	BPT-CNN	Detect and classify colon cancer
Ma and Pang [87]	Proposing a cloud-based hardware-in-the-loop simulation model for information mining.	-Efficient prediction -Lower risk assessment	-High complexity	Yes	Not mentioned	No	CNN	Sports medical data analysis

communication between people and various physical and digital objects, including fields of personalized healthcare. A method called Adaptive Domain Density Peak Clustering (ADDPC) was suggested due to sparse cluster loss in data sets with changing density distribution. Case analysis was also used to assess how well the model performed. So, the IoT can reduce the burden on sanitary systems even while offering personalized health services to enhance the quality of life. As a system of interconnected objects, IoT enables automation in several fields, including remote and intelligent healthcare systems [116]. The IoT utilizes common technologies like as *Wireless Body Area Networks* (WBANs), *Wireless Sensor Networks* (WSNs), and *Radio Frequency Identification* (RFID) to transfer data to the cloud for analysis and extraction of meaningful data for valuable decision-making [117–120].

In a relevant study, Niu et al. [88] created a COVID-19 classification framework based on lung CT scans by investigating a difficult topic called *Distant Domain Transfer Learning* (DDTL), which tries to address the drawbacks of classic ML and traditional TL. The suggested approach is divided into two components: semantic segmentation and *Distant Feature Fusion* (DFF), and the chosen algorithm was just one instance-based DDTL method: *Selective Learning Algorithm* (SLA), which may transmit information across apparently unrelated disciplines. Otherwise, DDTL is a recently established TL approach that primarily tries to solve the problem of negative transfer induced by loose relationships between the source and target domains. In contrast to conventional TL methods, their DDTL algorithm gains by combining distant features obtained from distant domains.

Besides, Połap et al. [89] suggested an agent architecture for IoMT based on the usage of ML systems relying on soft set theory, with the policy of sharing chosen data or trained classifier models and the protection of user data in the blockchain. The architecture was built on a *Multi-Agent System* (MAS) that separated security and data processing for medical reasons, as well as the ability to assign particular duties to agent units. Because of the number of threads, the agent concept is paired with *Federated Learning* (FL), allowing for concurrent training of classifiers and aggregating their weights to form a single classifier architecture. As a result of the division of jobs into agents capable of completing distinct activities, MAS may be highly effective in a real-world application.

Plus, Khan et al. [90] suggested a multi-modal DL data fusion system for skin lesion segmentation and classification by collecting two-segmented pictures from two separate CNN models in the first phase, which were afterward unified using *Joint Probability Distribution* (JPD) and Marginal Distribution Function (MDF). These two CNN designs were created from scratch and had 20 and 17 layers to pinpoint the lesion locations. In addition, a 30-layered CNN architecture was developed to learn features from the HAM10000, ISIC2018, and ISIC2019 datasets. This design has eight convolutional layers, three FC layers, and more. *Summation Discriminant Correlation Analysis* (SDCA) was used to combine a set of features from different FC layers, and the RF approach was used to choose the best discriminating features to improve the feature space. The findings show that the suggested fusion framework outperforms numerous current approaches with a larger margin of error.

In addition, Mahawaga Arachchige et al. [91] suggested a *Local Differentially Private* (LDP) approach for training a DNN named LATENT, which is both private and accurate. In their study, the privacy difficulties of DL were investigated, and a distributed privacy-preserving method based on *Differential Privacy* (DP) was devised to manage and restrict privacy breaches. The spread of the CNN structure across data owners and servers also improves data processing flexibility in the big data setting. This distribution also makes it easier for LATENT to react to breakthroughs, such as combining SDN and NFV in edge-cloud interaction. LATENT generated a huge feature space during the randomization phase, which resulted in greater accuracy for the CIFAR-10 dataset than the baseline CNN model without any privacy. The findings revealed that the novel model obtained 95- 96% testing accuracy for the MNIST dataset and 90% −91% testing accuracy for the CIFAR-10 dataset, with a high degree of privacy.

Finally, Mansour and Althobaiti [92] introduced an FDL-COVID approach for detecting and classifying COVID-19 on IoT-enabled *Mobile Edge Computing* (MEC) platforms. The suggested FDL-COVID approach used an IoT-based data collection procedure to acquire patients' CXR images. Furthermore, the SqueezeNet method detected and classified COVID-19 using CXR pictures. The IoT devices uploaded the encrypted variables into the cloud server, which then conducts FL on significant variables employing the SqueezeNet model to generate a global cloud model. Finally, a GSO algorithm-based hyperparameter optimizer is used to optimize the selection of hyperparameters in the SqueezeNet model, significantly improving COVID-19 identification results.

The IoT offers personalized health services, remote monitoring, and improved access to medical resources in the healthcare sector. It utilizes technologies such as WBANs, WSNs, and RFID to transfer data for analysis in the cloud. Several studies have explored the application of IoT in healthcare. For example, a COVID-19 classification framework based on lung CT scans was developed using DDTL, which combines semantic segmentation and DFF. Another study proposed an agent architecture for IoT in IoMT, incorporating ML systems, soft set theory, and blockchain for data sharing and protection. Additionally, a multimodal deep learning data fusion system was proposed for skin lesion segmentation and classification, achieving better performance than existing methods. Privacy-preserving techniques were also explored, such as an LDP approach for training a DNN and an IoT-enabled MEC platform for COVID-19 detection and classification. These advancements highlight the potential of IoT in revolutionizing healthcare systems and improving patient outcomes. Table 6 discusses the IoT platforms used in medical data processing and their properties.

5.3. Edge computing

Edge is a term for an open platform offering the closest service with the principle functions of a network, processing, storage, and apps on the network's edge, closest to the sources of people, devices, or data [121,122]. In a relevant work, Warnat-Herresthal et al. [93] proposed *Swarm Learning* (SL), a decentralized ML system that combines edge, blockchain-based *Peer-to-Peer* (P2P) networking and coordination while retaining anonymity without the necessity of a central coordinator, hence extending beyond FL. Their method can promote introducing medical data from any data owner worldwide without violating privacy laws. Also, four utilization cases of heterogeneous diseases were assessed in their study to demonstrate the feasibility of using SL in the development of disease classifiers using distributed data. Finally, SL is designed to offer confidentiality-preserving ML and may inherit future breakthroughs in differential privacy techniques, functional encryption, or encoded TL.

Besides, Kong et al. [94] developed an edge-based mask system to identify mask-wearing using DL, integrating VR, face recognition, and mask identification, capable of preventing COVID-19 infection while providing real-time public health precaution notifications. Through Intel NCS, an edge computing strategy was used in the video analysis process to improve the efficacy of detection and recognition at the edge devices. Moreover, many trials were designed to validate the ECMask's enhanced performance. The results demonstrated that VR can increase detection reliability based on the actual bus drive monitoring information. The edge computing-based method outperforms the entire video analysis regarding inference time efficiency.

In addition, Yang et al. [95] employed AI image recognition to retrieve a Digestive endoscopic photo and then processed the image using a 5 G DL edge algorithm to determine the patient's illness type and treatment strategy. The picture of the patients was obtained using a fluorescent probe and merged into the AI image recognition result for blood vessel identification. The illness was then matched based on the picture target recognition findings by performing image segmentation and AI image recognition feature extraction. Regarding feature identification accuracy, this article's 5 G DL edge method outperformed the basic Yolo approach by 68 percent while being identical in speed. Compared to the RCNN algorithm, the accuracy and speed were boosted by 21% and 85%, respectively.

Finally, Rahman et al. [96] primarily focused on the feasibility of *Inkjet-Printed* (IJP) sensors for biomedical applications, which included developing layout guidelines, wireless data transfer, on-device data processing, user interaction assessment, and so on for the connected community, and displayed a multi-modal framework for on-device data processing and inference, as well as analyzing the impact on system performance. The findings suggested that daily wearables and other sensors might be used to capture *Events of Interest* (EoI), such as biomarkers for illnesses, and the potential of on-device processing and ML at edge devices without significantly affecting device performance.

Edge computing provides network functions, processing, storage, and applications at the network's edge, close to data sources, devices, or people. SL is a decentralized ML system that combines edge computing, blockchain-based P2P networking, and coordination. SL allows the introduction of medical data from various owners globally while ensuring privacy and anonymity. An edge-based mask system was developed to identify mask-wearing using DL, VR, face recognition, and mask identification. This system prevents COVID-19 infections and provides real-time public health notifications. AI image recognition and 5 G DL edge algorithms were employed for digestive endoscopic photo analysis, achieving higher accuracy and speed compared to baseline approaches. IJP sensors were explored for biomedical applications, including on-device data processing, wireless data transfer, and user interaction assessment. On-device processing and ML at the edge were shown to have potential without significantly affecting performance. These advancements showcase the use of edge platforms in medical data processing for improved efficiency and real-time analysis. Also, Table 7 discusses the edge platforms used in medical data processing and their properties.

5.4. Fog computing

The fog platform is a modified subset of the cloud architecture from the center to the network's edge. It is a highly scalable platform that aims to connect end devices to conventional cloud servers by integrating computations, storage, and networking [123]. Various studies have investigated novel features of fog computing in medical analysis uses by proposing diverse frameworks. For example, because cardiovascular disease is one of the main causes of high mortality rates in numerous countries, Khan et al. [97] suggested a smart fog-based heart disease model architecture equipped with a supervised ML system—a

Table 6
The methods, properties, and features of IoT platforms in medical data processing.

Researchers	Idea	Advantages	Challenges	Security?	Dataset	Using TL?	Method	Usage?
Niu et al. [88]	Proposing a TL system for medical image classification.	-Low delay -Low energy consumption	-High complexity	No	-A small set of labeled COVID-19 lung CT as the target data.	Yes	FL	COVID-19 diagnosis based on lung CT
Połap et al. [89]	Proposing an architecture of IoMT that ensures the security of private data.	-High accuracy -High reliability -High flexibility	-High complexity	Yes	Skin Cancer MNIST: HAM10000	Yes	FL	Organizing medical tasks
Khan et al. [90]	Proposing a multi-modal fusion system.	-High accuracy	-High delay	No	The ISBI2016, the ISIC2017, and the ISBI2018	No	CNN	Skin lesion localization and classification
Mahawaga Arachchige et al. [91]	Presenting an algorithm for the redesigning training process.	-High accuracy	-Low scalability -High Complexity	No	CIFAR-10, MNIST	No	CNN	Big data analysis ~~Limiting privacy leaks~~
Mansour and Althobaiti [92]	Presenting an FDL-COVID detection model.	-High accessibility -High accuracy	-Only available in online mode	No	Benchmark CXR Dataset	No	FL	Detect and classify COVID-19

Table 7
The methods, properties, and features of edge platforms in the medical data processing.

Researchers	Idea	Advantages	Challenges	Security?	Dataset	Using TL?	Method	Usage?
Warnat-Herresthal et al. [93]	Introducing a method for data integration without violating privacy laws.	-High data privacy and security, -Low data traffic and duplication.	-Limited dataset, -Lower performance.	Yes	PBMC transcriptome dataset, Whole-blood-derived transcriptome datasets, and X-ray dataset	Yes	DNN	Detection of heterogeneous illnesses
Kong et al. [94]	Suggesting an edge-based mask identification architecture.	-High accuracy -Low energy consumption -Low cost.	-Limited dataset	Yes	Bus Drive Monitoring Dataset	No	Auxiliary model training	COVID-19 prevention
Yang et al. [95]	Proposing a 5 G DL edge algorithm.	-High accuracy -Lower Delay	-Low data coverage	No	MSTAR	No	RCNN +yolov3	Disease recognition related to digestive endoscopy
Rahman et al. [96]	Implementing pre-trained ML in the smartphone app for computing disease-related EoI.	-High scalability	-High energy consumption	Yes	9 participants conducted 480 data collection sessions in the "living lab" environment	No	RF +MLP	Early monitoring of a disease outbreak

supervised ML technique known as SVM (SVM is a set of supervised learning approaches utilized for classification, and regression through the training data set [124]) was studied to predict heart disease output to obtain maximum accuracy. Data was gathered via IoMT-enabled devices. The model was separated into two phases: training and validation, following the evaluation of the training forecast layer's accuracy using various statistical techniques such as accuracy, missing ratio, sensitivity, and so on. If the necessary training learning conditions were not fulfilled, the prediction layer was retrained, and its performance was assessed. A successful training model was stored in the cloud after meeting the requisite threshold learning criterion or the appropriate number of cycles. It was shown that the suggested system generated 93.33% accuracy.

In another study, Manocha et al. [98] offered a framework for assessing an individual's physical postures in real-time to forecast health issues using superior fog computing and video analytics. The goal of merging fog characteristics with video analytics was to improve hardware competency by lowering the cost of data transfer to faraway servers. The primary goal of the proposed research's fog computing was to deliver higher computational capabilities by minimizing the latency and computational cost of distant IoT nodes. The framework's structure was divided into 4 stages: 1) user subsystem: data gathering and pre-processing, 2) fog analytics: health condition prediction, 3) cloud subsystem: determination score recording, and 4) two-phased decision-making mechanism. All stages operated independently, providing an excellent operating environment for the next phase. In addition, the suggested framework's execution performance in determining the answer for each frame segment has to be evaluated. The suggested system was shown to be very efficient in live monitoring by merging many cutting-edge technologies such as Cloud-of-Things, Fog-of-Things, and IoT.

Besides, a hybrid fuzzy-based *Reinforcement Learning* (RL) method using NN evolutions techniques was suggested by Shukla et al. [99]. The suggested technique was employed for allocating and selecting IoT data packets for the healthcare industry in a fog environment using fog nodes. The healthcare IoT data were categorized using the *Fuzzy Inference System* (FIS) and the linear *Support Vector Machine* (SVM). The following metrics were used to analyze the high latency problem: network latency, communication latency, compute latency, network utilization, and RAM consumption. The suggested technique considerably decreased network utilization, RAM consumption, computational latency, communication latency, and network latency for healthcare IoTs. The findings showed improved execution of the suggested strategy for FC-based latency reduction. This methodology was determined to be ideal, demonstrating its usefulness in healthcare IoTs.

Plus, Horng et al. [100] created an anomaly detection approach utilizing DL with precise data to allow the NN to be trained, in addition to pre-processing the original file and effectively keeping just the portion of the brain region that has to be studied, normalizing the brain image to fulfill the parameters of model training. Furthermore, they employed *Variational AutoEncoder Wasserstein Generative Adversarial Network with Gradient Penalty* (VAE WGAN-GP) to create 3D medical pictures to address the issue of insufficient training data. The authors recommended adopting the generation model to overcome the issue of too little data. The model produced accurate brain images that were equivalent to the raw data, and the probability density of the visual data set suggests that the model had a typical amount of training. Automatically locating outliers in images and acquiring the input data characteristic were done using an AutoEncoder. With the model's input and output similarity of more than 50%, 76 percent of brain bleeding and non-bleeding accuracy was thus attained.

In addition, Mohamed Akram et al. [101] presented a system for COVID-19 detection by attempting to minimize the spread of the pandemic via early identification of the infected people. Also, the suggested approach permitted the detection of COVID-19 anywhere and anytime. The system was simple to use and easily accessible. Furthermore, they concentrated on the QoS of the cloud by establishing an interstitial layer between both the user and the cloud to decrease the latency and enable real-time response. For improved categorization and identification results, the combination of *Discrete Wavelet Transform and Principal Component Analysis* (DWT-PCA) was applied to decrease the dimension and extract the best features. Plus, the method reduced the complexity by decreasing trainable parameters and time. The assessment of this CNN model in the classification demonstrated effective performance in categorizing Covid-19, pneumonia, and healthy cases with a high accuracy rate.

Finally, Singh et al. [102] presented a fog-centric intelligent medical support service for controlling and monitoring the Swine Flu virus epidemic, which employs the concept of fog computing for delay-sensitive programs and a hybrid classifier to identify swine flu patients early on by sending alerts to health authorities and patients' caregivers. In the experimental context, they focused on obtaining low latency and improved energy efficiency compared to the current technologies, allowing the suggested scheme to provide real-time alerts with little delay. Compared with the previous cloud-only model, the results reveal the advantages of merging clouds and fog computing services by offering optimized network bandwidth stability, greater performance, and a faster response time despite generating real-time notifications.

The fog platform is a modified subset of cloud architecture that brings computations, storage, and networking closer to the edge devices.

It enables connecting end devices to cloud servers and has been explored for medical analysis purposes. A smart fog-based heart disease model architecture was proposed using supervised ML techniques to predict heart disease accurately. Real-time assessment of physical postures was achieved through the integration of fog computing and video analytics, enhancing computational capabilities and reducing latency. A hybrid fuzzy-based reinforcement learning method was suggested for allocating and selecting IoT data packets in healthcare, improving latency and resource consumption. An anomaly detection approach using DL was developed to detect brain anomalies accurately. A system for COVID-19 detection was introduced, leveraging discrete wavelet transform and principal component analysis for feature extraction and achieving effective classification performance. A fog-centric intelligent medical support service was presented for monitoring and controlling the Swine Flu epidemic, combining fog computing and cloud services to deliver real-time alerts with improved performance. These studies demonstrate the potential of fog computing in medical applications, offering enhanced efficiency and real-time capabilities. Table 8 discusses the fog platforms used in medical data processing and their properties.

5.5. *Hybrid systems*

The term "hybrid approaches" might apply to simultaneous acquisitions in platforms using two different methodologies [125]. In relevant research, Fan et al. [103] innovated the use of social networking health discussion data for *Adverse Drug Effect* (ADE) extraction from websites such as WebMD and Drugs.com, while previous research has used data from Twitter, EHR, and medical case reports. The suggested model produced fresh state-of-the-art F1 outcomes that may serve as the foundation for future improvements. By comparing ADE detection findings with the proposed model, They achieved an AUC of 0.94, demonstrating the viability of *Bidirectional Encoder Representations from Transformers* (BERT) word embeddings over other forms of non-pretrained word embeddings and pretrained embeddings.

In another study, Arabi and Zaidi [104] introduced a method to anticipate patient-specific *Attenuation Correction Factors* (ACFs) from PET emission data utilizing DL methods. In this instance, the data from the PET emission sinogram was used to train a deep CNN to forecast the associated attenuation map or, more precisely, the ACF sinograms. The deep CNN was trained and assessed using ACF sinograms produced from reference CT images. The reference CT-based attenuation correction was compared to the predicted ACF sinograms utilized for attenuation correction within PET image reconstruction. The DL-EM method outperformed the segmentation-based strategy typical of clinic algorithms in quantitative PET analysis. The DL-EM technique resulted in an absolute SUV bias of less than 8% in all brain areas, while the SEG method resulted in an absolute SUV bias of up to 14%.

Besides, Yuan et al. [105] suggested a Hybrid Network (Hy-Net) for blood vessel segmentation that incorporated FCN and U-net through a voting system on PA vascular images. They mostly discussed four techniques: threshold segmentation, region growth, Maximum entropy, K-means clustering, and three DL methods such as FCN, U-net, and Hy-Net. The four metrics, *Dice Coefficient* (DC), *Intersection over Union* (IoU), Sensitivity, and Accuracy, were used for each test trial to measure the performance of tests on different segmentation approaches. The maximum values of FCN in terms of DC, IoU, sensitivity, and accuracy were 84.07%, 72.52%, 87.43%, and 99.71%.

Plus, Al-Saffar and Yildirim [106] proposed a variety of techniques to enhance the results and reduce the challenges associated with the process of medical image analysis, including a brain tumor segmentation method based on *Local Difference in Intensity-Means* (LDI-Means), a feature selection method based on *Mutual Information* (MI), a dimensionality reduction method based on *Singular Value Decomposition* (SVD), and a brain tumor classification method based on both SVM and *Multi-Layer Perceptron* (MLP). They also introduced an innovative approach termed *Multiple Eigenvalues Selection* (MES) to select the most significant features as classifier inputs. It was used as a completely automated brain tumor identification, segmentation, and grading system. The most significant characteristics are found, which lead to good tumor grade detection and time savings. According to experimental findings, the suggested strategy performed well in terms of accuracy, recall, specificity, precision, and error rate with percentages of 91.02%, 86.52%, 94.26%, 87.07%, and 0.0897%, respectively.

In addition, Momenzadeh et al. [107] suggested a hybrid platform

Table 8
The methods, properties, and features of fog platforms in the medical data processing.

Researchers	Idea	Advantages	Challenges	Security?	Dataset	Using TL?	Method	Usage?
Khan et al. [97]	Proposing an intelligent-based heart disease prediction system.	-High accuracy -Lower miss rates	-High delay	No	UCI repository section of Cleveland Heart Disease dataset	No	SVM	Heart diseases diagnosis
Manocha et al. [98]	Presenting an analytic-assisted physical stance-based irregularity recognition.	-Low delay	-There are still some false results	No	NTU RGB + D dataset	No	3D CNN-LSTM	Monitoring anomalous physical activities
Shukla et al. [99]	Proposing a hybrid fuzzy-based RL algorithm in an FC environment.	-High robustness -Low latency	-Low reliability	No	Obtained from the online UCI ML repository	No	RL +NN +SVM	Healthcare IoT Devices analysis
Horng et al. [100]	Proposing a 3D deep convolution AutoEncoder model.	-Ultra-low latency -High accuracy	-Poor model performance for few training data	Yes	Digital Imaging and Communications in Medicine (DICOM)	No	GAN +AutoEncoder	Prediction the possibility of bleeding after treating brain ischemia
Mohamed Akram et al. [101]	Proposing a DL framework for COVID-19 detection.	-Lower delay -Better privacy	-Less complexity	Yes	Kaggle repository	No	CNN	Covid-19 detection
Singh et al. [102]	Monitoring the health of citizens concerning Swine Flu.	-High accuracy -Power saving -Low latency	-No deep analysis of the model due to lack of time.	Yes	Data from various sensors like location, health, climate, and prescription sensors	No	Ensemble classifier	Swine Flu detection

for estimating the survival rate of patients with prostate cancer by using the *Factor Analysis of Mixed Data* (FAMD) algorithm, along with undersampling techniques for the SEER dataset as a pre-processing stage ahead of the leading frameworks, namely XGBoost, RF, SVM, and *Logistic Regression* (LR), using a cross-validation approach for parameter modification to forecast both binaries labeled and multi-class labels, which has been rarely studied in previous relevant papers. Compared with similar studies, this technique successfully distinguished the patients based on their mortality status and whether the reason for death was prostate cancer. This technique can be beneficial for making clinical decisions or assessing whether medical doctors need to modify their treatment plans.

Finally, Seba and Benifa [108] established a useful classification algorithm for the accurate prediction of *Chronic Kidney Disease* (CKD) stages regarding the patient health profile as well as the laboratory test results by presenting a *Hybrid Ensemble Model* (HEM), which assists in minimizing the bias and deviation. HEM model efficiency was examined using the performance measures such as *Cross-Validation Score* (CVS), accuracy, specificity, recall, F1 measure, *Mean Squared Error* (MSE), bias, and deviation. It is evaluated with state-of-the-art classification schemes.

The term "hybrid approaches" refers to simultaneous acquisitions in platforms using two different methodologies. In one study, social networking health discussion data was utilized for extracting ADEsusing a model based on BERT word embeddings. The proposed model achieved state-of-the-art results, demonstrating the effectiveness of BERT embeddings. Another study introduced a deep learning method to predict patient-specific ACFs from PET emission data, outperforming clinic algorithms in quantitative PET analysis. A hybrid network incorporating FCN and U-net was suggested for blood vessel segmentation, achieving high-performance in terms of Dice Coefficient, Intersection over Union, sensitivity, and accuracy. Various techniques were proposed to enhance medical image analysis, including brain tumor segmentation, feature selection, dimensionality reduction, and brain tumor classification, resulting in accurate tumor identification and grading. A hybrid platform utilizing the FAMD algorithm was proposed for estimating the survival rate of patients with prostate cancer, enabling better patient stratification. Lastly, a HEM was developed to accurately predict CKD stages, achieving high accuracy and performance compared to other classification schemes. These studies highlight the effectiveness of hybrid approaches in various medical analysis tasks, demonstrating improved performance and accuracy. Table 9 discusses the hybrid platforms used in medical data processing and their properties.

6. Results and comparisons

In the previous section, we systematically analyzed 27 papers selected based on the specific criteria which are provided in Fig 2. Here in this part, we will discuss the article's main concept by summarizing the data analysis in the healthcare domain. The following subsections discuss the categorized platforms of distributed computing, DL and ML methods in medical data processing, security and privacy, datasets, big medical data processing, and an analysis of the results.

6.1. Platforms in the medical data processing

The present healthcare services idea aims to innovate in the medical business by utilizing fog, IoT, big data, and ML technologies. This section discusses several flexible applications in healthcare data processing by focusing on the practical function, their advantages, and their drawbacks, which significantly affect the process and the outcome. In the previous section, we investigated various applications of distributed computing platforms in healthcare data management based on the most recent research. This section briefly reviews and analyzes the platforms regarding their definition, practical usage, advantages, drawbacks, identified disparities, and applications.

- **Cloud computing platform**

Widely considered the future IT revolution, cloud computing has recently emerged as among the most researched topics among IT experts. Hence, in the field of medicine, the cloud has become increasingly significant as a trigger for providing storage and computational capacity for massive quantities of data. The primary characteristics of the cloud in medical data processing include on-demand self-service, wide-ranging access to the network, dynamic resources, quick flexibility, and quantified service. In the review studies in Section 5, the main purpose of the cloud application in medical data management systems was to assist HCP in to fast recognition of disorders which can enhance the accurate and effective treatment plans and following up of the patients.

Furthermore, cloud computing in EHR enables patients to access, record, and transmit their private health data. Several researchers have proposed the cloud as a cutting-edge and significant commercial model

Table 9
The methods, properties, and features of hybrid platforms in medical data processing.

Researchers	Idea	Advantages	Challenges	Security?	Dataset	Using TL?	Method	Usage?
Fan et al. [103]	Investigating the use of the developments in DL as accurate models.	-Large drug data source -Strong robustness	-High complexity	No	.Two primary datasets, WebMD and Drugs.com	Yes	SVM	Drug adverse events discovery
Arabi and Zaidi [104]	Proposing a framework to estimate ACF from TOF PET emission data.	-Low delay	-Remarkable overfitting -High complexity	No	CTAC	No	Deep CNN	Brain PET analysis
Yuan et al. [105]	Proposing a hybrid system consisting of both applied on PA vessel images.	-High accuracy -High robustness	-Not trained for capillary segmentation	No	A Swiss Webster mouse using an OR-PAM system	No	FCN	PA vessel images
Al-Saffar and Yildirim [106]	Proposing MES methods.	-Improving the generalization ability of the classifiers	-High complexity	No	TCIA	No	SVM +MLP	Brain tumor in magnetic MRI
Momenzadeh et al. [107]	Suggesting a hybrid method to predict the mortality of prostate cancer.	-High accuracy -Better recall	-Applied only for low amounts of variables - High complexity	No	SEER	No	RF +SVM +LR	Prostate cancer
Seba and Benifa [108]	Proposing a HEM model for estimation of CKD stages.	-High accuracy -Less bias	-High complexity	No	Benchmark	No	RF +Ensemble classifier	Prediction of CKD stages

for the exchange of biological data. Institutions in the healthcare sector may use cloud computing to support efficient big data management and dissemination processes for the industry's well-organized information systems. On the other hand, the dynamic capabilities of the cloud, together with the assistance from good use of its analytical and data interpretation skills and organizational resources like data governance, may enhance healthcare performance. This suggests that dynamic talents must be combined with other company resources to provide a sustained competitive advantage.

Undoubtedly, cloud computing is a highly practical method for the healthcare issue. Still, it must concentrate on privacy protection, data security, data control, trust, and lawful access to patients' sensitive data. Although cloud computing can collect and store large amounts of medical data, the key challenges are network disruption, security, and the privacy of patient records that could be misused by users, hackers, spyware, and other third parties. Future studies should take into account other issues, such as fierce competition, patient satisfaction, confidentiality, data volume, environmental concerns, investment value, and dependability.

- **IoT platform**

Due to high data creation velocity, IoT devices in the medical sector are also more stressed in research articles. Besides, when associated with cloud computing, the accessibility and flexibility of equipment are boosted. In particular, IoT-based healthcare systems can be used to identify patients' physical and chemical changes through various sensors. These have also contributed to establishing medical services for patient management in actual environments by conveying information to hospitals and healthcare-related medical organizations. In particular, technology for constantly monitoring a patient's well-being and wireless communication technology has been created.

IoT is transforming the healthcare sector by enhancing proficiency, decreasing expenditures, and preserving stability. It aggregates various intelligent services and equipment that affect daily functioning via e-learning, remote access, and assisted surveillance systems. IoT is a vital aspect of medical research and for increasing the effectiveness and quality of healthcare delivery. Because of this, the idea of healthcare has changed from being institution-centric to customized. We reviewed some applications of IoT in the healthcare domain in Section 5. Due to the COVID-19 pandemic, one of the most repeated usages of IoT in the most recent research was the fast and accurate detection of various diseases, including COVID-19, skin lesions, skin pigmentations, etc.

Although, for a more comprehensive insight into the healthcare domain, the DL applications for IoT can be categorized into four categories: applications for medical detection and classifying, personal and home-based health services, applications for disease prediction, and applications for human behavior assessment. Several technical guidelines for healthcare systems are provided in the IoT, but the key emphasis should be on assessing the appropriate technological development based on specific limits and digital devices. Besides, the generation of meaningful data from the IoT for bioengineering is a substantial research issue in this domain.

- **Edge computing platform**

Edge improves both the quality of care for patients and the effectiveness of medical staff by operating like a decentralized distributed system. Medical staff is not required to send patient health data to a distant data center for analysis and results waiting. They may build an edge data center to analyze, compute, and store patient health data acquired by edge devices locally, bringing significant advances to the medical field. Edge medical equipment gathers data and also offers an access point to a network connection. The edge computing paradigm distributes the management of a network's services away from local nodes to the opposite extreme: the sensor itself instead of servers or nodes. Edge has indeed been described as dew computing. In an edge computing framework, devices may conduct specialized calculations and interact with each other. They may also communicate data to a node for specified aggregating and responses, which can then be delivered to the cloud. Besides diabetes systems, the edge is currently utilized in plenty of other medical closed-loop systems in which the sensor input is designed to impact the actuator output, such as (1) cardiac pacemakers; (2) cardiac defibrillators; (3) systems interventional closed-loop mechanical ventilation that is still not on the market; (4) the Sedasys closed-loop anesthesia delivery service that was approved by the FDA but removed from the market due to poor sales; and (5) Brain activity which can be altered with closed-loop stimulation. Edge is well adapted for closed-loop systems which employ intelligent sensors to preserve physiologic homeostasis; however, the method is presently being used only to a limited degree due to the FDA's approval of only a few independent closed-loop systems. This method would be appropriate for an *Intensive Care Unit* (ICU) or an emergency medical department, where critically ill patients need quick solutions for changes in their condition. Edge is accomplished by linking sensors in a system to tiny, local control units that handle processing and communication. Edge computing can result in quick *Machine 2 Machine* (M2M) connectivity or machine-to-human interaction. Edge computing enables each web device to contribute to the data processing rather than having most of it done by a central or decentralized local server.

- **Fog computing platform**

To the degree that certain projects need quick data analysis, fog may help new concepts in big data analysis, privacy-sensitive distributed learning, citizen science applications, remote health monitoring, and medical data analysis. A cloud that is closer to the ground is called fog. In contrast to virtually totally up in the cloud, fog computing for medical devices focuses on processing "down to earth" near the patient. Fog computing distributes processing power to a local area network level where data is processed inside a hub, node, router, or gateway and then transferred to the relevant devices. This function can be performed using a smartphone.

Fog often uses open standard technologies, but the edge can employ open or private technology even though there is some overlapping between the two platforms. Under a fog computing paradigm, a device may broadcast vital data to a nearby fog node for quick analysis and reaction to the unit within milliseconds or seconds. The remainder of the data can be transmitted to the cloud for long-term archival and future processing. A device can also transfer data that can wait a few minutes to a larger aggregation fog node that supports multiple IoT devices. Data from the fog or aggregation nodes may be stored and analyzed in the cloud. Wearable and portable diabetics devices provide increased Bluetooth connectivity with a smartphone or tablet, which functions as a transportable fog gateway by conducting basic analytic procedures and transferring monitored data to the cloud. A fog node may send data from wireless portable diabetic devices to the cloud. These tools include insulin pumps, continuous glucose monitors, insulin pens, and continuous glucose meters. Closed-loop artificial pancreas systems are also included.

Between the edge nodes and the cloud layer is an intermediary layer called the fog computing layer. Local computing and storage are provided for local authorities by the fog computing layer, which expands the computation notion geographically. Cloud computing is not distributed via fog computing. To enable a new breed of programs and capabilities with an efficient interface with the cloud layer, it aims to bring a processing and storage architecture that is significantly closer to the final nodes. A better QoS for applications that require low latency is the anticipated benefit. When data is carefully processed at the fog computing layer, latency is reduced. Fog computing's data analysis is more limited; thus, the cloud computing layer should conduct more in-depth analyses and procedures. Naturally, certain activities do not demand real-time calculation or may require significant computational power; they are conducted at the cloud layer. For instance, in the scenario of a smart community, where residents are connected to the provision of local services, limited latency is projected for producing immediate decisions, and as a result computation is done locally rather than on a cloud layer that might be located in another location.

- **Hybrid platforms**

In medical imaging, a broad scope of visual input from other categories is already accessible to scientists globally. Several networks gather and distribute extremely diverse data from multiple modalities, diseases, and body zones. Consequently, hybrid platforms as a paradigm are becoming more popular. The physical integration of complementary imaging techniques, such as CT, PET/CT, and MRI, all of which give "Renato-metabolic" image information based on inherently synchronized morphological and functional data, is referred to as hybrid imaging. Routine hybrid imaging diagnosis relies mostly on data interpretation. However, this data has a lot more information that can be transformed into knowledge.

The acquisition and analysis of simple to elevated radiometric characteristics represent a paradigm shift in illness in vivo characterization. This notion looks to be very promising in cancer research. On both structural and metabolic levels, hybrid imaging may assist in depicting the total heterogeneity of malignancies. As a result, hybrid methods look to be a critical tool for developing precise tumor classification in vivo models. Per the research, advanced PET/CT and PET/MRI systems generate terabytes of data. Furthermore, hybrid platforms mix modalities like cloud, edge, fog, IoV, etc., reflecting varied image sizes and quality levels, resulting in essentially diversified datasets. All of these characteristics combine to form hybrid platform data, a significant aspect of medical big data. Several reports have indicated promising findings for disease characterization using sophisticated ML approaches integrated into Vivo evaluation in light of hybrid imaging. Real-time remote monitoring is now possible because of the rise of the MIoT. By collecting and integrating MIoT data with hybrid methods, predictive analytics accuracy may be significantly increased, potentially leading to automated *Clinical Decision Support Systems* (CDSS). As part of a completely patient-centric, individualized treatment, this leads to healthcare practices that help increase patient comfort while lowering healthcare costs. As a key component of this approach, hybrid imaging data plays a critical role in customized medicine.

6.2. DL & ML methods in the medical data processing

AI is defined as computer systems capable of carrying out tasks that people, such as decision-making, voice recognition, and visual perception, traditionally do. ML is a branch of AI that enables adequate statistical models to be built using computer sciences on data sets that are already available. ML models are multi-layered models with input, output, and one additional layer ("hidden" layers). These models occasionally provide visual representations of the structure of human brain transmission, replete with interconnected nodes and synapses. Within these models, data is fed into the input nodes and processed through each layer until it reaches the output layer. The number of hidden layers determines the depth of the model.

The capacity to train using backpropagation has been important to the precision of these models' performance. DL refers to ML models that use numerous layers of processing units. The output from one layer to the next becomes a more sophisticated and abstract composition. DL models can quickly and efficiently analyze huge amounts of data compared to typical ML models. Many ML models include layers; still, there is no standard definition of how many layers constitute a "deep" model. DNNs are those having two hidden layers, while shallow neural networks have one hidden layer. DL is a kind of ML approach that is based on ANNs. A CNN is a sort of NN capable of processing 2D image input that is often encountered in the field of DL.

Learning approaches such as supervised, unsupervised, and semi-supervised learning may be used to generate ML models. The distinction between the three is determined by how much training data has the labeled intended outcomes for the model. In most cases, supervised learning is used to map an input sample to an output label for classification. It is also used in regression, which aims to develop a mapping from continuous inputs to constant output. We want to identify the proper links between both the input and output in categorization and regression. Indeed, we are searching for a method to create proper output data successfully. If the training set is chaotic or has inaccurate labels, the trained model's performance will degrade significantly. The majority of typical ML models perform best when supervised learning approaches are used. Linear Regression, ANN, Decision Trees, RF, SVM, and Naive Bayes are among the models used. Unsupervised learning aims to discover the internal representation of unlabeled data. Segmentation, density estimation, and representation learning are the most prevalent unsupervised learning challenges. Several methods, such as auto-encoders, have been developed for this task. Exploratory analysis and dimensionality reduction are two frequent use cases utilized in unsupervised learning. Clustering techniques like *Density-Based Spatial Clustering of Applications with Noise* (DBSCAN), k-means, and Gaussian Admixture are typical examples of algorithms employed in unsupervised learning. Building features with desirable attributes may also be accomplished through unsupervised learning.

Also, RL is the process of learning to map conditions to appropriate behaviors to maximize a numerical reward signal. Unlike supervised learning, the learner in RL is not given the desired action and must experiment with alternative actions in different scenarios to determine the optimal actions leading to the highest compensation given the observed states. It is essential to learn action sampling to maximize long-term utility since focusing just on the immediate reward may result in inferior productivity in the long run. The CNN, a DL algorithm intended to handle data with natural spatial invariance, has emerged as a key player in this area. NLP is concerned with analyzing text and voice to derive meaning from words. In this sector, RNNs_DL methods that are adept at processing sequential inputs such as language, voice, and time series data play a significant role. Machine translation, text creation, and picture captioning are examples of notable NLP accomplishments. Sequential DL and language capabilities are used in healthcare to power applications such as EHRs, which are becoming widespread, and the in recent years, a large medical organization's EHR may collect the medical operations of over 10 million patients. A single hospitalization produces around 150,000 bits of data. The potential advantages of this data are substantial. An EHR of this size represents 200,000 years of clinician knowledge and 100 million years of patient outcome data, spanning a wide range of unusual diseases and disorders. As a result, applying DL algorithms to EHR data is a fast-growing field. The determination of model parameters is a convex optimization issue; hence the solution is always globally optimal, which is a key characteristic of SVM. In addition, many current convex optimization methods are easily adaptable to SVM implementation. As a result, SVM has been widely employed in medical research.

6.3. The dataset in the medical data processing

Also, Image information is vital in many steps of the patient care process, including detection, characterization, staging, treatment response evaluation, disease recurrence monitoring, and directing interventional treatments, surgeries, and radiation therapy. The use of multi-modality imaging increases the quantity of picture data that must be interpreted. Because of the increased workload, radiologists and doctors are finding it challenging to maintain workforce productivity while using all existing imaging information to enhance accuracy and patient care. With recent improvements in ML and computing approaches, the possibility and necessity for creating automated methods to help radiologists in image processing and detection have been considered essential medical imaging research and development field.

Additionally, different clinical imaging modalities, such as MRI, X-ray, and CT, make DL an appropriate choice for early and accurate disease detection. Medical imaging has developed from a purely visual tool to a major source of analytical methods for identifying diseases in vivo. This strategy includes hybrid imaging, which appears crucial for creating accurate tumor characterization in vivo models. Generally, from the perspective of hybrid imaging, various researchers have presented significant insights for disease classification using robust ML approaches for integrated into vivo analysis.

Data is the most precious property in the health industry. The vast majority of modern ML approaches are data-driven. The dataset relies almost entirely on DL-based methods. As a result, one of the main motivations in managing a disease epidemic is the dataset's sources. The database industry and academics have been researching data management-oriented issues in ML for almost a decade. This has resulted in a wide range of tools and platforms for scaled and rapid ML established by this community. Besides, analysis of massive datasets employing statistical ML techniques is essential to current data-driven applications in healthcare, research, and other disciplines and efforts that utilize database-inspired techniques to make ML quicker and more user-friendly. The variety of this environment of systems and programs might be daunting for data management academics, data analysts, and software engineers alike. The suppliers of the data generated for the DL application of physiologic signal analysis have been explored by various scholars. The accessible public datasets which are extensively utilized include CHB-MIT, PhysioNet, BCI competition II, MIT-BIH, DEAP, NinaPro, and Bonn university dataset. Also, the private dataset was obtained by authors with their lab, hospital, or institution. The private database was gathered if the info was not accessible as a public entity.

6.4. Security and privacy in the medical data processing

DL's privacy concerns have recently been exposed, and different attacks have been considered. Modeling privacy threats are divided into model extraction attacks and model inversion attacks. In model extraction threats, the adversary attempts to recreate the model's parameters/hyperparameters used to deliver cloud-based ML services, compromising the security and intellectual property of the network operator. The adversary uses accessible records to derive sensitive data in model inversion threats. Furthermore, a high-performing ML model needs a lot of training data, a lot of hardware, and a lot of effort to fine-tune the parameters. Consequently, it has been recognized that the labeled training dataset, system framework, and model parameters are instances of business intellectual property; therefore, they must be protected. Only a few works of watermark-based ML model protection for intellectual property are available at the moment, and it is still challenging to guarantee their efficacy. How to protect intellectual property more effectively and securely for NN models is yet unanswered. Recent research has established numerous privacy-preserving DL techniques to preserve the security of sensitive data. Nevertheless, much research remains to be done before it can be implemented. The most serious flaw with privacy-preserving DL approaches is their high computational cost. The calculation expense of DL is considerable because of its non-linear behavior, which severely limits its availability. Reducing the cost of privacy preservation is a critical challenge for DL techniques that protect privacy.

Also, DL security risks are divided into two categories poisoning attacks and adversarial attacks. DNN is vulnerable to adversarial attacks in the form of perturbations by incorporating them in the original image, which is imperceptible to the human visual system. Such assaults can cause a NN classifier to produce incorrect forecasts with high confidence. In poisoning attacks, the adversary attempts to contaminate the training data by inserting malicious samples or altering data so that the learner trains a faulty classifier, which misclassifies harmful instances or actions generated by the adversary during the testing stage. Protecting users' privacy in healthcare is crucial since it is a user-centric application and includes the acquisition of personal data. Any violation of privacy might lead to inevitable repercussions. Preserving privacy implies that ML model training and interpretation should not expose any new information about the persons from whose data was acquired. In general, ML/DL needs training data kept on a centralized database that may contain the users' details which presents numerous vulnerabilities. To resolve such issues, data anonymization methods are employed. However, the literature has noted that important information may be gleaned about individuals' private information even though the dataset is anonymized.

6.5. Big data analysis in the medical data processing

Big data medical data processing is defined as a collection of methods and instruments used to examine significant volumes of unstructured data. Big data in the medical sector include unstructured data, like images, information, data, and videos. Since of its frequent alternation, unstructured data is difficult to process because it lacks comprehensive structural data styles. Big data may profit from pattern recognition as well as other distinct techniques that depend on computing to provide new insights. DL, ML, and computational advancements in pattern recognition have also been merged with big data. This is connected to comprehending computational aspects discovered in data obtained with predicted investigative discoveries. Big data does not allow for the completion of all properties among identical data. There are two key differences in using big data technologies for visual pattern recognition. Big data refers to enormous volumes of data that cannot be stored on a single device. Second, since big data requires specific tools and techniques, the conventional data notion had to be duplicated because it lacked structure. Several programs, including basic databases, NoSQL, *Data Stream Management Systems* (DSMS), and Memcached, may be used for large data, with Hadoop being the most well-liked and suitable option.

So, Big data processing has been a critical aspect of being creative and competitive for medical corporations. it is one of the major topics of study in the scientific world. Alongside population growth internationally or the development of aging in certain industrialized nations, the public healthcare systems confront a growing proportion of healthcare expenditure and a massive volume of health records. Furthermore, cloud computing is now a concept to handle the vast data inside this big data generation.

6.6. Analysis of the results

This study identifies several innovative applications which have been popular in medical data processing and analysis. A total of 27 articles in 5 categorical applications of medical data processing were studied, including cloud, edge, fog, IoT, and hybrid platforms. The most studied platform was IoT, containing 43.4% of the total searched papers. Fig. 8 shows the distribution of the papers regarding the platforms. IoT, in combination with cloud computing, aids healthcare by analyzing medical data in ultra-low delay, whereas appropriate decisions can be made on time. In the field of HIoT, the special advantages might demonstrate by fog and edge computing concepts. They resemble the model where confidential material produced by body-worn clinical devices and smartphone sensing are prepared, evaluated, and extracted close to where it is obtained, on these devices themselves, rather than sending large amounts of signal data to the cloud. Only aggregated, context-enhanced data/events are transferred to the cloud for additional processing and analytics. The correct balance between Edge-Cloud should enable quick reaction to occurrences, network capacity conservation, latency reduction, security, and privacy protection.

Also, DL methods can be aggregated to propose methodologies and techniques which assist in fulfilling the gaps in the healthcare era as

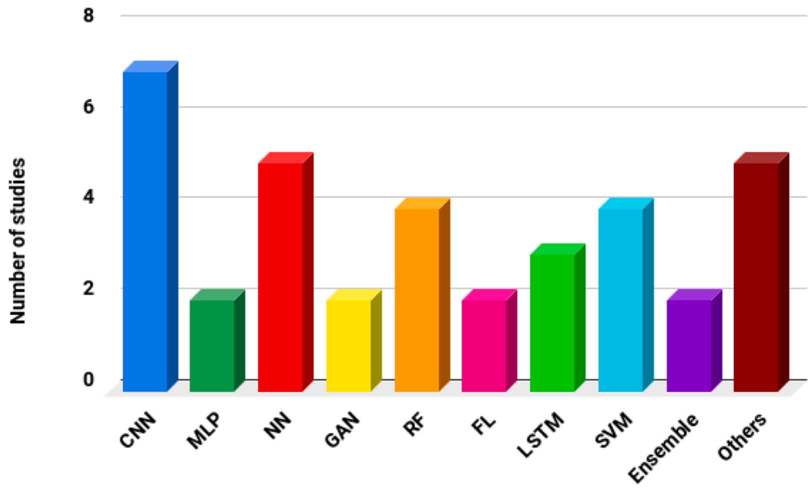

Fig. 8. Utilization of DL platforms and their frequency in the investigations.

disease recognition, remote health monitoring, accurate and robust results, etc. Section 5 presented several DL and ML platforms in the discussed articles, including CNN, GAN, LSTM, RF, SVM, FL, Ensemble methods, etc. The most utilized method was CNN, with a distribution of 19.4% among the analyzed studies, and in the second stage, SVM, with a distribution of 11.1%, was applied in the investigations. The prominent reason for the high utility of CNN and SVM can probably be the result of high accuracy and lower delay in their usage. Moreover, by application of CNN, there were fewer privacy leaks and better robustness and performance of the proposed framework. Fig. 9 shows the utilized DL and ML approaches in the studied articles. Also, Fig. 10 provides the geo-chart of the authors of the reviewed papers.

With the development of the machines' processing capability, several approaches were successfully established based on ML and DL in medical fields as a classification and recognition platform. In general, many diverse applications can be used for healthcare data analysis. The most discussed application, according to Section 5, is quick and accurate diagnosis of patients. It can help the healthcare staff better manage diseases with more efficient treatment plans in earlier stages, decreasing morbidity and mortality rates for economies. Also, the recent COVID-19 pandemic was a huge burden on practically all countries in the healthcare era, resulting in an emphasized outline of early, fast, and accurate detection and recognition of diseases. Meanwhile, DL has been used in various medical applications, including cancer diagnosis, heat disease recognition, localization of skin lesions and pigments, assessment of bleeding probability after brain ischemia, and digestive endoscopy.

Otherwise, various practical applications of the usage of distributed systems were discussed in Section 5, such as medical image processing and analysis, COVID-19 detection, sports medical data, face and pattern recognition, NLP, self-health monitoring, classification and staging of CKD, forecasting seizure episodes, outlining the progress of previous studies, designing an implantable device, drug discovery and possible adverse effects and big medical encoding. Fig. 11 shows an overview of the most popular applications of distributed systems via DL techniques in the healthcare era. The most repeated application in the studies was medical image analysis and COVID-19 detection (24% and 21%, respectively). Since the pandemic of COVID-19 was a great burden for the whole globe and had huge impact on the healthcare of all regions, it also resulted in various challenges in the medical healthcare era [126]. So, as a result of the pandemic, the most studied ML approaches were in the field of early analysis of COVID-19 and better analysis of recorded medical images, especially CT-scan, which had a prominent effect on efficient diagnosis and management of infected patients.

Perhaps one of the most significant topics for future study could be preserving the security and privacy of individuals' identities and processed data. Fig. 12 provides a pie chart of the evaluated parameters in the articles regarding the distribution of the parameters. Table 10 shows the overall parameters evaluated in the investigated articles in this study. The utmost parameter evaluated in the papers is related to accuracy and lower latency. Almost all analyzed studies had high accuracy, and about 80% had low latency time. In the next stage, security was the most applied parameter; in the next stage was high security and privacy setting with a distribution of about 25%. DL is becoming a trending concept due to its remarkable accuracy when practiced with vast data like generated IoT. Therefore, high accuracy was a remarkable parameter for selecting studied papers. Although, when trained upon more sensitive data, such as medical data, DL algorithms tend to lose privacy, which can impact the model's efficiency, so higher accuracy

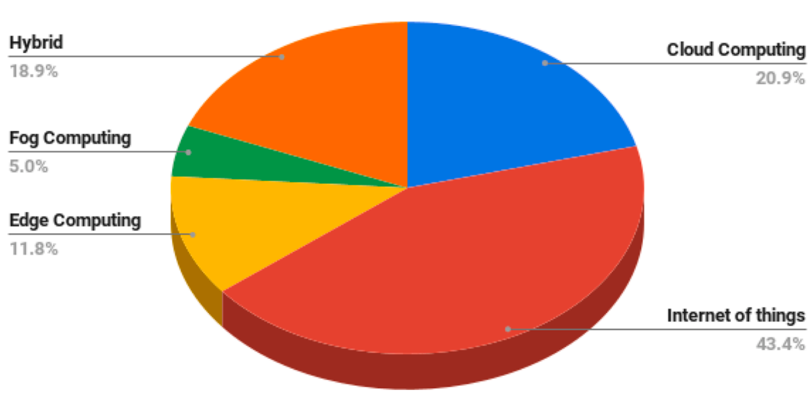

Fig. 9. The distribution of the studied platforms.

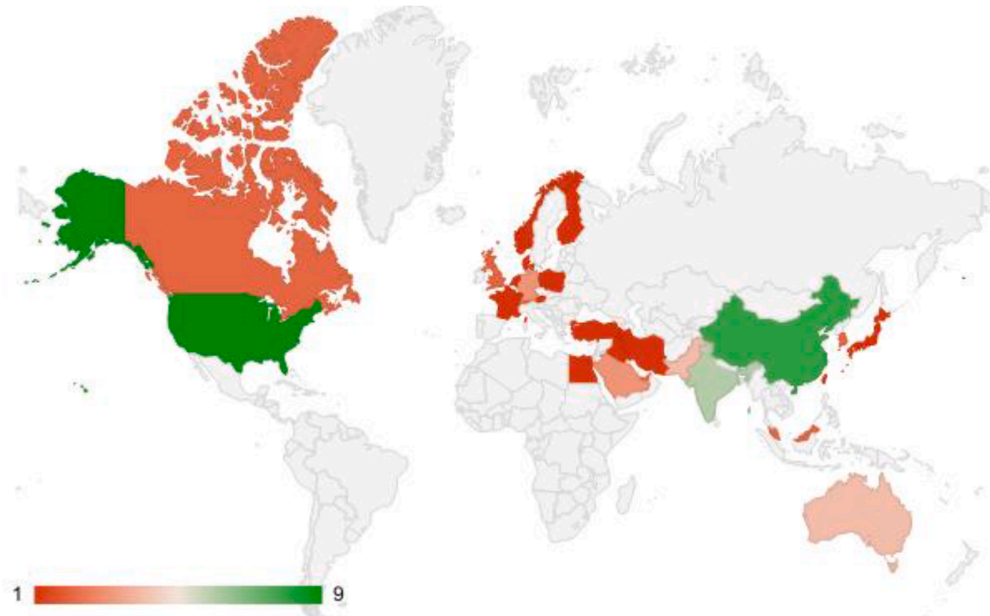

Fig. 10. The geo-chart within the studied countries based on the investigated articles.

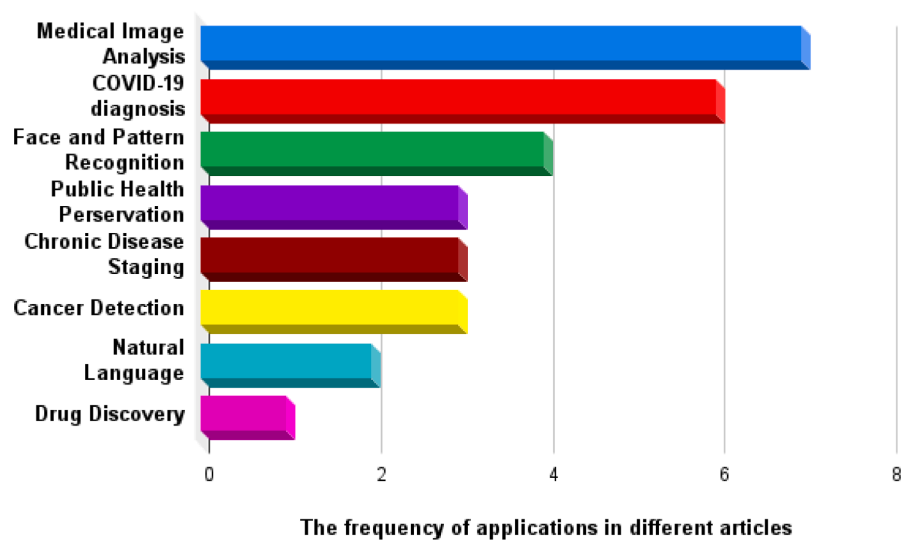

Fig. 11. The applications of various distributed system environments in the context of medical data processing.

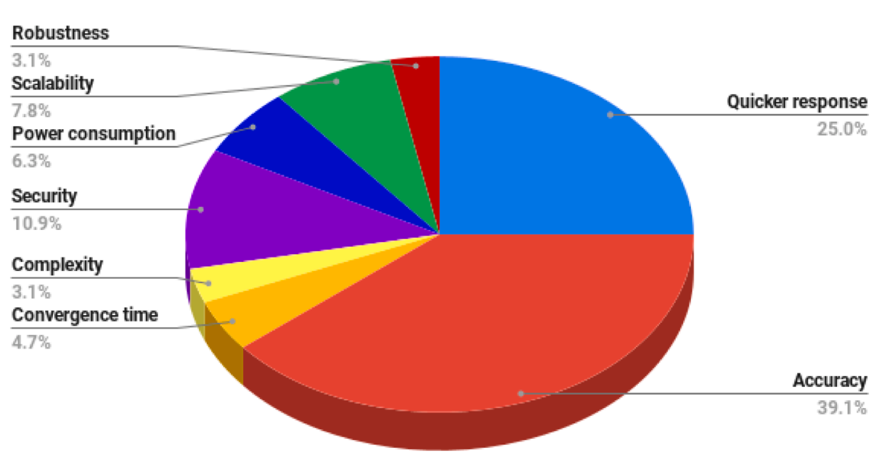

Fig. 12. Evaluated parameters in the articles.

Table 10
Evaluated parameters in the articles.

Type	Authors	Delay/Quicker response	Accuracy	Convergence time	Complexity	Security	Energy consumption	Scalability	Robustness
Cloud	Lee, et al. [82]	✓	✓	•	✓	•	•	•	•
	Egger, et al. [83]	•	✓	•	•	•	✓	•	•
	Stirling, et al. [84]	•	•	•	•	•	•	✓	•
	Aazam, et al. [85]	✓	✓	•	•	•	•	✓	•
	Liu, et al. [86]	✓	✓	•	✓	•	•	✓	✓
	Ma and Pang [87]	•	✓	•	✓	✓	•	•	•
IoT	Niu, et al. [88]	✓	•	•	✓	•	✓	•	•
	Połap, et al. [89]	•	✓	•	✓	✓	•	•	✓
	Khan, et al. [90]	✓	✓	✓	•	•	•	•	•
	Mahawaga Arachchige, et al. [91]	•	✓	•	✓	✓	•	•	•
	Mansour and Althobaiti [92]	•	✓	•	•	•	✓	•	•
Edge	Warnat-Herresthal, et al. [93]	•	✓	✓	•	✓	✓	•	•
	Kong, et al. [94]	•	✓	•	•	✓	•	•	•
	Yang, et al. [95]	•	✓	•	✓	•	✓	•	•
	Rahman, et al. [96]	✓	✓	•	•	✓	•	✓	✓
	Park, et al. [127]	•	✓	•	•	•	✓	•	•
Fog	Khan, et al. [97]	✓	•	•	•		•	•	✓
	Manocha, et al. [98]	✓	✓	•	•	•	•	•	•
	Shukla, et al. [99]	✓	✓	•	•	•	✓	•	✓
	Horng, et al. [100]	✓	✓	•	•	•	•	•	•
	Mohamed Akram, et al. [101]	✓	✓	•	✓	✓	•	•	•
	Singh, et al. [102]	✓	✓	•	•	•	•	•	✓
Hybrid	Fan, et al. [103]	•	✓	•	•	•	•	•	•
	Arabi and Zaidi [104]	•	✓	•	✓	•	•	•	•
	Yuan, et al. [105]	•	✓	•	•	•	•	•	✓
	Al-Saffar and Yildirim [106]	✓	✓	•	•	•	✓	•	•
	Momenzadeh, et al. [107]	✓	✓	•	•	•	✓	•	•
	Seba and Benifa [108]	✓	✓	•	•	•	✓	•	•

was of great importance in the selected articles for inclusion in this study.

7. Open issues

Medical data processing and distribution have developed as an appropriate strategy for a variety of emerging healthcare applications. However, several challenges remain throughout the setting of remotely monitoring health and behavior, such as data collecting, modeling, and processing. Furthermore, comprehending the regulatory environment is the only way to proceed with ongoing research and development. There has been an increase in academic work published on topics ranging from philosophy, concepts, and systems to deployments of large medical data platforms for ubiquitous healthcare services as remote patient monitoring and pervasive healthcare ideas have advanced. This section provides major challenges and concepts which have been discussed in the most recent research in this field.

7.1. The challenges and considerations in the implementation of AI applications in critical care

The use of AI applications in critical care presents a set of challenges that are similar to those faced in other healthcare domains. These challenges encompass various aspects, including technology, deployment concerns, and widespread acceptance. It is crucial to address these issues in-depth to ensure the safe and effective implementation of ML models in healthcare settings. One important consideration is the reliability and accuracy of AI models in critical care scenarios. Using ML algorithms for medical data processing introduces potential errors or biases in the predictions or recommendations generated. The lack of interpretability and explainability of some ML models poses challenges in understanding the rationale behind their decisions, which is critical in the context of patient care. Additionally, the ethical implications of using AI in critical care should be carefully examined. The responsible and ethical deployment of AI technologies requires addressing issues such as patient privacy, data security, and informed consent. Ensuring transparency and accountability in the decision-making process of AI systems is vital to maintain the trust of healthcare professionals, patients, and other stakeholders.

Another aspect to consider is the potential unintended consequences of hasty implementation. Rushing the integration of ML models into healthcare systems without thorough evaluation and validation may lead to adverse outcomes. It is essential to conduct rigorous testing and validation processes to ensure AI models' safety, reliability, and generalizability in critical care. Furthermore, relying on fog computing for medical monitoring introduces its own challenges. One limitation is that patients cannot submit real-time data for analytics if their smartphone or hub device is broken or not charged. Moreover, older medical devices, such as blood glucose meters, often require manual data transfer through wired connections to hubs or computers, hindering seamless and automated data analysis. Asynchronous telemedicine systems, although not true fog devices, may delay the identification of critical patterns that necessitate immediate response until data uploading is completed. In recent years, wireless connectivity capabilities have superseded these outdated devices, enabling real-time data transmission. However, addressing the limitations and challenges associated with data transfer and connectivity in critical care settings remains crucial to ensure timely and accurate medical data analysis. In conclusion, implementing AI applications in critical care entails various challenges and considerations, including the technology's reliability, ethical implications, potential unintended consequences, and limitations associated with fog computing and data transfer. A thorough examination of these issues is necessary to develop robust and safe AI systems for medical data processing in critical care environments.

7.2. Unregulated development and deployment of ML methods and concerns in clinical adoption

The unregulated development and deployment of ML methods in the context of medical data processing based on distributed computing and the IoT raise several critical concerns that need to be explored in-depth. These issues revolve around patient care, the accountability of healthcare professionals and software licensing, ML methods' adaptability, and patient data's security.

One significant concern is the potential for overdiagnosis and excessive testing resulting from unregulated ML methods. While ML techniques have shown promise in minimizing redundant testing and reducing costs, their inappropriate usage can lead to unnecessary interventions and increased healthcare expenses. It is imperative to evaluate ML methods thoroughly to ensure their effectiveness and safety in clinical adoption. Rigorous validation processes and adherence to high-level health system validation and regulation are essential to protect patients' lives and well-being. The responsibility for accurate diagnosis and management becomes complex in the context of ML-assisted decision-making. The extent to which software tools provide decision assistance raises questions about the distribution of accountability between healthcare professionals and software licensing. Inaccurate diagnosis or suboptimal management could potentially be attributed to either party. Clear guidelines and frameworks need to be established to define the boundaries of responsibility, ensuring that patients receive optimal care and appropriate measures are taken in cases of diagnostic errors or mismanagement.

The architectural design and adaptability of ML methods used in medical data processing are critical considerations. ML algorithms should be designed to evolve and adapt to changing clinical practices, ensuring that they stay aligned with the latest advancements and guidelines. Failure to update and incorporate new knowledge into ML models can disrupt their delivery and impact patient care. Establishing mechanisms for continuous monitoring, maintenance, and updating of ML algorithms is vital to guarantee their effectiveness and relevance in evolving clinical contexts. Another crucial issue is the security of patient data and the potential access of ML algorithms to other sources. The unexpected exposure of patient data to unauthorized sources raises privacy concerns and the risk of data breaches. Additionally, ML algorithms must be robust and resilient against external influences, whether unintentional or purposeful. Rigorous testing should be conducted to assess the sensitivity of ML algorithms to external influences and to ensure their ability to withstand potential attacks or manipulations.

Addressing these open issues requires the introduction of properly validated ML applications into clinical settings. The integration of validated ML methods can provide insights and solutions to the challenges in medical data processing. Additionally, a collaboration between regulatory bodies, healthcare institutions, and ML developers is crucial to establish guidelines and regulations that govern the development, deployment, and usage of ML methods in medical contexts. By delving deeper into these concerns, researchers, practitioners, and policymakers can identify potential risks, develop appropriate safeguards, and ensure the responsible and effective implementation of ML techniques in medical data processing. By comprehensively addressing these open issues, the potential benefits of ML applications in healthcare can be realized while maintaining patient safety, privacy, and the highest standards of care.

7.3. Challenges in training data availability and imbalanced data in DL for diagnostic imaging

One of the key challenges in the adoption of DL techniques in diagnostic imaging, within the context of medical data processing, based on distributed computing and the (IoT is the requirement for large training databases to demonstrate the reliability of DL classifications. However, the availability of appropriate data sources poses a significant barrier to achieving this goal. The reliability and performance of DL algorithms heavily rely on the quality and diversity of the training data. In the case of diagnostic imaging, the generation of massive datasets that accurately represent a wide range of medical conditions is highly complex. Annotating these datasets with ground truth labels requires substantial input from medical specialists, as their expertise is essential for accurate annotation. Multiple expert views are often necessary to address the issue of human error and ensure the quality of annotations.

However, the process of data annotation may not always be feasible due to several factors. Firstly, there may be a scarcity of skilled specialists available to perform the annotations, especially in the case of rare conditions or specialized areas of medicine. Limited access to experts who can provide accurate annotations poses a significant challenge in generating the necessary training data for DL models. Another critical problem is the imbalanced structure of data, which is particularly prevalent in the health industry. Uncommon illnesses or conditions are often underrepresented in the available datasets by their nature of being infrequent. If not appropriately addressed, this class imbalance can severely impact the performance and reliability of DL models. DL algorithms tend to be biased towards the majority class, leading to reduced accuracy and potentially missing crucial diagnoses or insights related to less common conditions.

To overcome these challenges, various strategies can be employed. Firstly, efforts should be made to expand the availability of comprehensive and diverse training datasets by collaborating with medical institutions, research organizations, and healthcare providers. Creating partnerships that enable the collecting and sharing of anonymized medical data can help address the scarcity of training data. Addressing the issue of data annotation requires the development of semi-automated or assisted annotation tools that can leverage the expertise of medical specialists more efficiently. These tools can assist in the annotation process, reducing the burden on specialists and increasing the scalability of dataset generation. Dealing with imbalanced data necessitates employing techniques such as oversampling, undersampling, or generating synthetic data to balance the representation of different classes. These approaches can help mitigate the negative impact of class imbalance on DL model performance and ensure accurate predictions for both common and rare medical conditions.

Furthermore, collaborations between the DL research community and medical experts can facilitate the development of specialized DL architectures and techniques tailored specifically for diagnostic imaging. These approaches can leverage domain knowledge and expert insights to improve the reliability, interpretability, and clinical relevance of DL models in medical applications. The adoption of DL techniques in diagnostic imaging can be enhanced by addressing the challenges related to training data availability and imbalanced data. These efforts will contribute to developing more reliable and accurate DL models, ultimately leading to improved diagnostic accuracy, better patient care, and advancements in medical data processing within the distributed computing and IoT paradigm.

7.4. Overcoming challenges for adoption and collaboration in DL for medical imaging

The potential advantages of DL in medical data processing based on distributed computing and the IoT are immense. However, several challenges and expenses are associated with the early efforts to implement DL in medical imaging. Major players in the industry, including

Google DeepMind, IBM Watson, academic laboratories, top hospitals, and medical equipment suppliers such as Siemens, Philips, Hitachi, and GE Healthcare, have made significant investments and are actively working towards the integration of DL into medical imaging solutions. These efforts indicate the potential of DL to revolutionize disease detection and treatment. However, despite the progress made by these substantial stakeholders and their optimistic projections for the future of DL in medical imaging, concerns and barriers still need to be addressed before widespread adoption can occur. One concern is the fear of replacing human expertise with automated systems. While DL provides clear benefits in terms of disease detection and treatment, there needs to be a thoughtful discussion and consideration of how DL can complement and enhance the capabilities of healthcare professionals rather than replace them entirely. Extensive collaboration is crucial to overcome these challenges and ensure the successful adoption of DL in medical imaging. Cooperation between healthcare providers, medical equipment suppliers, and ML experts is needed to inspire and empower the implementation of DL solutions. Such collaborations will help address the shortage of accessible data for ML researchers, as healthcare data is often fragmented and dispersed across various institutions. Moreover, the vast quantity of healthcare data, expected to increase as the healthcare sector transitions to body sensor network-dependent monitoring, poses a significant challenge. Sophisticated approaches and techniques are required to effectively manage, analyze, and interpret this large volume of data. ML experts and data scientists need to develop advanced algorithms, data processing methods, and scalable infrastructure to handle this growing data complexity.

Additionally, ethical and regulatory considerations play a crucial role in adopting DL in medical imaging. Patient privacy, data security, and regulatory compliance are paramount concerns that must be addressed to ensure the responsible and ethical use of DL techniques. Clear guidelines and regulations need to be established to govern the collection, storage, sharing, and analysis of medical data to safeguard patient confidentiality and maintain public trust. Addressing these challenges requires strong collaboration, interdisciplinary efforts, and shared expertise from healthcare providers, medical equipment suppliers, ML researchers, data scientists, and regulatory bodies. By working together, these stakeholders can collectively overcome barriers, foster innovation, and create a framework for the successful integration of DL techniques in medical data processing based on distributed computing and IoT. The resulting advancements will improve the effectiveness of healthcare, enhance patient outcomes, and revolutionize medical imaging practices.

7.5. Cloud computing, networking, security, and privacy challenges in medical data processing

The integration of cloud computing in EHR offers numerous benefits, such as easy access, data replication, and secure transmission of personal health information. However, there are significant challenges associated with networking breakdown, security, and privacy of patient data, which need to be addressed to ensure the safe and responsible use of the cloud in medical data processing. One of the main concerns is the potential abuse of patient data by unauthorized individuals, including consumers, hackers, and malware. The sensitive nature of health information makes it a valuable target for malicious actors, emphasizing the importance of robust security measures. Data breaches and unauthorized access to patient records can lead to severe consequences, including identity theft, compromised patient confidentiality, and the misuse of personal health information. Therefore, strict security protocols, encryption mechanisms, access controls, and regular security audits are essential to protect patient data and maintain trust in cloud computing solutions.

Furthermore, the reliability, security, and stability of the *Internet of Medical Things* (IoMT) pose significant challenges. The IoMT refers to the network of interconnected medical devices, sensors, and systems that collect and transmit health-related data. As more medical devices become connected, ensuring their reliability and safeguarding against cybersecurity threats becomes crucial. The potential vulnerabilities in IoMT devices can expose patients to risks, including unauthorized access, data manipulation, and disruptions in healthcare delivery. Efforts should be made to establish robust security frameworks, encryption protocols, and monitoring mechanisms to mitigate these risks and maintain the integrity of the IoMT ecosystem. Data privacy and security concerns related to ML systems have gained attention recently. Regulations such as the *Health Insurance Portability and Accountability Act* (HIPAA) play a vital role in safeguarding the accessibility and appropriate use of health data. However, as new data patterns emerge and new data partnerships are formed, regulations must evolve to address emerging challenges. It is essential to balance facilitating the accessibility and sharing of health data for research and innovation purposes while ensuring the privacy and protection of sensitive patient information.

Continuous advancements in security technologies, including encryption algorithms, authentication mechanisms, and intrusion detection systems, are necessary to address these challenges. Collaborative efforts between healthcare organizations, cloud service providers, regulatory bodies, and cybersecurity experts are crucial to establishing industry standards, best practices, and guidelines for the secure implementation of cloud computing in medical data processing. Regular security assessments, audits, and training programs should be conducted to maintain a proactive stance against emerging threats and vulnerabilities. By addressing the networking, security, and privacy challenges associated with cloud computing and the IoMT, the applications of Machine Learning techniques in medical data processing can benefit from the vast amounts of data collected while ensuring the privacy and confidentiality of patient information. This will lead to improved healthcare outcomes, enhanced research capabilities, and greater patient trust in the use of advanced technologies for medical data processing.

8. Conclusion and limitations

The rapid development of information technology has led to advancements in machine learning, deep learning, big data processing, and distributed systems, which have had significant and far-reaching effects on the structure and efficiency of traditional healthcare businesses, as well as the design and maintenance of contemporary medical management information systems. In this study, a total of 27 papers were selected for analysis. Due to inclusion criteria, the selected articles were original research, written in English, and published in high-ranked journals. Conference papers, editorial letters, and book chapters were excluded. We presented an SLR for applications and methods of distributed computing platforms in healthcare data analysis and performed a comprehensive overview of various present applications in 5 categorical environments underlying distributed systems such as cloud, IoT, edge, fog, and hybrid systems. Most of the papers were published in 2021 (46%). IoT was the most discussed environment (43%). Medical image analysis and COVID-19 detection were the most discussed applications, with a total percentage of about 45%. Otherwise, high accuracy, high security and robustness, and low security were the remarkable parameters that were evaluated in this study. The evolution of medical DL systems has improved the uniformity and precision of clinical decision-making while expanding the data collection capabilities of medical knowledge-based systems (Knowledge-based systems use a data repository known as a knowledge base to provide a method for problem-solving [127]). Examples of these systems include EHR, medical imaging technology, medical big data, intelligent medication design, and innovative health management systems. These advancements may also help clinicians and researchers optimize treatment programs and make decisions regarding the best therapy alternatives. As a subset of ML, DL is the most prominent issue with various techniques such as computer vision, NLP, voice recognition, visual object identification, disease prognosis, drug discovery, bioinformatics, biomedicine, etc. Healthcare and scientific health implementations are significant in these industries' growth. As with the machines' processing capability development, several approaches were successfully established based on ML and DL in medical fields as a classification and recognition platform. The massive big data expansion, the IoT, connected devices, and HPC are the major factors why DL is so popular. Based on their unique functions, medical IoT, digital pictures, EHR data, genetic data, and centralized medical datasets are the primary data inputs for DL systems. However, several possible concerns like privacy, QoS optimization, and implementation emphasize the vital element of DL. In conclusion, the use of data mining and ML techniques can offer the medical staff insight beyond the field of profession, which will help them make more reasonable decisions faster. Hence, these methods are not intended to replace the position of academia and medical professionals but rather to provide a suggestion system for more effectively allocating resources.

There are some limitations to this study. First of all, several of the investigated publications did not include comprehensive descriptions of their methodologies or had challenges in data selection, power consumption, or security mechanisms. Plus, most of the studied methods were done quickly due to the urgent need for DL platforms in the recent pandemic. Otherwise, non-English documents were excluded due to inaccessibility. Further studies for more detailed method descriptions, including all published papers in recent years, are recommended to provide better insights into DL techniques in medical data processing. Also, the future of DL techniques in medical data processing holds significant potential for advancements. Researchers should focus on refining and enhancing DL methodologies to overcome previous challenges, particularly in terms of improving the accuracy, robustness, and interpretability of DL models in healthcare applications. Exploring novel applications, such as personalized medicine, disease prediction, and treatment optimization, can greatly enhance patient care and outcomes. Ethical and privacy implications should also be a crucial consideration in DL techniques for medical data processing. Future research efforts should prioritize the development of robust security mechanisms and privacy-preserving techniques to safeguard sensitive patient information while maintaining the effectiveness and efficiency of DL-based healthcare systems.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data are reported in the paper.

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