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Edge Computing in Healthcare Using Machine Learning: A Systematic Literature Review

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Abstract

Healthcare is undergoing a significant transformation, driven by rapid technological advancements. In recent years, it has become evident that artificial intelligence is boosting new opportunities in diagnosis and treatment as well as patient management. Among these components, edge computing is especially noteworthy, as it enables real-time analysis of data and rapid decision-making based on it, directly at the patient's point of care.

This thesis explores the integration of edge computing and machine learning in healthcare. To do this, it considers some of the previous research conducted on the topic to understand the benefits, challenges, and future trends through a systematic review of the literature.

By formulating nine research questions within four categories, we aim to examine the selected studies in terms of frequency and type, challenges and limitations, motivations and major contributions, tools, frameworks, types of data, processing methods, and future opportunities.

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Chapter 1

Introduction

Healthcare as a discipline, will face many challenges. For example, when a pandemic like COVID-19 strikes, it is impossible to hospitalize all infected people. Transporting from home to hospital can also be a challenge. This is where the concept of home health monitoring comes in, which can include monitoring the patient's activities, sleep status, respiratory status, etc. [MRD19]. Nowadays, these parameters can be monitored with the help of wearable and cloud technology. This combination gave rise to several applications enabled by the use of deep learning and computer vision [SSST18][LHB+18][YRC+20]. Training deep models, however, is still challenging and often requires powerful computational resources such as GPUs.

In this regard, Cloud Computing (CC) can provide additional computational power through virtual environments. Transferring data to cloud services introduces issues related to data transmission, privacy, and bandwidth [SAG+21]. Edge Computing (EC) [Sat17] can solve some of these issues since computations are moved close to the data sources. The combination of edge computing and Machine Learning (ML) can help to make healthcare services much faster, more accurate and more efficient. Much of this progress must be attributed to the increasing popularity of Internet of Things (IoT) devices, such as wearable devices and smart home systems. These devices are based on the Internet of Medical Things (IoMT), which allows data to be easily shared and analyzed across user, edge, and cloud layers [HLT+19, LSM+22].

Edge computing processes data close to their source, reducing the load on central, cloud-based servers, lowering transmission costs, and speeding up response times [APP+23, YZ23, RBFE23]. This can be highly beneficial in smart healthcare systems, where faster data processing can influence better patient care and more efficient utilization of medical resources. When you add machine learning, these systems become more powerful. ML-enabled systems are capable of analyzing data and computing highly accurate predictions.

This thesis discusses the intersection of edge computing and machine learning in healthcare. We go through some of the expected current research and applications that show the benefits, challenges, and future potential of this intersection of technologies in areas such as data processing and analytics, speed and security on the overall impact on patient care. This research aims to provide a clear view of how edge computing and machine learning can address some of the biggest challenges in healthcare today.

By reviewing existing studies and identifying where more work is needed, this thesis aims to contribute to the development of better, more efficient healthcare technologies. The migration from traditional cloud computing to edge computing is critical for the real-time analysis of data associated with vital signs monitoring and emergency response [Bhu15].

This systematic literature review (SLR) will serve as a useful resource for anyone interested in how these technologies can enhance patient care and healthcare systems around the world.

As suggested in [ZBB+11], for conducting this SLR, we carefully analyzed the studies with three main steps (planning the review, conducting the review, and reporting the review). We used several Electronic Database Systems (EDS) for automated searches. These databases include the ACM Digital Library, IEEE Xplore, Science Direct, SpringerLink, Wiley Online Library, Scopus, and Google Scholar.

The primary contributions of this thesis include conducting a comprehensive review of existing studies, analyzing the demographic details of published research such as the types and frequency of publications and the geographical distribution of authors, and exploring the solutions, themes, tools, motivations, and challenges presented in selected studies. Additionally, the thesis reviews articles in terms of their architecture, implementation, and data sources, and examines these articles for emerging trends and potential future directions .

Plan of the Thesis

The remaining chapters of this thesis are organized as follows: Chapter 2 provides the background on edge and cloud computing. Chapter 3 explains the methodology used in the SLR and presents the considered research questions. Chapter 4 offers an in-depth literature review. Chapter 5 engages in a detailed discussion. Finally, Chapter 6 concludes the thesis.

Chapter 2

Background

2.1 Cloud Computing (CC)

Cloud computing is a critical driver of healthcare transformation, scaling computing power, safe storage, and on-demand access to a pool of resources [CC15]. It has wide application in the healthcare fiels, in which genomics, proteomics, and molecular medicine are included, and shows potential improvement in the services and research of these fields [GPK$^+$15]. Cloud computing integrated into the architecture of e-healthcare enhances resource and processing power sharing and, therefore, contributes to the more efficient delivery of healthcare services [DST17]. Cloud infrastructure has found a place in real-life healthcare systems for example, in the UK (Electronic Health Record backbone) or the United States of America (Independent Practice Association software solutions) [GD22]. The shift to cloud computing in healthcare provides advantages like access to information technology services from any location at any time, potentially reducing costs and enhancing overall efficiency in healthcare organizations [Kom23].

2.2 Edge Computing (EC)

Edge computing is an innovative technology that positions substantial computational and storage capabilities close to the edge of the Internet, near mobile devices, sensors, and IoT devices. Its goal is to improve latency, bandwidth, reliability, and resilience [Sat17]. By processing data close to the source and then sending it to a central server or the cloud, it optimizes data processing, increasing speed and decreasing reaction times [SCC19].

Based on the work of [YLH$^+$17] [SCC19], Figure 2.1 depicts an ecosystem for edge computing.

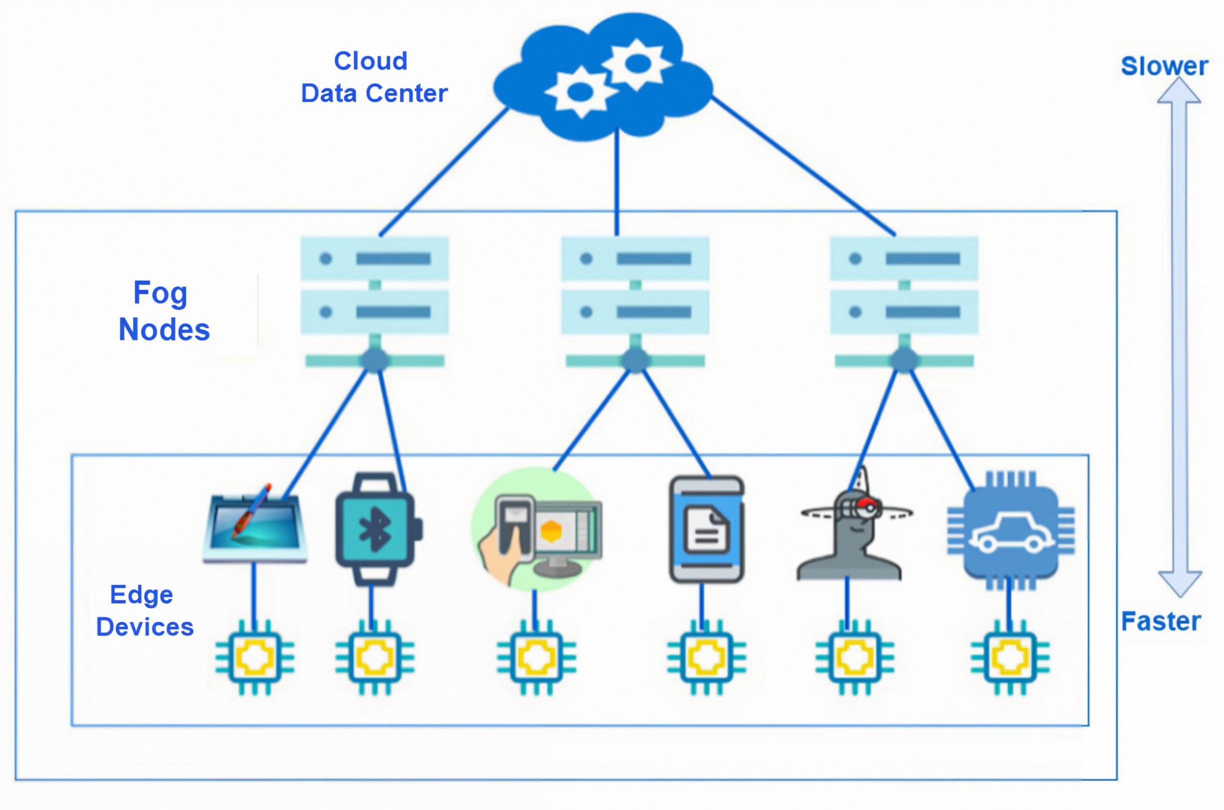


Figure 2.1: Edge and cloud Computing

This system is made of three main parts: devices and sensors, Fog Nodes, and cloud services. Devices and sensors, such as smartphones, tablets, smart bracelets, and laptops, generate and gather data while directly interacting with users. Though offering some real-time services, they have a limited capability and, therefore, need to offload tasks on the Fog Nodes.

Fog computing (FC) extends cloud computing by serving as a middle layer between edge devices and the cloud. It helps mitigate issues such as latency and network congestion [GB23]. In a typical FC architecture, data from edge devices are first processed by fog nodes, which analyze and filter out critical information. Only the important data are sent to the cloud for storage, while non-essential data is either discarded or kept locally for further steps [KKF+23].

On the other hand, the cloud offers extensive computing, storage, and networking resources; hence, it supports state-of-the-art applications related to machine learning, big data analysis, and business intelligence [SCC19].

Given the substantial volume of data, the use of cloud computing for analysis is essential in the healthcare sector. To address this, the edge and a cloud layers take in charge distinct responsibilities. For instance, in a study conducted by Singh and Chatterjee [SC23], they introduced an edge computing-based secure health monitoring framework (see figure 2.2), which comprises four primary layers: the data generation layer, the edge computing layer, the cloud storage layer, and the smart healthcare community.

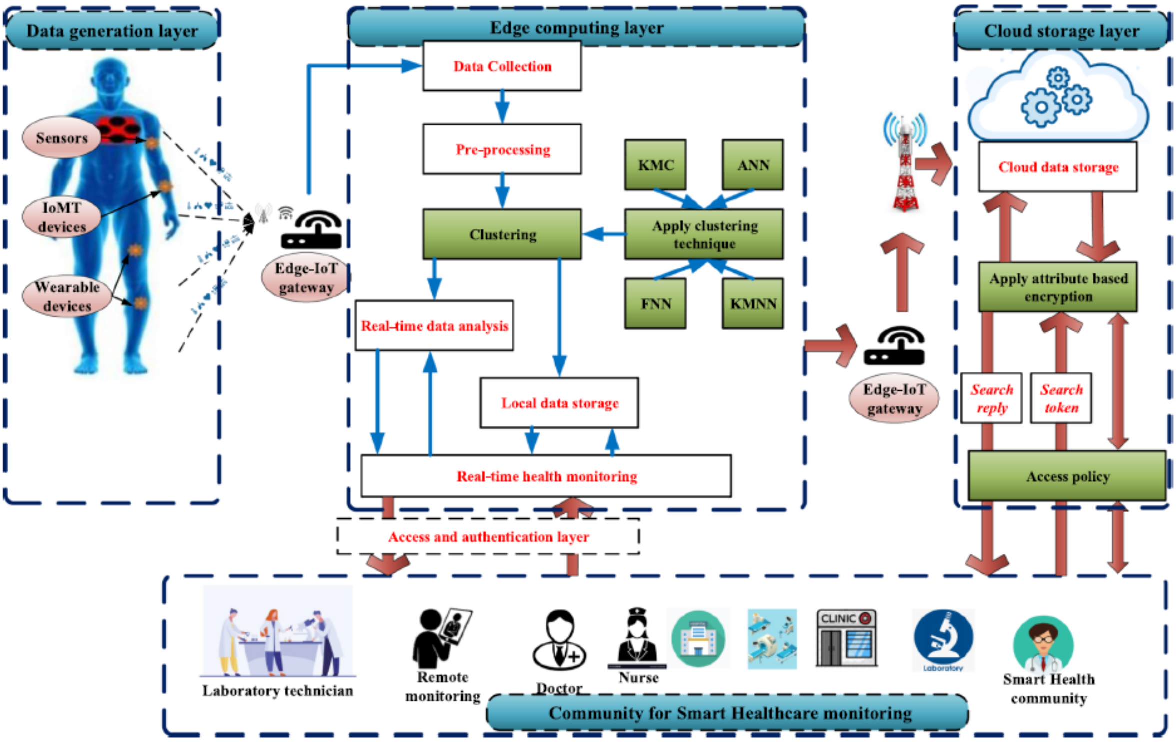


Figure 2.2: Edge computing framework from [SC23]

2.3 Fog Computing (FC)

Connecting sensors directly to the cloud is not feasible in many real world healthcare applications. Some applications won't allow medical data to leave the hospital, prioritizing patient safety in case of network or data center failures [KBTP17]. Fog computing steps in to address these issues.

Fog computing expands on cloud computing by placing resources between the cloud and IoT devices. Instead of constantly sending data to distant cloud servers for storage and processing, fog computing brings those services closer to where the devices are located [QT19]. Healthcare applications, which require quick responses and minimal delays, benefit from fog computing's ability to analyze data from IoT devices in real-time [VS18]. Fog computing is pretty fascinating; it actually helps ease the burden on the cloud by placing computing power closer to where it's actually needed. Unlike the distant cloud, fog nodes sit right at the edge of the network. This setup cuts down on delays, making things happen faster. These nodes don't handle heavy computing tasks; instead, they collaborate with devices such as routers, set-top boxes, and mobile phones to manage basic operations. This arrangement enables real-time analysis of data right at its source[SDW+15]. In healthcare, this makes a huge difference. Fog-based health services are great for seniors who want to take care of their health at home, which helps them live better and longer.

2.4 Internet Of Things (IoT)

The Internet of Things (IoT) is significantly transforming healthcare, demonstrating its potential as a paradigm-shifting innovation in the field. All is about the monitoring of patients in real-time and delivering healthcare from any place, which is very important for patients who are facing long-term health issues. Doctors use wearable sensors and remote monitors to continuously gather and analyze patient data. This allows them to respond promptly when needed and create personalized treatment plans that truly fit each person. Overall, it enhances patient care and cuts costs by minimizing hospital trips and optimizing resource allocation [NKM+24]. The use of IOT technology in healthcare has attracted a lot of attention and a lot of research has been done by researchers in this field and we briefly mention a few of them here.

Concerning the application of IoT in healthcare, in [Alm23] the authors mention that the importance of IoT in healthcare management is increasingly evident. The main advantages here include IoT's ability to monitor patients remotely, administer treatment, and address challenges such as handling large volumes of data, ensuring security, and managing costs. Additionally, future research directions include predictive applications and using prosthetic sensors to retrieve patient data in real time. Researchers, as mentioned in [ANJ+22], are investigating how IoT can continuously monitor health, with the aim of identifying problems early and supporting patients remotely. Similarly, in studies such as [AOA+23], researchers are looking at how IoT-driven telemedicine systems can let doctors and patients talk in real-time. This breakthrough makes healthcare easier to reach, especially for older people and those with ongoing health issues.

Regarding security concerns, in [SNP+20] the authors conduct a comprehensive analysis of the security landscape in IoT, exploring attack surfaces, threat models, security issues, and unresolved challenges. Additionally, the study presented in [JBC20] addresses the complexities of digital forensics in the IoT era.

2.5 Internet Of Medical Things (IoMT)

Over recent years, there has been a growing integration of IOT solutions into various applications, significantly impacting our daily lives. The IOMT includes a branch of IoT that is exclusively intended for healthcare applications[GSZ+20]. The future of existing healthcare systems lies in the IoMT, wherein every medical device is interconnected and remotely monitored by healthcare professionals through the Internet. This evolution promises more efficient and cost-effective healthcare delivery[RS22].

2.6 Healthcare

Healthcare services in the present and the future will need to meet new standards for response time and processing power [GCW+23]. Mobile cloud computing (MCC) predated edge computing and was plagued by the same issues of expensive data transmission, slow response times, and limited coverage [HHI22]. Data costs are rising due to network traffic delays. Cloudlet solutions have lower latency than MCC but do not support required mobility due to limited Wi-Fi [VRK+21].

Unlike cloud-based computing, studies show that only edge-based computing meets modern latency, mobility, and energy efficiency needs. Thanks to EC systems, medical professionals may now provide in-home care for patients with chronic diseases by employing wearable monitors and ambient sensors [Udd19]. Thanks to EC systems, medical professionals may now provide in-home care for patients with chronic diseases by employing wearable monitors and ambient sensors. Furthermore, doctors can determine whether a patient is at risk using information from these sensors, whether inside or outside the building[GPR+20].

2.7 Machine Learning (ML)

Machine learning is transforming healthcare by analyzing large datasets to identify risk factors promptly, improve resource management, and enhance patient care [MPC21]. It supports decision-making by uncovering hidden connections in complex medical information and utilizing Artificial intelligence (AI) tools to evaluate diverse health data for research [KSVK22].

Currently, numerous studies and applications are merging the trending fields of AI and edge computing. This integration is driven by two main factors[HLW+23]: AI algorithms are essential for optimizing and deploying edge computing systems, and edge computing offers the crucial computational support needed for AI applications, enabling them to operate near end-user devices to ensure low latency and high network reliability [HMA18].

AI algorithms are also widely used in edge computing, as highlighted in [HLW+23]. These algorithms are classified into several categories, such as traditional machine learning, which includes support vector machines, boosting, random forests, K-means, and dimension reduction algorithms like the principal component analysis (PCA). Deep learning comprises deep neural networks, convolutional neural networks, and recurrent neural networks. Other categories include reinforcement learning, deep reinforcement learning, federated learning, and evolutionary algorithms.

Chapter 3

Methodology

As part of our research approach, we used the SLR method to carefully analyze and investigate the existing literature related to our research questions. An overview of the research methodology for this SLR is presented in Fig. 3.1.

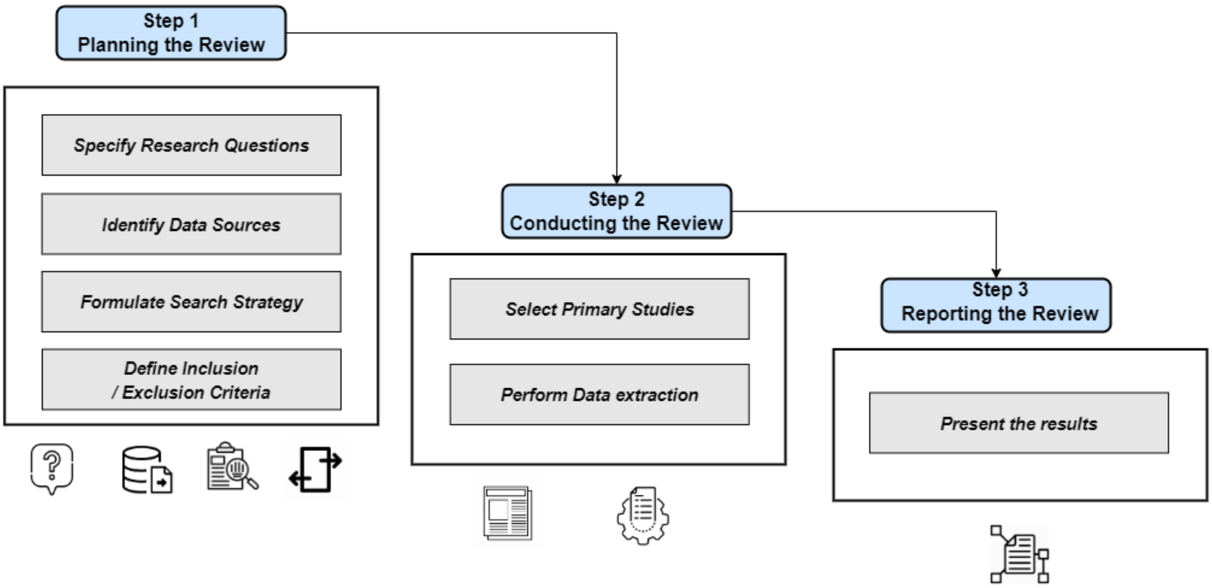


Figure 3.1: An overview of the research methodology for this SLR

3.1 Planning the review

3.1.1 Specify Research Questions (RQs)

Our research questions are listed below:

Demographic details of published research

RQ1.1: What are the types and the frequency of published research on Edge computing in Healthcare Using ML? What is the geographic distribution of the authors' affiliations?

Rationale: This research question seeks to identify the various forms of publications, such as journal articles, conference proceedings, etc., and emphasizes how often they occur, measured by the number of publications in a given year. It aims to shed light on the evolution of research within the chosen topic by examining the types and frequency of published research throughout the years. We use the geographic distribution of authors' affiliations to ensure a diverse range of perspectives, enhance the generalizability of findings, and identify regional trends or biases in research.

RQ1.2: What are the most prominent publication forums and what type of research has been published on edge computing in healthcare using ML?

Rationale: Publication forums generally refer to the platforms or venues where research findings are published and shared with the scientific community and the public. These platforms can be widely varied: academic journals, conferences, workshops, and others. The type of research can be solution proposals, validation, and so on.

Themes, Tools, proposed Solutions, motivations, and challenges

RQ2.1: What are the prevalent research themes in edge computing applications within healthcare using ML techniques?

Rationale: Identifying prevalent research themes helps in understanding the primary areas of focus, innovation, and potential gaps in knowledge within the field.

RQ2.2: What motivations drive researchers to explore edge computing in healthcare using ML? What are the major challenges during the implementation?

Rationale: Understanding researchers' motivations provides insight into the perceived benefits, societal impact, and industry demand driving the adoption of edge computing solutions in healthcare. Understanding the major challenges that arise during the implementation phase is essential for better planning, resource management, engaging stakeholders, and ensuring the overall success of projects across different fields. Combining motivations and challenges into a single research question helps us understand what drives people and the obstacles they face, leading to more practical and well-rounded solutions.

RQ2.3: What are the most prominent tools and technologies?

Rationale: Identifying the most prominent tools and technologies helps in recognizing the key technological advancements and resources that facilitate edge computing in healthcare.

Architecture, Implementation, and Data Sources

RQ3.1: Where is processing taking place (edge, fog, cloud), and for what tasks?

Rationale: Understanding where the processing is performed helps to identify the distribution of computational tasks across the edge, fog, and cloud layers. This is important information to understand where exactly the performance of the applications in healthcare IoT is heading. By knowing how processing takes place, one can see that edge computing will be utilized for quick response, fog computing for medium-level tasks, and cloud computing for heavy data processing.

RQ3.2: Do applications effectively exploit the resources of IoT, edge, and cloud seamlessly?

Rationale: Is edge computing used for performing part of the computation and the cloud for finer analysis and data integration? Or are applications usually fully executed on cloud resources?

RQ3.3: Do the applications use a single or multiple data sources?

Rationale: Understanding whether applications utilize a single data source, multiple data sources, or data fusion techniques provides insight into the data management strategies and complexities involved in edge computing for healthcare.

Emerging and future trends

RQ4.1: What are the emerging trends and potential future dimensions in edge computing research within healthcare utilizing ML?

Rationale: Identifying emerging trends helps to understand future directions, innovative approaches, and evolving focus areas in edge computing research within healthcare. This insight highlights the cutting-edge developments and new challenges. Identifying the potential future dimensions provides a comprehensive view of the current advancements and future possibilities in edge computing research within healthcare.

3.1.2 Identify data sources

In systematic reviews and mapping studies, EDS helps automate the exploration process by using predefined and often customized search terms to find relevant scholarly works related to a specific topic of interest.[CBZ10]. We followed the recommended guidelines for conducting a systematic search and identifying the most relevant sources of information. We used more than five EDS for an automated search, as suggested in [ZBB+11]. These databases include the ACM Digital Library, IEEE Xplore, Science Direct, SpringerLink, Wiley Online Library, Scopus, and Google Scholar which are all well-known repositories of scholarly literature.
It's important to mention that the list of EDS provided here isn't comprehensive, and it doesn't claim to cover all possible sources of literature. However, previous studies based on empirical evidence regarding SLRs have emphasized the importance and suitability of these electronic repositories for finding relevant literature. [ZBB+11] [CBZ10].

3.1.3 Formulate search strategy

To conduct our search, a search string is used for the data search. our search string is presented in Listing 3.1.

```
(("Edge Computing" AND ("Health" OR "Medical"))
 AND ("Machine Learning" OR "Artificial Intelligence" OR "AI"))
```

Listing 3.1: Search String for Literature Search.

The provided search string is created by combining key terms through the use of 'OR' and 'AND' boolean operators.

3.1.4 Define inclusion and exclusion criteria

To systematically gather relevant literature for this study, it is essential to define clear inclusion and exclusion criteria. The following criteria outline the specific parameters for selecting studies that align closely with the research focus on edge computing in the healthcare sector utilizing ML techniques.

- Inclusion criteria:
  - Research articles that specifically focus on the application of edge computing in the healthcare sector utilizing ML techniques.

  - We limit our selection of related studies to the first ten pages of each EDS.
  - Exclusively considering research that has undergone peer review and has been published.
  - Only peer-reviewed studies provide access to the full text.
  - Studies written and published in the English language.
- Exclusion criteria:
  - Exclude the studies that do not discuss healthcare.

3.2 Conducting the review

3.2.1 Select primary studies

The primary studies search process started with examining chosen digital repositories using a specific search string. The search process began on 10 February 2024 and ended on 20 March 2024. We employed a snowballing approach to systematically expand our paper selection and identify additional relevant studies for inclusion in our research. Snowballing refers to the method of identifying additional relevant studies by examining the references cited in already-known relevant papers. The supervisors reviewed the selected articles in this SLR to ensure their relevance to the topic.

The selection process started by a comprehensive search across multiple digital libraries and online databases. Using the search string shown in Listing 3.1 that combines terms like “Edge Computing”, “Health/Medical”, and “Machine Learning/Artificial Intelligence”, the initial search pulls in a large number of studies from sources like IEEE Xplore, Springer Link, Science Direct, Wiley Online Library, ACM Digital Library, Scopus, and Google Scholar. This step resulted in a broad pool of 255 studies to start with.

Next, the process involved a careful screening phase where the titles, keywords, and abstracts of these studies are reviewed to remove less relevant ones, narrowing the list down to 127 studies. These shortlisted studies then went through a thorough full-text review, ensuring that only the most relevant and high-quality studies are considered. This rigorous filtering resulted in 32 studies that met all the necessary inclusion criteria, ensuring the review to be focused and precise.

To make the review even more comprehensive, the snowballing method was employed. This involved looking at the references of the selected studies to find more relevant research that might have been missed in the initial search. This step uncovered three more valuable studies, bringing the total to 35. Snowballing added depth to the review by leveraging the network of citations among scholarly papers, ensuring a well-rounded and robust literature base. The graphical representation of our selection process studies is presented in Fig 3.2.

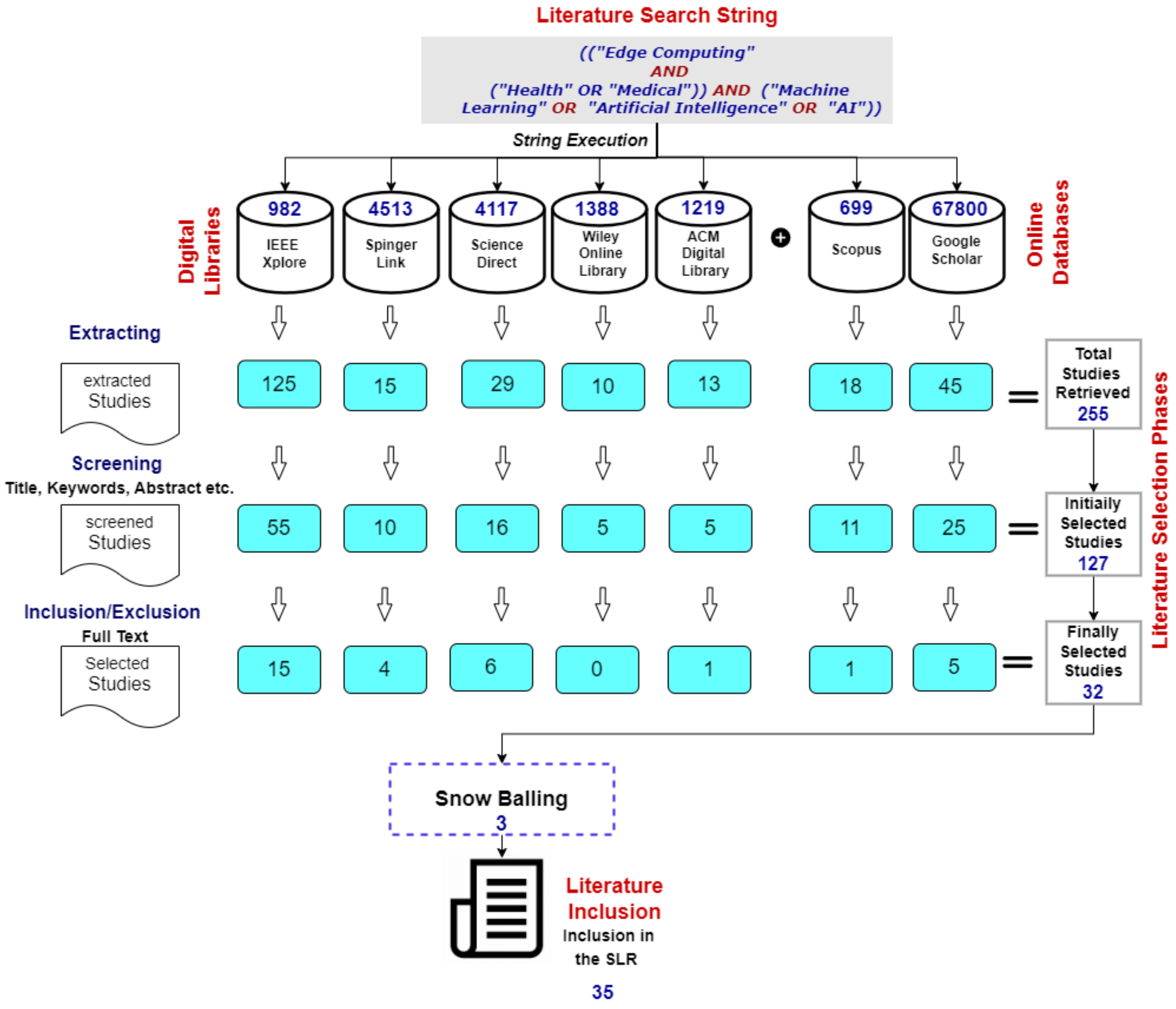
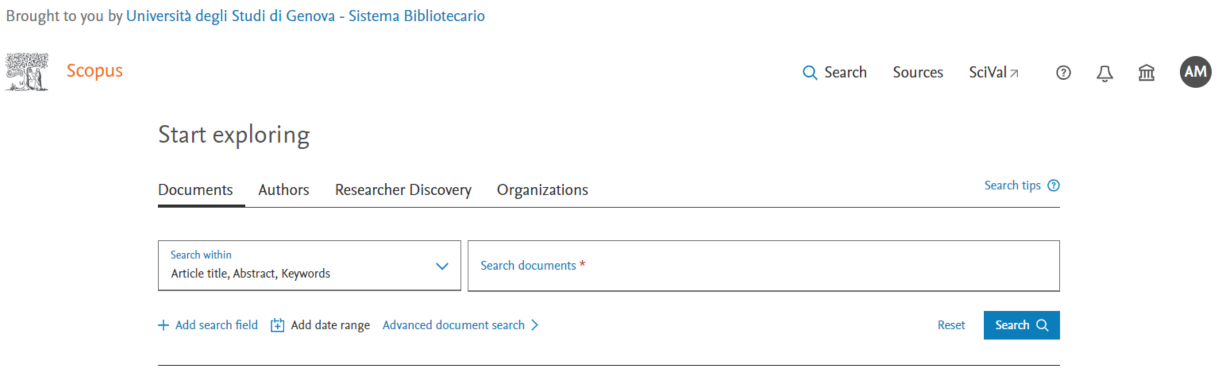


Figure 3.2: Studies selection process

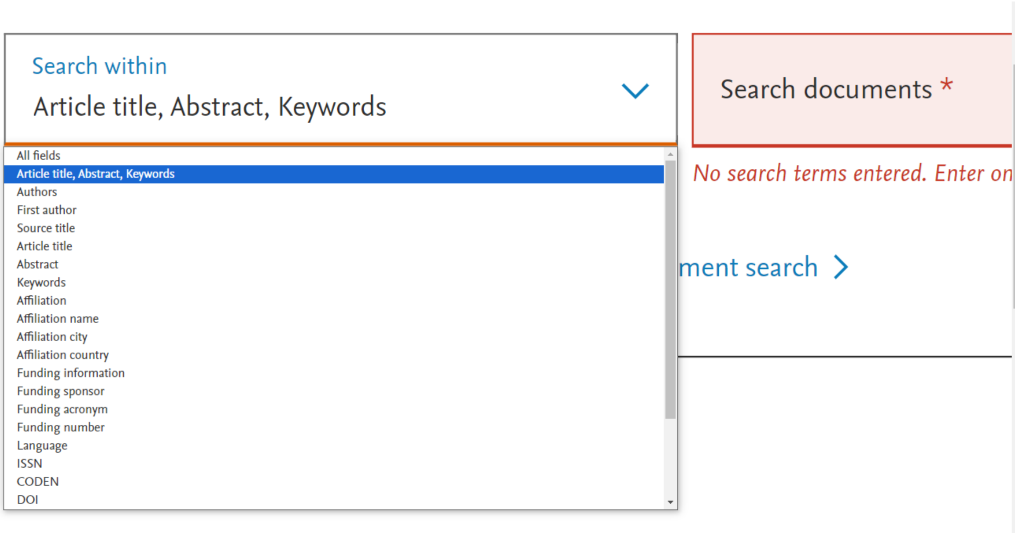
To find related articles on a given topic, we will demonstrate the process using Scopus as an example. Figure 3.3 shows a screenshot of the Scopus database search page.



Search within
Article title, Abstract, Keywords

Figure 3.3: Search in Scopus

Scopus is a comprehensive academic database used for locating scholarly articles, authors, and institutional affiliations. To search for an article, users should navigate to the Scopus homepage, usually via their institution's library portal. The main search interface allows for document searches by default, where users can input keywords, article titles, or abstract details. Advanced searches can be refined by adding additional fields, setting date ranges, and using Boolean operators (AND, OR, NOT). After entering the search criteria, clicking the "Search" button retrieves a list of matching documents, enabling users to explore a wealth of academic literature efficiently. In the search document field, you can write your desired title or search string to display the articles for you based on the title or your search string. The other field allows you to filter articles based on more factors (see Figure 3.4).



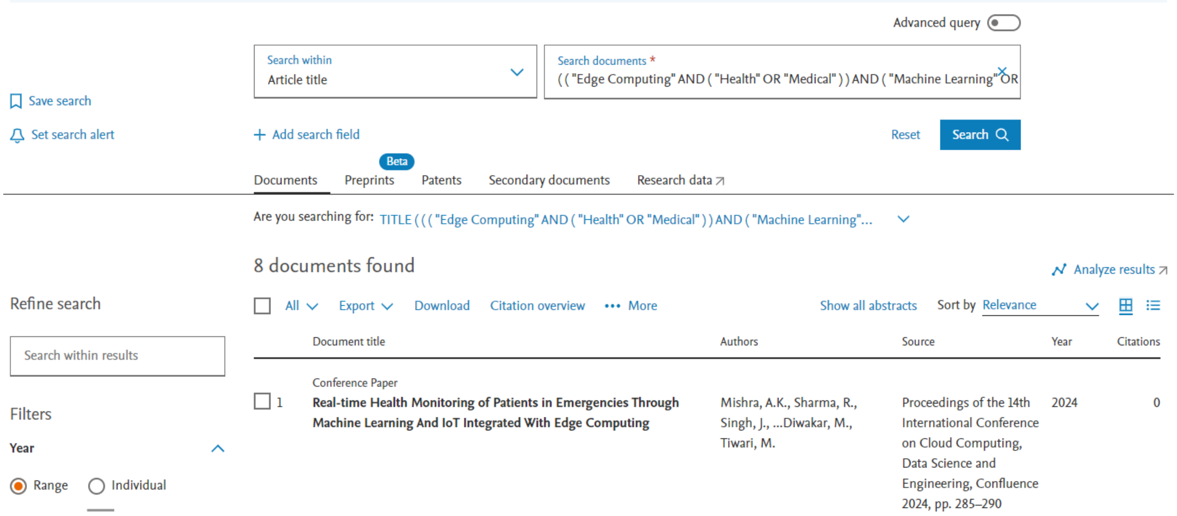
Search within
Article title, Abstract, Keywords

No search terms entered. Enter on

Figure 3.4: Filtering the search in Scopus

As an example, we entered our search string (see listing 3.1) into the Scopus database. We then filtered the results based on the article titles. The results are shown in Figure 3.5, where the system suggested 8 relevant articles.

Therefore, the articles were selected according to specific principles and rules. It is important to note that our selection process involved filtering based on the first ten pages of each EDS. The papers that appear on those ten first pages have a higher relevance percentage for the considered search string.



Search within: Article title

Search documents *: (("Edge Computing" AND ("Health" OR "Medical")) AND ("Machine Learning" OR

Are you searching for: TITLE ((("Edge Computing" AND ("Health" OR "Medical")) AND ("Machine Learning"...

8 documents found

Sort by Relevance

	Document title	Authors	Source	Year	Citations
☐ 1	Conference Paper **Real-time Health Monitoring of Patients in Emergencies Through Machine Learning And IoT Integrated With Edge Computing**	Mishra, A.K., Sharma, R., Singh, J., ...Diwakar, M., Tiwari, M.	Proceedings of the 14th International Conference on Cloud Computing, Data Science and Engineering, Confluence 2024, pp. 285–290	2024	0

Figure 3.5: An example of searching in Scopus using a search string

3.2.2 Perform data extraction

We defined a set of data extraction items (See Table 3.1) to address our research questions. Data items are the particular types of data extracted from each selected study that directly map to the study research questions.

Table 3.1: Relevant data items extracted from the selected studies.

Data Item	**Description**	**Related Research Question**
Index	The study ID	Demographic
Study title	The full title of the primary study	Demographic
List of authors	The full names of all authors who contributed to the study	Demographic
Publication type	The category of the publication, such as journal article, conference paper, book chapter, etc	Demographic
Journal or conference name	The name of the journal or conference where the study was published or presented	Demographic
Journal or conference rank	The ranking or impact factor of the journal or conference, if applicable	Demographic
Name of publisher	The name of the organization or company that published the study	Demographic
Geographic distribution of authors	Relevant data items extracted from the selected studies by country	Demographic
Publication year	The year in which the study was published	RQ1.1
Research type	The nature of the research, such as validation research, proposal solution, philosophical papers, etc	RQ1.2
Research themes	The main topics or areas of focus addressed by the study	RQ2.1
Papers motivation	The underlying reasons or objectives that prompted the research	RQ2.2
Papers challenges	The difficulties or obstacles encountered during the research process	RQ2.2
List of tools	The specific tools, and software used in the study	RQ2.3
Papers data source	The origin of the data used in the study, including primary data collected by the authors or secondary data obtained from existing sources	RQ3.2

3.3 Reporting the review

3.3.1 Present the results

We presented the findings of our SLR in chapter 4.

Chapter 4

The Systematic Literature Review

This chapter is organized into two sections. The first section comprehensively analyzes the selected studies, while the second section addresses the questions outlined in the methodology.

4.1 Selected studies

Studies conducted in the year 2017:

Hosseini et al.[HTP$^+$17] proposed research aimed at improving the detection and localization of epileptogenic zones within the human brain using the advanced autonomic edge computing methodology. The integrated platform for EEG and rs-fMRI features applies deep learning principles extracting relevant features from both modalities. The edge computing approach allows for the processing and analysis of large-scale medical data in real-time, hence reducing latency and increasing data privacy by processing data locally using the edge gateway, which is supported by cloud servers for storage and intensive computation. The core contributions of this research include a general mobile edge cloud-based framework for real-time data processing, an optimized model for the localization of the epileptogenic zone, and an unsupervised feature extraction model combining convolutional neural networks and support vector machines.

Studies conducted in the year 2018:

Kumar et al.[KM18] explored the integration of cloud and edge computing along with machine learning in a distributed framework of IoT, particularly in the area of healthcare applications. In this research, the primary focus has been on how real-time data processing can be handled through edge computing to reduce latency and hence improve decision-making procedures. In this framework, the timely intervention of critical health data is focused on with the help of sensors like SPO2 and ECG to support effective medical responses. It uses resource-constrained protocols like MQTT and CoAP between IoT endpoints and back-end servers for efficient usage of resources and developing a long battery life. This will present an efficient solution for healthcare applications by comprehensively improving the response mechanism for patient health monitoring and emergencies.

Azimi and their team [ATMA+18] studied how to improve healthcare IoT systems using hierarchical edge-based deep learning. Their work focuses on overcoming challenges in remote health monitoring, especially the need for high availability and accuracy to care for patients in critical conditions. They proposed a hierarchical computing architecture integrating edge and cloud computing resources in such a way as to guarantee the optimization of the deep learning model deployment. The authors investigated in particular the possibility of the deployment of Convolutional Neural Network -based classification models within this kind of architecture. This HiCH system, proposed in this paper, used cloud servers to offload highly computationally intensive tasks and allowed local decision-making at the edge, which granted high availability of a system not dependent on connectivity to the Internet. In this paper, a case study has been used to perform real-time health monitoring with the help of electrocardiogram data to show the efficacy of the approach. The evaluation was according to response time and accuracy. According to the results, a high level of availability and accuracy could be guaranteed by the HiCH architecture, which is very important in timely and reliable health monitoring.

Zubair Md. Fadlullah and his co-authors [FPG18] proposed an intelligent approach. Given the exponential growth of the Internet of Things, there is a great need for efficient processing and analysis of health data. Conventional approaches transfer data from a good number of biosensors to a central cloud for processing. The aforementioned approach suffers because of huge latency due to network congestion and a large volume of data transmission. The authors presented a deep learning-based edge analytics approach to address the above challenge. This means that data will be processed closer to where it is generated or its origin, eliminating delays and increasing real-time capabilities for decision-making. Their contribution involves the application of Convolutional Neural Networks at the edge in the analysis of healthcare data from sensors and wearables in patients' homes. This would be more useful in older patients and those requiring constant monitoring so that timely interventions could be instituted after analyzing critical health parameters like heart rate, blood sugar levels, and respiratory rates. Their simulations also show that their proposed method has extremely low loss rates, very high accuracy, and the least execution time.

Jian Yu et al.[YFC+18] propose a hybrid architecture, EdgeCNN, designed to improve real-time acquisition and analytics of healthcare data collected from IoT devices. One of the major focuses is to create a balance between edge computing and cloud computing to make the processing of healthcare-based data faster and more efficient. Subsequently, using EdgeCNN, it will be possible for the system to realize deep learning on edge devices. This, therefore, enables real-time evaluations, hence the advantages that accompany it, including lower delays, reduced network traffic, less burdening of cloud platforms, and lower maintenance costs. In this paper, the authors have presented a streamlined diagnosis model with the edge-based learning algorithm using convolutional neural networks that can identify and make real-time inferences of electrocardiograms—a critical application in smart healthcare using edge devices. Experimental results prove that EdgeCNN, compared with the traditional cloud-based architecture, significantly reduces diagnosis delay, and network I/O, improves application usability, and shortens resource cost while improving the protection of user data privacy. EdgeCNN enables deep learning at edge devices, hence giving low latency for real-time diagnosis, consequently saving time and bringing efficiency and user privacy without relying on the cloud.

Studies conducted in the year 2019:

Ram et al. [RAS19] base their approach on challenges with an aging population and a shortage of healthcare workers by using cloud-based systems combined with Machine Learning at edge computing for any mobile health monitoring and improving the accuracy in the monitoring of human activities by using data from multiple sensors. The authors performed pre-processing to sanitize the dataset from sensor data and classify activities within it. They have used two machine learning algorithms—Random Forest —to compare them for the classification of activities. The results show RF with an accuracy of approximately 99% against the 98% realized by SVM. For mismatched data analysis, they used a confusion matrix; this mismatching was mainly on the initial sensor values when the activities were being recorded. Further visualizations of the data were also presented to make it more understandable.

In 2019, Zia Uddin [Udd19] proposed a different health monitoring approach using wearable sensors and edge computing. Their system uses RNNs to finally predict human activities from data originating from multiple sensors, which range from but are not limited to ECG to magnetometers, accelerometers, and gyroscopes. It is then processed by edge devices, personal computers, or laptops, and does not require cloud computing. It improves real-time processing by processing these huge amounts of healthcare data locally. Experiments proved that this system performed better than traditional methods on a publicly available dataset and turned out to have huge potential for continuous and inexpensive health monitoring without visiting hospitals. Besides, the employment of GPUs inside edge devices accelerates data processing, thereby rendering this system efficient and reliable for smart healthcare applications.

Manogaran et al. [MSF+19] designed the Wearable IoT Smart-Log Patch system incorporating an edge computing-based Bayesian deep learning network for an improved physical Monitoring System. The state-of-the-art device gathers multi-dimensional physiological data like blood pressure, temperature, ECG, EMG, and EEG, among others, with the help of IoT sensors. Edge computing, along with the Bayesian deep learning network (EC-BDLN), is used to process that data and increase the accuracy and efficiency of health condition analysis. The high accuracy, mean residual error, delay, energy consumption, and overall strong solution in this study are supported by empirical evidence for real-time and continuous health monitoring. The research greatly supports the development of wearable health monitoring systems, leading to more accurate and continuous health monitoring technology in the future.

Studies conducted in the year 2020:

Chang and Yoo [CY20] have developed an approach, where edge-computing with P2P is used to work for deep neural networks to improve health data processing. The model sends numerous issues, including neural net overfitting and high computational requirements, because multiple edge nodes are connected directly to modifying deep neural networks; yet the data processing load is distributed, and central servers are not overloaded. The measures of success gathered in their experiments showed an order of magnitude performance boost in response times compared to the corresponding server-based models they used to justify the model's role in real-time health monitoring and decision-making in IoT healthcare settings. This work offers a substantial contribution to health information processing in edge computing with the aid of P2P networking.

Abu Sufian and his co-authors [SGSS20] provided an outline of current Deep Learning and edge computing frameworks to address issues raised by the COVID-19 Pandemic. They highlighted the use of AI, especially deep learning, to offer solutions in cases such as diagnosis, treatment, and patient support. The authors also pointed out several issues related to older deep learning models, noting their data-hungry nature and demand for large-scale computational platforms, which posed challenges during a pandemic when data or computing resources were restricted.

Saqib Hakak et al. [HRKS20] proposed another approach to using edge computing and Federated Learning for improving healthcare analytics, where the data from the wearable devices updates the local machine learning model, allowing the user's data to be private while reducing cloud resources required in the process. This framework provides personalized health insights and can be used for monitoring chronic diseases or on real-time health. The authors add challenges like data privacy, security, and edge device resource constraint issues that will show the great potential of this technology in healthcare.

Yan He et al. (2020) [HFY$^+$20] proposed Edge Convolutional Neural Networks to enhance healthcare data processing from IoT devices. The system deals with noisy data, slow network speeds, and privacy concerns in remote health monitoring. Accordingly, a deep learning model working on edge devices for the rapid diagnosis of ECGs was proposed, along with the technique for augmenting ECG data through generative adversarial networks known as DCGAN. Their experiments prove that EdgeCNN works much better than the traditional cloud-based system in diagnostic accuracy, processing speed, and privacy protection.

Zien Sheikh Ali and his co-authors [ASE20] suggested a system for epileptic seizure identification at the edge using deep learning and edge computing. In their proposal, the authors used a CNN to classify the brain wave data, which is a rather general approach. Most specifically, it decreases the amount of data sent after edge computing is done locally on the part of the data before it is transmitted to the cloud server, making the system faster and more efficient. Their approach gives an accuracy of 92% in the time domain and 99.22% in the frequency domain for seizure detection, while the system's complexity and response time remain low.

Irina Valeryevna Pustokhina and her team [PPG⁺20] proposed a new method called ETS-DNN, which provisions for monitoring patient health from smart devices at the edge level. Their model collects health data from IoMT devices and Conse of them rapidly and precisely with advanced computing techniques. After that, they further optimized their DNN model with an optimization algorithm that was developed to make better predictions. They experimented with ETS-DNN; it worked much better compared to older methods, hence promising the improvement of healthcare services.

Sadman Sakib and colleagues [SFFN20] in their paper discuss adding smart features to IoT sensors for health monitoring. They focus on detecting heart arrhythmias using ECG signals with a new method that uses deep learning. Their system is simple and accurate, achieving an accuracy of 95.27% without needing complex data processing steps. This method is better than older techniques like K-Nearest Neighbor and Random Forest, and it shows that using smart sensors can make health monitoring faster and more private by reducing the need for cloud computing.

Abdur Rahman, Md. et al. [RHAG20], have investigated the potential of advanced 5G technology integrated into edge computing in fighting COVID-19. The authors suggest that the data is going to be processed both locally and in the cloud to achieve better diagnosis and management in the case of this nasty disease. It will have inbuilt fast, private, and scalable data handling, which shall allow the analysis of COVID-19 cases in real-time. The operationalizing of deep learning models has been underlined by the authors to make them more explainable and for experts to understand and trust those decisions. Their framework has turned out to perform well in several scenarios related to COVID-19, hence becoming one of the very useful tools in pandemic management.

Qiong Wu et al. [WCZZ20] propose FedHome, a system for in-home health monitoring that allows user data to be privacy-preserving by being stored locally. This uses a special balancing method, GCAE, for balancing data to improve accuracy. FedHome thus handles data that is not evenly distributed and further cuts down communication costs. It earned very high performance in human activity recognition with an accuracy of 95.41%, hence making it a strong option in smart healthcare while protecting privacy and improving efficiency.

Studies conducted in the year 2021:

Abu Sufian et al. [SAG^{+}21] developed a solution for monitoring health at home with the help of smart technology. Herein, pre-trained computer models are fine-tuned with a little extra data for small devices at home. Because of this, data remains private and secure, internet use is reduced, and it supports real-time monitoring. Their approach is very helpful, especially during pandemics or in the care of elderly people, since monitoring their health can be both effortless and effective without transferring data outside the home.

Mohammad Aazam et al. [AZF21] have explained how edge computing, when integrated with machine learning, creates value-added services in health care. The general problem that they address is the inability of global devices, as simple as smartphones and smartwatches, to execute resource-intensive tasks because of a lack of power and resources to perform them. They try to offload such tasks to other available nearby devices or systems, termed edge nodes, fog computing, or femto-clouds. The authors test this idea using machine learning algorithms, such as k-nearest neighbors, naive Bayes, and support vector classification on healthcare data, and the results turn out quite effective. This approach not only improves edge computing performance but also enhances its capacity to support smart healthcare, notably COVID-19 symptom monitoring.

A smart system on buses to monitor mask-wearing conditions in real-time has been developed by Xiangjie Kong and his team[KWW^{+}21]. That is ECMask, applying innovative technologies such as edge computing and deep learning in processing video footage from bus cameras to improve video quality, detect faces, and identify whether one is wearing a mask. It has been tested on a variety of datasets by the team, and this mask operates fast and accurately, making it very useful in keeping public transport safe during the COVID-19 pandemic.

Abhinav Kumar et al. [KSB^{+}21] have developed "MobiHisNet," an effective intelligent tool for the analysis of medical images that could run seamlessly on mobile devices such as smartphones and Raspberry Pi. The authors were aware of the fact that conventional deep-learning models are too complicated and slow to run on such devices. Hence, MobiHisNet has been lightweight and made fast without compromising on its accuracy. This model outperforms popular alternatives, such as VGG16 and ResNet50, especially in breast cancer diagnosis based on histopathological images. It is hence highly applicable and, therefore, will become very helpful to all in performing the most complicated medical image analyses on the go, hence enabling more powerful diagnostic tools for many more people.

The paper of Sadman Sakib et al. team [SFF21] focuses on improving heart arrhythmia detection with deep learning. The traditional methods for its detection are intrinsically complex and, hence hard to adopt on small medical devices. Sakib and his team took a much simpler approach with a one-dimensional CNN that simply skips over these complicated steps, hence becoming much easier to fit into those devices. The performance of this method was exceptionally great on four public datasets, showing that the works are quite applicable elsewhere. This work has also demonstrated that intelligent AI can be effectively performed on small medical devices with limited resources, improving the practicality and reliability of continuous health monitoring.

Md. Abdur Rahman et al. [RH21] have proposed a smart healthcare framework for health monitoring at home with IoMT and deep learning, accompanied by efficient strategies against COVID-19. The framework represents health data privacy and security by local processing at its source. He describes the designing and testing of the system, proving its practicality in real-life clinical trial scenarios. This solution is very handy during a pandemic period, ensuring more reliable treatment from home.

Ghulam Muhammad and M. Shamim Hossain [MH21] have developed an AI system to enhance COVID-19 screening and diagnosis using the latest 5G technology. It uses a mobile app to check vital signs like temperature and pulse. Further, medical images like X-rays and CT scans can be analyzed through it. The system processes data on-site with devices of higher power and provides privacy through blockchain to ensure quick and secure results. It is also adaptable to other diseases; works to make healthcare more efficient, and protects patient privacy.

Xilin Liu and Andrew G. Richardson [LR21] of the University of Pittsburgh detail in an IEEE Spectrum commentary how their team plans to develop neural implants for real-time seizure detection and prediction. The group tried DNN, CNN, and LSTM models in a very small microcontroller. Of the three, an LSTM model generally stood out: While it accurately picked up on a seizure 97.61% of the time and had the lowest rate of false alarms, it also tended to use more power. The CNN model struck a good balance, being both accurate (96.70%) and efficient with memory. The DNN model was the quickest but was less accurate, identifying seizures 87.36% of the time with a higher rate of false alarms. Their work shows that using deep learning in neural implants can significantly improve their effectiveness in treating conditions like epilepsy.

E. Laxmi Lydia and her team [LLAB$^+$21] have evolved a smart system that uses chest X-ray images to aid in the detection of COVID-19. In the method, data from patients are collected through IoT devices, encrypted, and transmitted to a cloud server for analysis using a deep learning model called SqueezeNet. Thereafter, an optimization algorithm was employed to tune the model to perform better. These experiments clearly showed that this new system was much better than the methods existing at that moment, thus becoming a great tool to help doctors diagnose COVID-19 more accurately and faster.

Studies conducted in the year 2022:

Taiyu Zhu et al. [ZKD$^+$22] developed a wearable device to help people with type 1 diabetes track their blood sugar levels by predicting it in real-time. Their device uses an efficient deep learning model on a small, low-power chip for its functioning. The Bluetooth-enabled wearable device would be able to predict the blood sugar level and warn against hypoglycemia. They also developed a smartphone app that could plot the trends in blood glucose and platforms to back up data and further improve the model. Their model was tested on 47 patients. The trials showed that the device helped reduce low blood sugar events and an overall improvement in blood sugar control.

Vipul Kumar Singh and Maheshkumar H. Kolekar [SK22] provided a deep learning model to enhance the diagnosis of COVID-19 through chest CT scan images, optimized for mobile and edge devices, with an accuracy of 96.4% and achieved faster diagnosis time. Their proposed system uses edge-cloud technology for real-time diagnosis and helps remote/rural areas where access to quality healthcare infrastructure is poor and, hence is one of the effective solutions for the management of the pandemic.

Mahmuda Akter and her team [AMLR22] designed a framework of Federated Edge Aggregator for the protection of healthcare data. The architecture processes patient information on IoT devices with additional privacy enhancement mechanisms before sharing, which lowers the risks of data breaches without affecting accuracy. This architecture demonstrated an accuracy of 90% on several benchmark datasets like MNIST, CIFAR10, STL10, and COVID-19 chest x-rays, outperforming traditional approaches.

Adnan Qayyum and his team [QAA^{+}22] worked out a new technique utilizing edge computing and clustered federated learning to improve the diagnosis of COVID-19 using X-ray and ultrasound images. Their approach improved shortcomings such as security and privacy inherent in traditional cloud-centered healthcare systems. Its accuracy for diagnosis improved by 16% based on the F1 score for X-rays and 11% for ultrasounds. This model further provides a way for safe data sharing between remote health centers without a breach of privacy.

Studies conducted in the year 2023:

Abdulrahman K. Alnaim and Ahmed M. Alwakeel [AA23] provide the integration of ML, IoT, and edge computing in applications toward healthcare improvement. Edge computing will be used for handling huge volumes of data produced by medical sensors, improving real-time responses, and ensuring the security of patients' data by using hard encryption. Their research shows that this approach may lead to a reduction in time lags and hence better security and efficiency in health systems.

Piyush Gupta and his team [GCW^{+}23] developed a health monitoring system with deep learning, and edge computing to process data quickly in 2023. In their case, IOTDs collect health data and are analyzed by nearby servers. It attained a high accuracy of 99.23%. This is more effective and cost-efficient than other methods and works very well for real-time fall detection.

The paper by Sai Mani Krishna Sistla and Bhargav Kumar Konidena [SK23] focuses on the issue of how to deal with large amounts of data coming from medical sensors with the help of machine learning to identify unusual patterns and reduce response time. Some of them include requesting the offloading of some of the operations to backend systems to extend the battery lifespan while at the same time enhancing the computational capacity of the appliances. The paper also highlights the need to improve opportunities for privacy and security as we successfully implement artificial intelligence and machine learning with cloud and edge computing for healthcare data and patients' services.

Alain Hennebelle and his team [HMI23] developed HealthEdge to predict Type 2 diabetes using data from medical sensors connected by IoT, edge, and cloud computing. According to the applied approach, a comparison between Random Forest and Logistic Regression machine learning algorithms is expected. RF showed an accuracy that was 6% better compared to LR in their study. HealthEdge looks to improve the prediction of diabetes and healthcare with advanced technology analysis of health data.

Studies conducted in the year 2024:

Kemeng Wang et all.[WKCZ24] research tackles issues in cloud-based healthcare like data syncing and migration. They propose the FETCH framework, which uses edge computing and deep learning to make healthcare systems more efficient and scalable. By using fog computing and the FogBus system, they reduce delays and power use while improving performance. This framework is useful for real-time health monitoring and diagnosing heart disease, making healthcare faster and more accurate. Their work offers a better, more secure solution for modern healthcare needs.

4.2 Addressing to the Research Questions

In this section, we will answer our Research questions.

4.2.1 Demography details of published research

Types, frequency of publications, and geographical distribution of authors (RQ1.1)

The classification of our selected primary studies based on their frequency and publication type is a crucial step in our analysis. This procedure facilitates an understanding of the predominant research trends within our research field, providing a window into the collective interests of the wider scholarly community. By examining the frequency of publication occurrences over time and identifying the various types of publications, such as journal articles, as depicted in Figure 4.1, we gain a comprehensive understanding of the research landscape. Our investigation spans from the earliest publication in 2017 to the most recent in 2024. Notably, our analysis reveals that a significant proportion (77%, comprising 27 studies) of our selected studies were published within the last five years (from 2020 to February 2024). This finding underscores the growing importance of edge computing in healthcare research and highlights the substantial efforts within the research community to develop machine learning solutions tailored for edge computing applications.

Furthermore, our examination indicates that 63% (25 studies) of the primary research appeared in journals, while 37% (10 studies) were presented in conference proceedings. the geographic distribution of authors of this SLR is presented in Table 4.1 and the visualization with a map is presented in Figure 4.2. We considered the affiliations of all authors of the articles. To prevent label overlapping, we have not included the names of all countries on the map.

Key Findings of RQ1.1:

Finding 1: The highest number of primary studies (n=27, 77%) were published between 2020 and 2024. This demonstrates that edge computing in healthcare using ML is an emerging research area that has attracted significant attention from the research community.

Finding 2: Regarding publication type, the results highlight that journals are the preferred venue for publishing relevant studies, with 63% (25 studies) of publications appearing in journals compared to 37% (10 studies) in conferences.

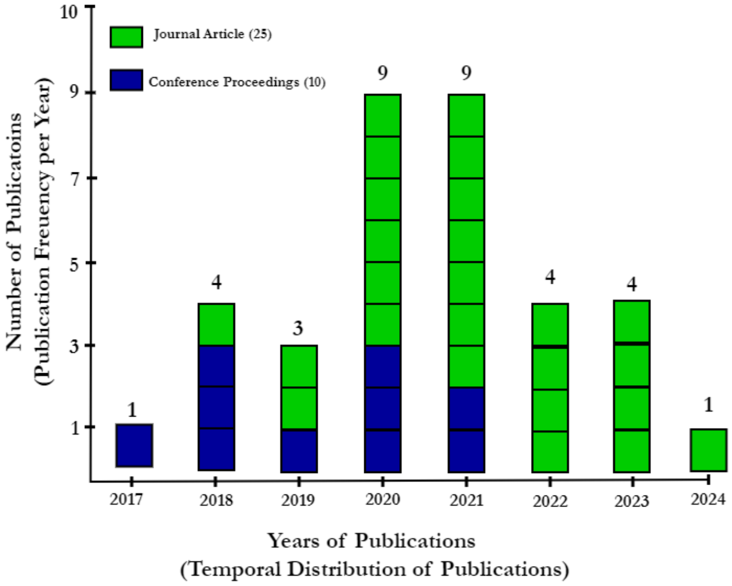


Figure 4.1: Overview of frequency and types of publications.

Table 4.1: Geographic distribution of authors.

Country Name	**Number of Studies**	**Related Studies**
Japan	3	S1, S2, S15
Saudi Arabia	7	S3, S14, S21, S22, S27, S32, S33
India	9	S2, S4, S5, S10, S19, S23, S27, S29, S31
South Korea	2	S6, S29
Malaysia	2	S7, S29
United States of America	11	S7, S8, S10, S11, S17, S20, S24, S27, S29, S33, S34
United Arab Emirates	1	S9
Finland	2	S10, S11

Continued on next page

Country Name	**Number of Studies**	**Related Studies**
United Kingdom	1	S12
China	5	S13, S16, S18, S30, S34
Canada	3	S14, S20, S32
Qatar	4	S7, S10, S25, S35
Australia	3	S9, S26, S29
Norway	1	S28
Vietnam	1	S31
Singapore	1	S2
Bangladesh	1	S15
Belgium	1	S15
Iran	1	S17
Egypt	3	S27, S29, S29
Russia	1	S31
Pakistan	1	S35
Ireland	1	S35

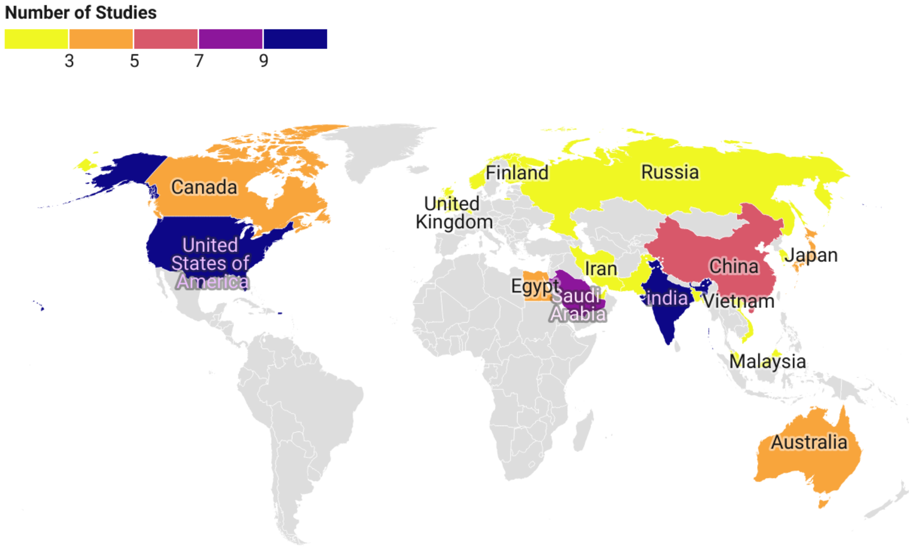


Figure 4.2: Geographic distribution of authors.

Prominent publication forums and types of research (RQ1.2)

The selected publications are classified according to six established research types delineated by Wieringa et al.[WMMR06]: solution proposals, validation research, evaluation studies, philosophical papers, opinion papers, and personal experience papers. The proposed solution articles aim to introduce a novel approach or enhance existing techniques to address pertinent issues, prioritizing conceptual development over validation. Validation research aims to assess the quality attributes of the proposed solution, which has not yet been implemented in requirements engineering practice. Evaluation research assesses a particular problem or resolution in real-world applications by employing various empirical research methods. Philosophical papers endeavor to outline perspectives or conceptual frameworks. Opinion papers express the author's perspectives on the strengths or weaknesses of a specific framework, model, or solution. In personal experience papers, the authors report their own experiences with a particular project(s). The primary focus of these papers is on delineating the actions taken or events experienced ('what'), rather than delving into the underlying reasons or motivations ('why'). The process of thematic analysis aims to address RQ1.2 by categorizing the 35 chosen primary studies according to their research types (as depicted in Fig 4.3). Out of these, we found that 14 papers (40%) were related to proposed solutions, 1 paper (2.86%) presented opinion papers, 1 paper (2.86%) conducted evaluation research, 6 studies (17.14%) focused on validation research, and 2 papers (5.71%) delve into philosophical papers. Additionally, we pinpointed 4 (11.43%) studies that straddle both proposal of solution and validation research categories and 7 (20%) studies that encompass validation research, proposal of solution, and evaluation research. These studies are categorized separately as illustrated in Fig 4.3. We did not identify any papers fitting into the personal experience papers category; hence, it was excluded from the mapping process.

Key Findings of RQ1.2:

Finding 1: Examining the types of published research reveals that solution proposals constitute the most frequent publications. 14 studies (40%) fall into this category.

Finding 2: A notable portion of the articles (6 out of 35, 17.14%) simultaneously cover validation research, proposal solutions, and evaluation research. So, it can be concluded that these articles are of high value.

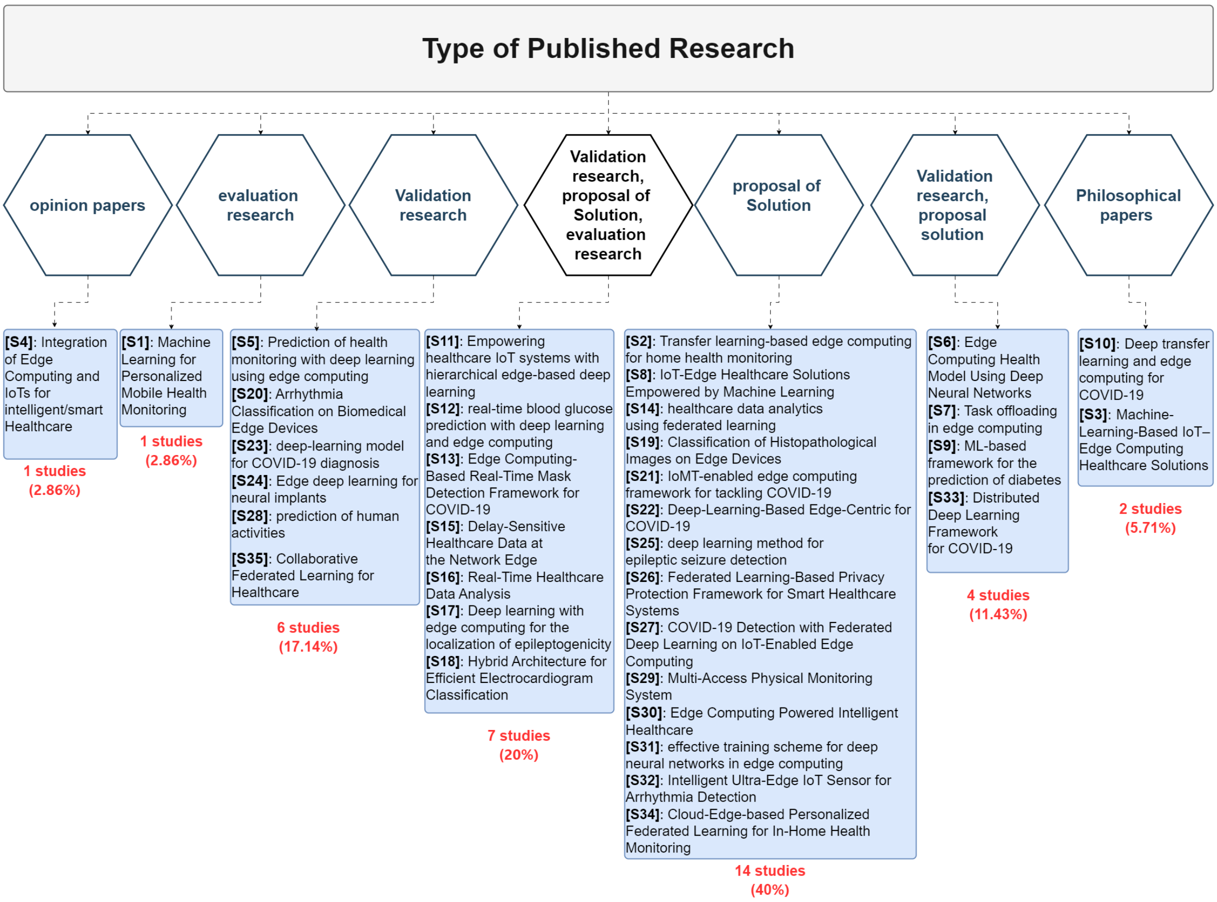


Figure 4.3: Overview of types of research

4.2.2 Exploring Solutions: Themes, Tools, and Challenges

This section analyzes the state of the research, including three research questions (RQ 2.1 – RQ 2.3).

Prevalent Research Themes(RQ2.1)

In this part, we focus on the results for RQ 2.1, which addresses the question: What are the prevalent research themes in edge computing applications within healthcare using ML techniques?

To understand how all the existing research fits together, we first examined individual studies to uncover the main themes using a method called thematic analysis [Boy98]. We then organized these themes into a taxonomy, which is illustrated in Fig 4.4.

By reviewing some relevant studies [MT00] [AB16], and following guidelines from the ACM Computing Classification System [1] and the Computing Research Repository [2], we decided to classify them into two categories:

1. **Generic Classification.** It categorizes the reviewed studies into the following six distinct areas:
   - I) Applications and Solutions;
   - II) Techniques and Architectures;
   - III) Integration and Platforms;
   - IV) Specific Healthcare Challenges;
   - V) Frameworks and Methods;
   - VI) Privacy and Security.
2. **Thematic Classification.** It extends the generic classification by adding details that are based on the main focus of research in related studies. It uses thematic analysis to identify and represent common research themes [Boy98]. The thematic Classification is as follows:
   - I) Applications and Solutions: 11 studies, i.e., 28.95%;
   - II) Techniques and Architectures: 8 studies, i.e., 21.05%;
   - III) Integration and Platforms: 6 studies, i.e., 15.79%;

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[1] http://www.acm.org/ about/class/1998/

[2] http://arxiv.org/corr/home

IV) Specific Healthcare Challenges: 5 studies i.e., 13.16%;

V) Frameworks and Methods: 5 studies i.e., 13.16%;

VI) Privacy and Security: 3 studies i.e., 7.86%.

Overlapping themes: If a study's contributions were pertinent to more than one (sub-) theme, it could be categorized into multiple themes or sub-themes in the taxonomy (see Fig 4.4). Our primary studies are 35, but here we have 38 sub-themes because some of the studies overlapped and we divided them into more than one category.

Key Findings of RQ2.1:

Finding 1: The Sunburst chart in Figure 4.4 illustrates the taxonomy divided into the above-mentioned six theme categories.

Finding 2: The taxonomy reveals that privacy and security are critical considerations in the deployment of ML and DL methods in edge computing for healthcare, emphasizing the need for robust frameworks and methodologies to protect sensitive health data.

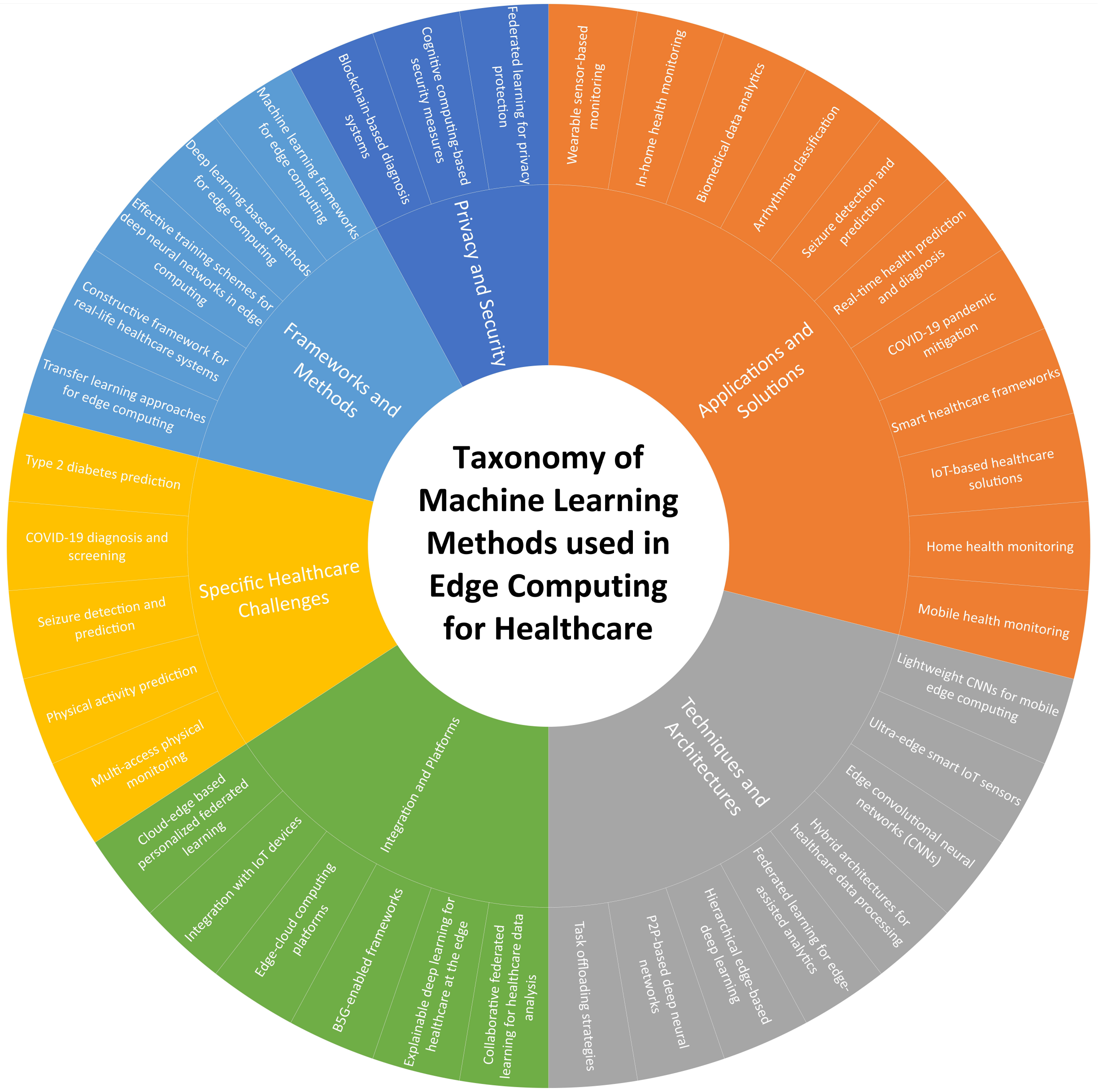

Figure 4.4: A taxonomy of research themes on edge computing in healthcare using machine learning.

Motivations and Implementation challenges (RQ2.2)

By reviewing the selected studies, we could list the motivations and the challenges encountered in each research endeavor, as depicted in Table 4.2 The subsequent analysis led to the categorization of the challenges into six distinct domains, as depicted in Figure 4.5.

The identified challenges are defined as follows:

- Algorithm and Data Processing: Edge computing in healthcare creates challenges in terms of algorithms and data processing. Unlike the more traditional centralized systems, edge computing occurs right where the data is generated, often at a medical device or sensor with limited processing power. That means the algorithms have to be powerful enough to handle real-time data processing to make quick, at-point decisions. The data involved is varied(everything from medical images and sensor readings to patient records), so the system needs to be able to efficiently merge and analyze all these different types of information.

- Resource and Computational Efficiency: Resource challenges in edge computing within healthcare are significant due to the increasing reliance on wireless telemedicine solutions and IoT technologies in Smart Hospitals [KHO$^+$23] [BSM$^+$23]. A critical decision in edge computing integration to the healthcare sector is related to how much processing has to be done at the edge and how much at the central cloud servers to meet real-time requirements efficiently. This further constrains edge computing resources and necessitates the intelligent scheduling of ultra-low-latency tasks for running at the edge. The remaining less time-critical tasks are offloaded to remote servers in a context that achieves optimal resource utilization while reducing dropping rates. This presents one of the biggest challenges in developing machine learning-based solutions to enhance resource efficiency required by healthcare edge computing while satisfying strict QoS demands [KHO$^+$23] [BSM$^+$23].

- Privacy and Security: Privacy and security issues within edge computing in healthcare are huge because health data is so sensitive, and protecting patient information should be paramount. Various research papers [GM23] [AA23] [WLZ$^+$22] [RME23] [GMLMS23], have discussed the integration of machine learning into healthcare systems which raised concerns about the privacy and security of data. Edge intelligent computing in the Internet of Medical Things ensures high efficiency but suffers from privacy disclosure and limited computational power [WLZ$^+$22]. As an example, to address these challenges, Privacy Protection Schemes for Federated Learning under edge computing (PPFLEC) have been proposed, which use methods like lightweight privacy protection protocols and digital signatures to ensure data integrity and confidentiality while maintaining efficiency [WLZ$^+$22].

- Real-time and Latency Concerns: In edge computing analysis takes place near the data origin such as mobile health trackers, and hospital devices, and reduces the time needed to send the data to the cloud servers [SDV$^+$23]. Such swift processing is critical for applications such as remote patient monitoring, procedures that require quick analysis so that timely decisions can be made to save the patient's life, and robotic surgery, which must make quick decisions. Elimination of delay helps to respond to emergencies in health and make correct diagnoses with the help of current information as well as develop the quality of patient care. Thus, having lower latency in edge computing is essential to increase the responsiveness, efficiency, and reliability of healthcare services [YPE22] [CAB22].

- Data Heterogeneity and Communication: Data communications is an important challenge in edge computing for healthcare. data quality is important because the data has to be accurate and free from error. The implementation of IoT, ML, and DL in the enhancement of healthcare calls for a harmonized structure to facilitate the transfer of data as a means of enhancing the time taken to make sound decisions [MBL23]. As more data is generated by medical sensors the data transfer and processing becomes crucial to prevent network issues and provide fast results [AA23].
- Other Challenges: Several other challenges are faced when applying machine learning in edge computing for healthcare. For instance, we need to ensure that all the considered system backgrounds scale, enhance device collaborations, and keep everything updated. Other concerns include preserving good data quality while channels of energy and resources are saved by efficiently utilizing them. We also need to update machine learning models and ensure strong connections.

  We are also expected to comply with regulations, take ethical considerations into account, provide integration with legacy systems, support multiple environments, control costs, plan disaster recovery, and implement solution customization for special requirements.

Key Findings of RQ2.2:

Finding 1: The challenges are categorized into six categories: Algorithm and Data Processing: Resource and Computational Efficiency, Privacy and Security, Real-time and Latency Concerns, Data Heterogeneity and Communication, and Other Challenges.

Finding 2: As depicted in Figure 4.5, over a quarter of the challenges identified in the selected studies were associated with security concerns.

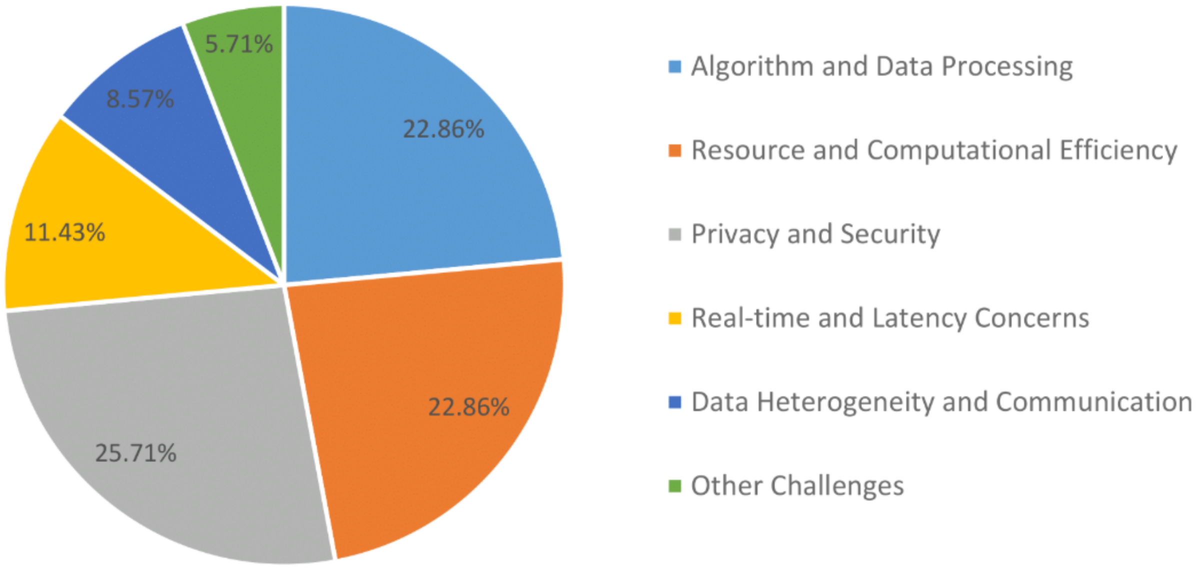

Figure 4.5: List of challenges

Table 4.2: Motivation and Challenges

Study ID	Motivation	Challenges
S1	Detecting and improving of the predictability accuracy in mobile health monitoring	Algorithm Selection, Data Preprocessing, ECG Classification
S2	Overcome infrastructure challenges, accommodate the needs of an aging population, limitations of centralized computing, privacy and real-time processing	Reduce the computing resources required for on-site visual computing at an Edge Device

Continued on next page

Study ID	Motivation	Challenges
S3	Enhanced Patient Monitoring and Care, Improved Treatment Plans and Medication management, Preventive Healthcare and Disease Detection, Remote Care for the Elderly, Cost Reduction and Improved Efficiency	Effective management and analysis of large volumes of data generated by medical sensors in a body sensor network, identifying data anomalies, optimizing real-time response and data transfer efficiency, Privacy and security
S4	Addressing the limitations of traditional cloud computing for real-time applications	Handling Massive Data Volume, Real-time Responsiveness Optimization, Decentralization of Computation, Power Consumption Optimization
S5	Fast response times, high bandwidth utilization during data transmission	Latency and Response Time, Mobility, Data Transmission Costs, Security and Privacy
S6	Improve data fitness, response speed	Computation Costs, Network Load, Time Delay
S7	Efficient task-offloading strategies and the role of middleware entities in optimizing system performance.	Challenges in indoor scenarios: Inaccessibility in Hard-to-Reach Area, Detection Without Phone Presence or Sound, Dependence on Triggers and Confirmation, Dumb/Mute Individuals. Challenges in outdoor scenarios: Limitations of Internal Triggers, Facial Recognition and CCTV Coverage, Detecting Kidnappings and Abductions, Intelligent Detection of Unusual Situations
S8	Identify pertinent data signatures	Volume of Data, Computational Tasks and Backend Systems, Battery Drain and Security
S9	Analyzes diabetes risk factors	Diabetes Risk Factors

Continued on next page

Study ID	**Motivation**	**Challenges**
S10	Addressing the challenges posed by pandemics like COVID-19	Shortage of Reliable Datasets, Variety of Data, High Computational Resources
S11	Ensuring high-level availability and accuracy, system performance, response time	Limitation of computational capacity
S12	Enhance the management of Type 1 Diabetes	Computational constraints, memory limit, security and privacy, data transmission, task offloading, limited capacity of batteries
S13	Leveraging the edge computing technology to develop practical solutions for mitigating the spread of COVID-19	Blur problems from low-cost cameras
S14	Data privacy in healthcare data	Cyberattacks, Data Bias, Constrained Nature of Edge Devices, Acceptance of Technology
S15	The necessity and benefits of transitioning from cloud-based analytics paradigms to IoT edge analytics	Delay-sensitive data, the difficulty of achieving near real-time analytics for delay-sensitive healthcare data within the conventional cloud-based analytics paradigm
S16	Addressing the privacy concerns	Delay, Network I/O, Cost, Privacy, High Availability
S17	Explore and develop advanced technologies like brain-computer interface (BCI) to provide effective treatment options for epilepsy patients	Differentiation Among Brain States, Learning from patient data to optimize the autonomic system in real-time, Transferring knowledge from neurologists to the autonomic computing system, Self-Mechanism for Detection and Response, Robustness

Continued on next page

Study ID	Motivation	Challenges
S18	Data enhancement for ECG data	Data imbalance, power consumption
S19	Histopathological image classification in breast cancer diagnosis	Limited memory, computation power, bandwidth
S20	Decision-making capability into resource-constrained sensors	Time complexity
S21	Capturing psychological, emotional, and physiological states through an edge IoMT system	User data privacy, security, low-latency
S22	Guaranteeing the secure transmission of data at the edge through blockchain	Data Privacy and Security
S23	Remote COVID-19 diagnosis using chest CT scan images with minimum latency	Storage issues, resource constraints, overfitting problem with limited data
S24	Real-time seizure detection	Resource constraints, Model Optimization
S25	Develop a smart healthcare system for epileptic seizure detection	Reducing the size of the data being sent to the cloud
S26	Privacy protection	Privacy Attacks and Manipulation, Centralized Server Vulnerabilities, Data Traffic and Congestion
S27	Reduction of transmission costs through federated learning	Storage costs, network traffic
S28	Monitor human behaviors and predict activities	Data Handling, Privacy Concerns

Continued on next page

Study ID	Motivation	Challenges
S29	Develop a physical monitoring system	Data privacy
S30	addressing the limitations of cloud-based architecture in healthcare systems, specifically focusing on issues such as data syncing, scalability, and device latency	Robust algorithms, Standardized datasets, Scalable architectures, and Rigorous evaluation.
S31	Enable efficient collection and processing of data to support prompt decision-making	Time complexity and latency
S32	Enhancing the ultra-edge IoT sensors	Analytics Delay, Bandwidth Consumption, Privacy Concerns, Secure real-time ECG monitoring
S33	Using DL algorithms and B5G networks instead of doing manual tests	Adversarial attacks, Data Privacy and Security
S34	Limitations of existing approaches to in-home health monitoring especially in user data privacy	Statistical and communication challenges inherent in federated learning, degraded accuracy, overfitting with a few data samples, imbalanced data
S35	Using a collaborative learning paradigm without sharing local data	Resource scarcity and heterogeneity, network communication, data heterogeneity, statistical heterogeneity, privacy and security, adversarial ML

Common Tools, Frameworks, Software, and Technologies (RQ2.3)

RQ2.3 was designed to identify the set of tools and frameworks used to support Machine Learning applications in the selected literature. During our examination of the selected primary studies, we observed that only a portion (n = 4, 11.43%) of studies is based on custom tools or developed frameworks (see Table 4.3). We specifically considered executable frameworks. The source type classification denotes whether the tools are open-source (OS) or closed-source (CS). Open source means that the people who own the copyright allow others to check, use, or change the tool, framework, or system. The number of tools and frameworks is also shown in Figure 4.6. According to this figure, we can say that Tensorflow is one of the most popular tools.

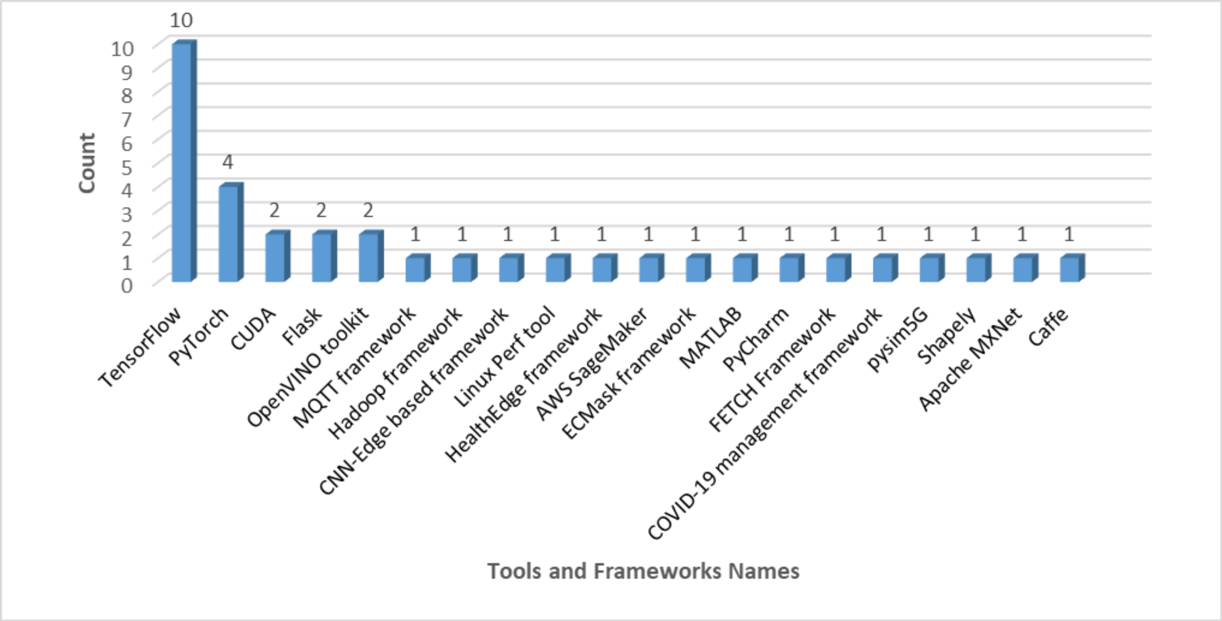

Figure 4.6: Frequency analysis of tools and frameworks names

Key Findings of RQ2.3:

Finding 1: We observed that the TensorFlow tool was used in ten studies. This software has become a widely used software.

Finding 2: The data presented in Table 4.3 highlights the widespread adoption of open-source software, including well-known platforms/tools such as TensorFlow, PyTorch, and OpenVINO, within research studies.

Table 4.3: List of identified tools

Study ID	**Tool/Framework**	**Source Type**	**Type of Tool/Framework**	**Main Aim/Focus/-Support**
S4	MQTT framework	Open-Source	Existing	Implementation
S4	Hadoop framework	Open-Source	Existing	Implementation
S4	TensorFlow	Open-Source	Existing	Implementation
S5	CNN-Edge based framework	Close-Source	Custom	Transferring information from IoT devices to the doctors
S7	Linux Perf tool	Open-Source	Existing	Computing the number of CPU cycles required by the execution of each algorithm
S9	HeatlhEdge framework	Close-Source	Custom	Diabetes prediction
S12	AWS SageMaker	Open-Source	Existing	Deploying the deep learning models in the cloud
S12	TensorFlow	Open-Source	Existing	Deploying the deep learning models
S13	ECMask framework	Close-Source	Existing	Identifying the condition of mask-wearing

Continued on next page

Study ID	**Tool/Framework**	**Source Type**	**Type of Tool/Framework**	**Main Aim/Focus/-Support**
S13	OpenVINO toolkit	Open-Source	Existing	Model Optimization, Inference Engine, Distributed Computing
S13	PyTorch	Open-Source	Existing	Implementation
S13	CUDA	Open-Source	Existing	Implementation
S15	TensorFlow	Open-Source	Existing	Performance Evaluation
S18	TensorFlow	Open-Source	Existing	Data Training
S19	TensorFlow	Open-Source	Existing	Implementation (execution time, maximum memory consumption)
S21	TensorFlow	Open-Source	Existing	Data Training
S21	PyTorch	Open-Source	Existing	Data Training
S21	Flask Server	Open-Source	Existing	Deployment (docker container)
S21	CUDA	Open-Source	Existing	To access the GPU over the container
S23	TensorFlow	Open-Source	Existing	Implementation (fine-tuning the model in terms of its size and latency)

Continued on next page

Study ID	Tool/Framework	Source Type	Type of Tool/Framework	Main Aim/Focus/Support
S24	MATLAB	Close-Source	Existing	Data Handling
S24	TensorFlow	Open-Source	Existing	Data Training
S26	PyTorch	Open-Source	Existing	Development
S26	PyCharm	Open-Source	Existing	Development
S30	FETCH Framework	Close-Source	Custom	automated diagnosis
S33	COVID-19 management framework	Close-Source	Custom	Testing
S33	pysim5G	Open-Source	Existing	Implementation
S33	Shapely	Open-Source	Existing	Implementation
S33	flask	Open-Source	Existing	Implementation
S33	TensorFlow	Open-Source	Existing	Testing
S33	PyTorch	Open-Source	Existing	Testing
S33	Apache MXNet	Open-Source	Existing	Testing
S33	Caffe	Open-Source	Existing	Testing

Continued on next page

Study ID	Tool/Framework	Source Type	Type of Tool/Framework	Main Aim/Focus/-Support
S33	OpenVino toolkit	Open-Source	Existing	Testing
S35	TensorFlow	Open-Source	Existing	Implementation

4.2.3 Architecture, Implementation, and Data Sources

Where is the processing performed? (RQ3.1)

Research Question 3.1 (RQ3.1) aims to pinpoint where processing tasks are executed within the system. This information is very useful for determining how and to what extent computational loads are processed and how effectively the utilization of system resources is done. Knowing the place where the processing is occurring will allow us to know more about the internal structure of the system and allow for improvements in efficiency and potential areas of the system that need enhancement. The findings for this research question are illustrated in the following Table 4.4. based on the table 4.4, we decide to visualize the tasks in a wordcloud for edge, cloud, and fog. The wordcloud of cloud, edge, and fog are presented in figure 4.7,figure 4.8 and Figure 4.9. Tasks that appear more frequently in the table are displayed in a larger size in the wordcloud.

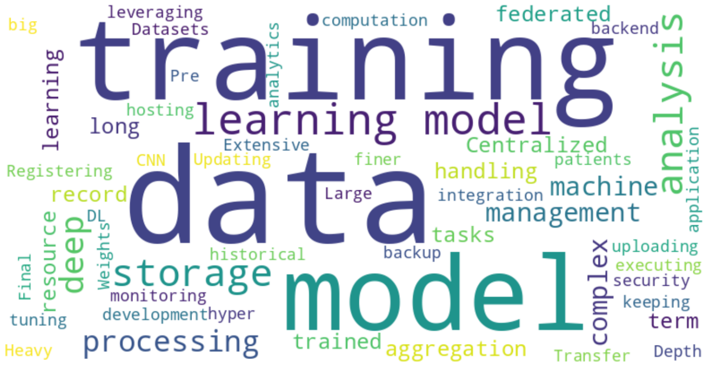

Figure 4.7: Wordcloud of cloud tasks

Figure 4.7 Focuses on keywords including “data”, “model”, and “training”. This shows the importance of using the cloud to train the machine learning models.

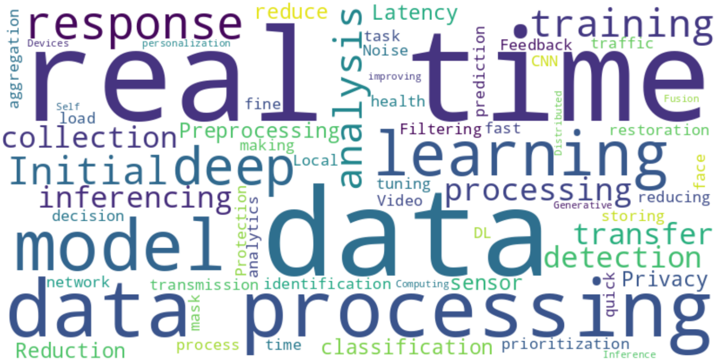

Figure 4.8: Wordcloud of edge tasks

Figure 4.8 emphasizes key tasks and concepts in data processing and real-time analytics. Frequent terms like “data processing”, “real-time analysis”, “model training”, and “deep learning” highlight the importance of handling and analyzing data swiftly and effectively. Notable themes include privacy protection, reducing latency, and improving response times, reflecting a focus on both performance and security in data-driven tasks. Additionally, the repetition of terms related to initial data processing, inferencing, and decision-making indicates their critical role in the overall workflow.

Figure 4.9: Wordcloud of fog tasks

Figure 4.9 showcases a range of tasks centered on data management and processing. Prominent terms such as “Data preprocessing”, “preparing data”, and “Data quality checks” indicate a strong emphasis on ensuring data integrity and readiness for analysis. The appearance of “Dynamic allocation”, “real-time interaction”, and “Fast Response” suggests a focus on adaptability and timely processing. Security and privacy are also highlighted, underscoring their importance in handling data. Overall, the word cloud reflects a comprehensive approach to data handling, emphasizing both preparation and real-time responsiveness.

Key Findings of RQ3.1:

Finding 1: Many studies show a clear division of tasks between edge and cloud computing. Edge devices handle real-time data processing, inferencing, and local decision-making, while cloud computing takes care of model training, complex data analysis, and long-term data storage. For example, S2 uses edge devices for real-time inferencing and the cloud for training deep learning models.

Finding 2: Several studies highlight the integration of IoT devices with edge and cloud computing. Typically, IoT devices gather data, which is then processed at the edge for immediate tasks, with the cloud handling long-term storage and intricate analysis. For example, S9 illustrates how IoT devices collect data from medical sensors, which are processed by edge servers and analyzed in the cloud.

Table 4.4: Data Processing Location

Study ID	Where is the processing performed (edge, fog, cloud)?
S1	**Edge Devices** (data preprocessing, activity prediction, and real-time inferencing)
S2	**Edge Devices** (data processing, real-time inferencing), **Cloud** (initial training of deep learning models)
S3	**Edge Devices** (Data processing, real-time inferencing, privacy preservation, and real-time DDoS attack prediction), **Cloud** (Initial training of machine learning models, backend data analysis, and providing recommendations to edge devices)
S4	**Edge devices** (real-time responses and data prioritization), **Cloud** (initial training of model)

Continued on next page

Study ID	Where is the processing performed (edge, fog, cloud)?
S5	**Edge** (Data processing and transmission, fast response times, timely health-prediction reports), **Fog** (dynamic allocation for real-time interaction), **Cloud** (data storage and long-term analytics)
S6	**Edge devices** (data processing and real-time inferencing using P2P-based deep neural network model), **Central server** (gathering results and providing them to users)
S7	**Edge** (Initial data collection), **Fog** (data trimming, Data quality checks, preprocessing, security, privacy measures, and preparing data for doctors' feedback), **Cloud** (Management of the overall system, real-time resource monitoring, historical record-keeping, identity management, and handling complex data processing tasks)
S8	**Edge devices** (Data processing and real-time inferencing using machine learning algorithms), **Cloud** (extensive data analysis and storage, leveraging machine learning models on backend servers to identify relevant data signatures)
S9	**IoT Devices** (Data collection from medical sensors and devices), **Edge Servers** (Transformation of the collected data into a structured format, data preprocessing, removal of missing values, data transformation), **Cloud** (Machine learning model development, hyper-parameter tuning, model training)
S10	**Edge devices** (equipped with deep transfer learning models), **Cloud** (training the deep learning models)
S11	**Edge** (local decision-making task), **Cloud** (heavy computation tasks, training the deep learning models, complex data analysis)
S12	**Edge** (real-time blood glucose prediction and hypoglycemia detection), **Cloud platform** (model training and data backup)
S13	**Edge nodes** (model training, real-time video analysis), **Edge Devices** (video restoration, face detection, mask identification), **Edge server** (model training)

Continued on next page

Study ID	Where is the processing performed (edge, fog, cloud)?
S14	**Cloud Module** (registering patients, maintaining the database, and uploading trained models to the Cloud), **Edge Module** (improve the overall learning process of the global model, storing data samples from end-user devices, aggregation), **Application Module** (supporting)
S15	**Edge devices** (Performing the deep learning-based processing at the access point of the user's residence)
S16	**IoT device layer** (Data Collection, Data Transmission), **Edge Devices** (deep learning, real-time Processing, Data Filtering and Preprocessing, Latency Reduction, Privacy Protection), **cloud platform layer** (In-Depth Analysis, Data Storage), **third-party service layer** (Extended Services)
S17	**Edge** (preprocessing), **Cloud** (storing patients' long-term medical records and executing data processing tasks that require significant computational power)
S18	**EIOT layer** (Data Collection), **Edge Layer** (computing tasks), **Cloud layer** (long-term big data processing and analysis), **third-party service** (User Data Management)
S19	**Edge devices** (real-time histopathological image classification)
S20	**Cloud** (The training phase of the CNN model), **Edge devices** (The execution of the trained CNN model)
S21	**Edge devices** (data processing and real-time inferencing), **Cloud** (initial training of deep learning models)
S22	**Edge** (Initial data processing, real-time analysis, and fine-tuning of DL models with local data), **Cloud** (Centralized training of DL models using a large dataset from various hospitals, global data storage, and finer analysis and integration of data across different edge nodes)
S23	**Edge layer** (initial data processing and classification, providing quick responses and reducing data traffic), **Cloud layer** (performs more complex, centralized tasks such as data storage, model updates, and resource management)

Continued on next page

Study ID	**Where is the processing performed (edge, fog, cloud)?**
S24	**Edge Layer** (Initial processing and classification of data)
S25	**Edge** (initial data processing and real-time analytics to reduce latency and network load), **Cloud** (deep learning model training, data storage, and centralized analysis)
S26	**Edge** (Initial data processing, model training, and adding privacy-preserving noise), **Fog** (handle aggregation and preliminary analysis), **Cloud** (Final aggregation, complex analysis, and overall coordination of the federated learning models)
S27	**IoT devices** (capture patient data), **Cloud** (Federated Learning)
S28	**Edge Devices** (processing the healthcare sensor data with GPU)
S29	**Edge** (Data Processing, Real-Time Data Analysis, Noise Reduction), **Cloud** (Data Storage, Handling Large Datasets)
S30	**Edge Computing** (Data Collection, Initial Processing, Real-Time Feedback),**Fog Computing** (data preprocessing, remove noise), **Cloud Server** (data storage, data processing, application hosting, resource management, and security)
S31	**Edge** (Preprocessing, classification)
S32	**Edge** (data processing)
S33	**edge nodes** (Running the local deep learning (DL) models), **Cloud** (Running the global deep learning model)
S34	**Edge Devices** (Local data processing, model training, and personalization), **Cloud** (initial training of the global model), **cloud server** (updating the global model)
S35	**Edge** (Inference, Sensor Fusion, Self-improving Devices, Transfer Learning, Generative Models, Decentralized Distributed Computing), **Cloud** (Weights Aggregation and Updates, Pre-trained Models and Transfer Learning), **Fog** (Fast Response, Addressing Quality of Service)

Do applications effectively exploit the resources of IoT, edge, and cloud seamlessly? (RQ3.2)

The answer to this question is yes. The considered applications do use the resources of IoT, edge, and cloud without any problems, in a seamless manner. It is a unique feature that enables the system to allow the best form of integration, performance, efficiency, and scalability. Hence, applications can perform data analytics at the edge for immediate responses, IoT devices for data gathering and transferring, and the cloud for large-scale data storage, complex analysis, and centralized management.

IoT devices also fit and integrate into this ecosystem offering the advantage of continuous data collection, and the first processing of the data. This seamless interaction between IoT, edge, and cloud resources can guarantee the system's performance.

Another question that arises here and needs to be examined is whether it is correct to say that edge computing is used for performing part of the computations and the cloud is used for data analysis or integration.

We answer this question by reviewing all the articles and determining what role edge computing and cloud computing play in them, as captured in Table 4.4. the answer to this question is yes because in most studies edge computing is used for computing and the cloud is used for data analysis. For instance, in S5, in Table 4.4, the Cloud plays the role in long-term analytics and data storage, with Edge handling data processing, response time, and health prediction reports on time. The authors of S4 propose some computations, especially data prioritization at the IoT device level, are performed via edge computing. On the other hand, heavy computation and finer analysis are the main uses of the cloud. You can also look at S3, S8, and S22 for further examples.

In terms of execution, a question arises: are applications typically executed entirely on cloud resources? Based on a review of the selected studies, the answer is generally no. As illustrated in Table 4.4, most of the articles describe using a combination of cloud and edge computing for execution.

As for the implementation, a question would be: Are applications typically executed entirely at cloud resources? The answer to this, based on the review of selected studies, would generally be no. As can be seen in Table 4.4, most articles describe a combination of cloud and edge computing for execution.

Key Findings of RQ3.2:

Finding 1: Applications typically do not execute entirely on cloud resources. According to the majority of selected studies, a combination of cloud and edge computing is commonly used for execution.

Finding 2: Applications seamlessly use IoT, edge, and cloud resources, which allows for optimal integration, performance, efficiency, and scalability.

Do applications use a single or multiple data source?(RQ3.3)

Research Question 3.3, in the context of our study: Is it true that all of these reviewed applications use a single data source? The given research question is very important for understanding the complexity level of an application and the corresponding data integration strategies. In addition, being able to use more than one data source might indicate a higher degree of interoperability among different subsystems and could suggest more rigorous data handling within an application. This question based on the research is answered to bring out an in-depth analysis focused on their data source. We checked on various things, such as the types of sources of data, the type of data, and even the name given to the dataset. The results of the analysis are presented in Table 4.5. The results are presented in tabular form to make them easier to visualize, compare, and interpret.

Key Findings of RQ3.3:

Finding 1: The majority of the studies (15 out of 35) use signal data as their primary data type. Image data is the second most common (9 studies), followed by a few that use video, tabular, or a combination of these types.

Finding 2: Many studies rely on well-known and publicly available datasets such as the MIT-BIH databases (used in multiple studies like S11, S15, S18, S20, S24, S32).

Finding 3: A significant number of studies (13 out of 35) utilize data from a single source. The remaining 15 studies use multiple data sources.

Finding 4: Several studies (S3, S4, S8, S10, S14) do not provide specific information about their datasets, indicating gaps in data reporting. This lack of detail could affect the transparency of the research.

Table 4.5: Data Source Analysis for selected studies

Study ID	**Dataset Name**	**Data Type**	**Single Data Source or Multiple Data Source**
S1	ECG dataset, Multi-modal sensors	Signal	Multiple Data Source

Continued on next page

Study ID	**Dataset Name**	**Data Type**	**Single Data Source or Multiple Data Source**
S2	Sensors Data	Image, video	Single Data Source
S3	N/A	N/A	N/A
S4	N/A	N/A	N/A
S5	Real dataset	Image	Single Data Source
S6	Sensors Data	Signal	Single Data Source
S7	PAMAP2 dataset	Signal	Single Data Source
S8	Transaction Data	N/A	N/A
S9	PIMA Indian, Sylhet	Tabular Data	Multiple Data Source
S10	N/A	N/A	N/A
S11	MIT Arrhythmia dataset	Signal	Single Data Source
S12	OhIOT1DM dataset, ABC4D dataset, ARISES data set	Signal	Multiple Data Source
S13	Bus drive monitoring dataset, FDDB data set, WIDER FACE data set	Video	Multiple Data Source
S14	N/A	N/A	N/A
S15	MIT-BIH database	Signal	Single Data Source
S16	ECG DataSet	Signal	Single Data Source
S17	ECoG dataset, rs-fMRI data	Signal, image	Multiple Data Source
S18	PhysioNet/CinC2017, MIT-BIH dataset	Signal	Multiple Data Source

Continued on next page

Study ID	**Dataset Name**	**Data Type**	**Single Data Source or Multiple Data Source**
S19	BreakHis dataset	Image	Single Data Source
S20	MIT-BIH Supraventricular Arrhythmia database, MIT-BIH repository, INCART 12-lead Arrhythmia database, Sudden Cardiac Death Holter Database	Signal	Multiple Data Source
S21	Tufts Face Database, EEG Brainwave Dataset: Feeling Emotions, EEG brainwave dataset: mental state	Signal	Multiple Data Source
S22	Chest X-ray images	Image	Single Data Source
S23	SARS-CoV-2 CT-scan dataset, ImageNet dataset	Image	Multiple Data Source
S24	CHB-MIT database	Signal	Single Data Source
S25	EEG signals dataset	Signal	Single Data Source
S26	MNIST database, CIFAR10 dataset, STL10 dataset, COVID19 Chest X-RAY image dataset	Image	Multiple Data Source
S27	COVIDx dataset, CXR dataset	Image	Multiple Data Source
S28	MHEALTH dataset	Signal	Single Data Source
S29	IoT sensor datasets	Signal	Single Data Source
S30	ECG data and wearable sensor data	Signal	Multiple Data Source

Continued on next page

Study ID	Dataset Name	Data Type	Single Data Source or Multiple Data Source
S31	UCI repository data, IoMT devices data	x	Multiple Data Source
S32	MIT-BIH, St Petersburg INCART 12-lead Arrhythmia Database	Signal	Multiple Data Source
S33	Collected datasets	Image	Multiple Data Source
S34	MobiAct dataset, generated class-balanced dataset	Signal	Multiple Data Source
S35	Chest X-ray Dataset, chest ultrasound images dataset	Image, video-based image	Multiple Data Source

4.2.4 Emerging and future trends

Emerging trends and Potential future dimensions (RQ4.1)

Research Question 4.1 will examine the dimensions of future research directions in the scope of each study. To answer this research question, we decided to deeply analyze each study and attempt to identify the future work of each study as illustrated in Table 4.6.

Key Findings of RQ4.1:

Finding 1: Several studies (S3, S8, S9) emphasize the importance of enhancing real-time systems and exploring various deep-learning models. This focus aims to improve the efficiency and accuracy of edge computing applications, particularly in real-time data processing and analytics.

Finding 2: Studies such as S12, S17, and S33 focus on the healthcare domain, aiming to validate and deploy algorithms in real clinical trials. These studies plan to enhance the accuracy of monitoring and diagnosing patients, especially in remote locations, by using wearable devices and advanced deep-learning models.

Table 4.6: Future Work of Selected Studies

Study ID	What is the Future Dimension / Future Work of Selected Studies?
S1	Developing a framework on data semantization for intelligent edge analytics
S2	Simulation study, conducting a pilot study using the proposed method with the creation of a dataset and the analysis of the data, improving home health monitoring by integrating visual sensor-based monitoring with ambient sensors
S3	Working on real-time systems and deep learning models
S4	Examine multiple IoT edge servers including their interactions with one another and with the End Point devices
S5	Apply the proposed mechanism to large datasets, utilize alternative deep learning models to enhance accuracy and reduce classification costs, implementing and refining mobile edge computing offloading frameworks to handle large volumes of patient data
S6	Scaling up for practical applications, collecting data with peaceful condition
S7	N/A
S8	Investigating real-time systems and deep learning models to bolster efficiency
S9	Explore a diverse range of machine learning and deep learning algorithms to evaluate the proposed system
S10	Running the model with real data, adding an optimized sensor networking protocol to efficiently connect edge devices with the cloud server, employing the EC-Fog-Cloud integrated model for transfer learning, training a deep learning model on a cloud server for feature extraction, a novel simulation model for experimental studies

Continued on next page

Study ID	What is the Future Dimension / Future Work of Selected Studies?
S11	N/A
S12	Evaluating the wearable device with the proposed algorithm in real clinical trials, deploying the prediction algorithm in other T1D IoMT wearable devices
S13	N/A
S14	N/A
S15	N/A
S16	Developing an open platform that can be deployed on edge devices, creating a comprehensive service ecosystem
S17	Enhancing and expanding the suggested methodologies using historical patient medical records to facilitate more informed decision-making, exploring a wide range of neurological disorders (sleep disorders, coma, encephalopathies, and brain necrosis) to establish a comprehensive neurological disorder system, utilizing a suitable stimulation signal to stop an impending seizure, enhancing the autonomic loop through responsive neurostimulation signals, developing a system that utilizes additional vital biosignals beyond EEG and involves processing multiple models to estimate various neurological diseases in real-time
S18	Further investigating the representation of ECGs' medical morphological features while taking into account the complexity and diversity of waveforms associated with various heart diseases, enhancing data augmentation techniques to improve diagnostic accuracy across all ECG categories, incorporating individual differences into the model
S19	Developing a robust algorithm for histopathological image classification (HIC) by considering each component's computational costs and energy consumption, adapting the proposed framework to address the multiclass problem by developing a more reliable membership function
S20	N/A
S21	Improving the accuracy of each application, clinical trials

Continued on next page

Study ID	What is the Future Dimension / Future Work of Selected Studies?
S22	Implementing mobile deep learning models to decrease the number of weights in the model, utilizing parallel processing on edge devices
S23	Identifying the right set of hyperparameters through the use of a genetic algorithm, enhancing the training data through the use of Generative Adversarial Networks (GANs)
S24	N/A
S25	N/A
S26	Developing a fine-grained microservices-based Federated Edge Aggregator
S27	Implementing data offloading and resource management strategies on the IoT-enabled mobile edge computing platform
S28	N/A
S29	Integrating intelligent Internet of Things (IoT) to enhance the device's scalability, alongside employing advanced multimedia methods to mitigate cost factors and privacy concerns
S30	Automation of Diagnosis and Treatment, Integration with Other Healthcare Systems, Optimization of Resource Allocation
S31	Implementing the suggested ETS-DNN model in hospitals for monitoring and diagnosing patients in remote locations
S32	N/A
S33	Collaborating with local hospitals to deploy the model and conduct clinical trials, enhancing the accuracy of deep learning (DL) models to ensure satisfactory clinical trial results, addressing adversarial attacks on deep learning algorithms by developing robust defense mechanisms, developing an efficient deployment model using lightweight containers with B5G-based deep learning algorithms for treating COVID-19
S34	N/A

Continued on next page

Study ID	**What is the Future Dimension / Future Work of Selected Studies?**
S35	Investigating the performance of the clustered federated learning (CFL) under varying data distribution scenarios and specifically focusing on the number of samples per client, addressing the integration of resource heterogeneity at the client level including computational and communication resources, developing federated learning algorithms that can effectively manage the challenges posed by heterogeneous data

Chapter 5

Discussion

This discussion chapter is a critical examination of the findings from the systematic literature review. It aims to examine the findings of the research questions and analyze the selected studies and their results.

First, we explore the contributions of the selected studies, providing an in-depth analysis of their significance. Then, we discuss the results of the research questions, delving into the results and what they mean in the context of our review.

Research in edge computing and machine learning within healthcare presents enormous potential for improvement in the field, considering that real-time, efficient processing with health data security is very important. Some of the early research, like Hosseini et al. [HTP$^+$17] or Kumar et al. [KM18], showed that edge computing has very rich potential for reducing latency and increasing data privacy. Hosseini et al. [HTP$^+$17] worked on localizing the epileptogenic zone using a framework of mobile edge clouds. They indicated that edge computing has certain advantages over regular cloud systems.

In the subsequent years, the applications and methodologies spread drastically. For instance, hierarchical edge architectures have been designed by Azimi et al. [ATMA$^+$18], while Fadlullah et al. [FPG18] focused on deep learning-based edge architectures for solving challenging problems related to remote health monitoring and healthcare data analytics. They have presented efficient and accurate solutions to deal with massive volumes of health data. HiCH, Azimi's hierarchical computing system, improved the performance of the deployment of deep learning models, while Fadlullah's case reduced latency issues through local processing. Thereby, both approaches empowered the big difference in response time and reliability of the system.

In 2019, researchers like Ram [RAS19] and Uddin [Udd19]worked on incorporating advanced machine learning algorithms like Random Forest and Recurrent Neural Networks into health monitoring with edge computing. Their studies identified not only improvements to the accuracy and real-time processing but also details about how to make health monitoring systems user-friendly and accessible. A Systems was developed by Jian Yu et al. [YFC$^+$18] and they introduced EdgeCNN also a very recent study conducted by Saqib Hakak et al. [HRKS20] was focused on federated learning which has been a giant trend in edge computing. These top-notch machine learning techniques not only tend to preserve data privacy but also reduce dependence on cloud resources.

During the COVID-19 pandemic, researchers attempt to do research using edge computing to handle health problems. Abu Sufian et al. [SGSS20] and Abdur Rahman et al. [RHAG20]demonstrated how edge computing frameworks could be leveraged for rapid, scalable, and private data processing during pandemics. This study has shown that edge computing is going to increase the responsiveness and efficiency of health systems under unprecedented strain by providing adaptive and resilient frameworks.

Recent studies in 2022 and 2023, such as those by Piyush Gupta et al. [GCW$^+$23]and Taiyu Zhu et al.[ZKD$^+$22] thoroughly examine specific health conditions like diabetes and real-time fall detection to prove that edge computing can be used to meet certain health monitoring needs with ultra-high accuracy and efficiency. consequently, the progress in combining edge computing with machine learning for better health monitoring was highlighted.

One of the aspects of the research questions is aimed at investigating demographic information regarding the published literature. Indeed, the application of edge computing in healthcare(much more with machine learning) revealed the area of research. 77% of the literature was published from the year 2020 to 2024. This increasing trend demonstrates that there are ample advantages involved in integrating edge computing and machine learning into healthcare.

Several key themes of edge computing applications in healthcare were identified in the research. The themes include different applications and solutions, techniques and architectures, integration and platforms, specific healthcare-related challenges, frameworks and methods, privacy, and security. Among the important issues discussed, privacy and security were the most significant. They highlight the need for strong rules to keep health information private and secure. This is crucial because as more health data is generated and managed at the edge, strict privacy measures are essential to ensure data accuracy.

This discussion also looked at the tools and technologies often used in edge computing for healthcare. The selected studies used different tools and platforms for implementation, such as TensorFlow and CUDA.

A Summary of the key findings of this SLR is presented in Table 5.1.

Table 5.1: A Summary of the key findings of this SLR

Research Question	**Key Findings**
Demographic details of published research	
RQ1.1: Types, frequency of published research, and geographic distribution of the authors' affiliations.	**Frequency:** Years of publications = 2017 to 2024 with the most number of publications from 2020 – 2024 (27, 77%). **Types:** Journal articles (25, 63%), Conference proceedings (10, 37%).
RQ1.2: Types of published research	Most studies focused on solution proposals (14 studies, 40% of the total).
Themes, Tools, proposed Solutions, motivations, and challenges	
RQ2.1: Research themes	A taxonomy were presented with six categories.
RQ2.2: Motivations and challenges	The challenges are categorized into six categories: Security was the main challenge.
RQ2.3: Tools and technologies	The TensorFlow tool was used in ten studies and was the most popular.
Architecture, Implementation, and Data Sources	
RQ3.1: Processing	Many studies indicate that edge computing focuses on real-time data processing and decision-making, while cloud computing is responsible for model training, complex analysis, and long-term storage.
RQ3.2: Seamless resource exploitation	Most studies show that applications typically use a mix of cloud and edge computing resources instead of relying solely on the cloud. Applications use IoT, edge, and cloud resources seamlessly.
RQ3.3: Data sources	Out of 35 studies, 13 rely on data from a single source, while the remaining 15 utilize multiple data sources.
Emerging and future trends	
RQ4.1: Future dimensions	Many studies highlight the need to improve real-time systems and investigate different deep learning models.

Chapter 6

Conclusion

This thesis aims to explore how edge computing and machine learning can work together in the domain of healthcare. By reviewing existing studies, this thesis shows that combining these technologies can greatly improve healthcare services. Benefits include faster data processing, better patient monitoring, and improved data security. The review highlights the need to keep developing these technologies to meet healthcare challenges now and in the future.

Our review included nine research questions, which were divided into four sections. We provided answers to the research questions. The responses yielded interesting results, which you can find in the “Key Findings” section for each research question.

The findings of the research show that the frequency of publication of papers in this area, particularly from 2020 to 2024, is growing. With such increases in academic work, there is a clear understanding of the importance of edge computing and machine learning in healthcare.

Despite the promising advancements, by reviewing the selected studies, it became evident that there are numerous challenges in this field. We have categorized these challenges and we recommend that all researchers and developers consider these challenges in their research and projects.

This systematic literature review has provided an overview of the current knowledge, discussed the existing challenges and limitations, as well as outlined recommendations for further research. Thus, the conversation for future research on these premises will improve the present and future picture as well as the theoretical and applied advancements of this subject.

In summary, this study looks at how edge computing and machine learning are used in healthcare. It looks at the kinds of articles written about it, what ideas come up, and the tools and technology people use. It shows how far things have come and what still needs work in this fast-changing field. It shows how important edge computing is for improving healthcare by doing better analysis in real-time, keeping data safe, and using resources well. Future work should keep working on these big problems, especially how to mix edge and cloud systems and keep health data safe.

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Appendix A

Selected Studies

When we talk about how prestigious academic publications are, it's really important to understand what criteria we're using to rank them. One big factor is the journal's impact factor. This factor tells us how influential the journal is in its field. We also use something called quartile classification to organize journals into different tiers based on their prestige. So, there are four tiers: Q1, Q2, Q3, and Q4. Q1 is like the top tier; it includes the most respected journals. Then we have Q2, Q3, and Q4, which represent progressively less prestigious journals within their respective fields. It's a way of categorizing them based on their standing in the academic world. We used SCImago Journal Rank[1] to determine the ranking of our selected studies.

In the realm of conference categorization, they're sorted kinda like how journals are. There are four main groups: A*, A, B, and C. It's sort of like the quartile system for journals. A* is the top tier, the top-ranking conferences. Then comes A, B, and C, each one a step down in how prestigious they are. We used the ICORE Conference Portal[2]to understand the ranking of conferences.

The **Study ID** column is attached to each study for ease of referral and listing. **Title and Reference** contains the full title of the article, including its volume, issue, and page details. **Authors Name** lists the names of the authors; for papers with one or two authors, list all names, but for papers with three or more authors, use the first author's name followed by "et al." (e.g., Amir Mashmool et al.). The **Major Contributions** column shows the significant contributions or findings that are presented in every paper, including the most important results and theories developed or improvements made. **The name of the journal/conference** is a very important thing to note as it tells us where the research work was published and how widely the results could have been circulated. **Rank** provides

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[1] https://www.scimagojr.com/

[2] https://portal.core.edu.au/conf-ranks/

information on the ranking or impact factor of the journal or conference. The **Publisher** names the entity responsible for the publication, thereby often adding further detail about the source type. Then there is the column headed by **Year**, which refers to the year of publication.

Table A.1: Selected studies for this SLR.

Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S1	A Machine Learning Framework for Edge Computing to Improve Prediction Accuracy in Mobile Health Monitoring [RAS19]	Ram, S. S. et al.	Evaluating Machine Learning Algorithms for Personalized Mobile Health Monitoring System Using Mobile Health Data	Conference - Computational Science and Its Applications(ICCSA)	C	Springer	2019
S2	A Deep Transfer Learning-based Edge Computing Method for Home Health Monitoring [SAG+21]	Sufian, A. et al.	Proposing a transfer learning-based edge computing method for home health monitoring.	Conference - Conference on Information Sciences and Systems (CISS)	N/A	IEEE	2021

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S3	Machine-Learning-Based IoT–Edge Computing Healthcare Solutions [AA23]	Alnaim, A. K., & Alwakeel, A. M.	Exploring the Integration of Cloud, Edge Computing, and Machine Learning in a Distributed Edge Computing Based IoT Framework for Medical Data Analysis	Journal - Electronics	Q2	Mdpi	2023
S4	Healthcare solution based on machine learning applications in IOT and edge computing [KM18]	Kumar, S. M., & Majumder, D.	Exploring the Integration of Edge Computing, IoT, and Machine Learning for Healthcare Applications	Journal - International Journal of Pure and Applied Mathematics	N/A	Academic Publications Ltd	2018
S5	Prediction of health monitoring with deep learning using edge computing [GCW+23]	Gupta, P. et al.	Integrating IoT, Edge Computing, and CNN-Based Deep Learning for Efficient Fall Detection in Smart Healthcare Systems	Journal-Measurement: Sensors	Q3	Elsevier	2023

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S6	Edge computing health model using P2P-based deep neural networks [CY20]	Chung, K., & Yoo, H.	Proposing an Edge Computing Health Model Using P2P-Based Deep Neural Networks for Efficient Processing of Health Big Data	Journal - Peer-to-Peer Networking and Applications	Q2	Springer	2020
S7	Task offloading in edge computing for machine learning-based smart healthcare [AZF21]	Aazam, M. et al.	Enabling Intelligent Healthcare Services through Edge Computing and Machine Learning-Based Task Offloading	Journal - Computer Networks	Q1	Elsevier	2021
S8	IoT-Edge Healthcare Solutions Empowered by Machine Learning [SK23]	Sistla, S. M. K., & Konidena, B. K.	Optimizing Real-Time Response and Security in Medical Sensor Networks through Edge Computing and Machine Learning-Based Analytics	Journal - Journal of Knowledge Learning and Science Technology	N/A	N/A	2023

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S9	HealthEdge: a machine learning-based smart healthcare framework for prediction of type 2 diabetes in an integrated IoT, edge, and cloud computing system [HMI23]	Hennebelle, A. et al.	Developing HealthEdge: A Machine Learning-Based Smart Healthcare Framework for Type 2 Diabetes Prediction in Integrated IoT-Edge-Cloud Computing Systems and evaluating it with mostly used machine learning algorithms and real-life diabetes datasets	Journal - Procedia Computer Science	N/A	Elsevier	2023
S10	A survey on deep transfer learning to edge computing for mitigating the COVID-19 pandemic [SGSS20]	Sufian, A. et al.	Exploring the Role of Deep Learning, Deep Transfer Learning, and Edge Computing in Mitigating COVID-19: A Systematic Study	Journal - Journal of Systems Architecture	Q1	Elsevier	2020

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S11	Empowering healthcare IoT systems with hierarchical edge-based deep learning [ATMA+18]	Azimi, I. et al.	Enhancing Remote Health Monitoring Using Hierarchical Computing Architecture and Convolutional Neural Networks: A Feasibility Study and Performance Evaluation	Conference - International Conference on Connected Health: Applications, Systems and Engineering Technologies	N/A	IEEE	2018

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S12	IoMT-enabled real-time blood glucose prediction with deep learning and edge computing [ZKD+22]	Zhu, T. et al.	A novel deep learning model employing an attention-based evidential recurrent neural network is proposed for real-time blood glucose prediction and hypoglycemia detection. This model is embedded into a low-cost, low-power IoMT device, leveraging Bluetooth connectivity and edge computing for efficient performance.	Journal - Internet of Things Journal	Q1	IEEE	2022

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S13	Real-time Mask Identification for COVID-19: An edge-computing-based deep learning framework [KWW+21]	Kong, X. et al.	Introducing ECMask: An Edge Computing-Based Real-Time Mask Detection Framework for Public Health Precautions	Journal - Internet of Things Journal	Q1	IEEE	2021
S14	A framework for edge-assisted healthcare data analytics using federated learning [HRKS20]	Hakak, Saqib et al.	Proposing an Edge-Assisted Federated Learning Framework for Leveraging User-Generated Data from Wearable Devices in Healthcare	Conference - International Conference on Big Data	B	IEEE	2020

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S15	On delay-sensitive healthcare data analytics at the network edge based on deep learning [FPG18]	Fadlullah, Z. M. et al.	Proposing Deep Learning-Based IoT Edge Analytics for Near Real-Time Smart Healthcare: Addressing Delay-Sensitive Healthcare Data at the Network Edge	Conference - International Wireless Communications & Mobile Computing Conference (IWCMC)	B	IEEE	2018
S16	EdgeCNN: A hybrid architecture for agile learning of healthcare data from IoT devices [YFC+18]	Yu, Jian et al.	Introducing EdgeCNN: A Hybrid Architecture for Real-Time Healthcare Data Analysis Using Edge and Cloud Computing	Conference - International Conference on Parallel and Distributed Systems (ICPADS)	B	IEEE	2018

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S17	Deep learning with edge computing for localization of epileptogenicity using multimodal rs-fMRI and EEG big data [HTP+17]	Hosseini, M. P. et al.	Developing Autonomic Edge Computing Solutions for Epilepsy Management: Integrating Noninvasive and Invasive Methods for Monitoring and Regulation of the Epileptic Brain	Conference - International Conference on Autonomic Computing (ICAC)	B	IEEE	2017
S18	Efficient learning of healthcare data from IoT devices by edge convolution neural networks [HFY+20]	He, Y. et al.	Introducing EdgeCNN: A Hybrid Architecture for Efficient Electrocardiogram Classification in Smart Healthcare Applications	Journal - Applied Sciences	Q2	Mdpi	2020

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S19	MobiHisNet: a lightweight CNN in mobile edge computing for histopathological image classification [KSB+21]	Kumar, A. et al.	developing an efficient lightweight CNN model based on MobileNet for the Classification of Histopathological Images on Edge Devices	Journal - Internet of Things Journal	Q1	IEEE	2021
S20	A rigorous analysis of biomedical edge computing: An arrhythmia classification use-case leveraging deep learning [SFF21]	Sakib, S. et al.	Efficient Arrhythmia Classification on Resource-Constrained Biomedical Edge Devices Using Customized 1-D CNN Model	Conference - International Conference on Internet of Things and Intelligence System (IoTaIS)	N/A	IEEE	2021

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S21	An internet-of-medical-things-enabled edge computing framework for tackling COVID-19 [RH21]	Rahman, M. A., & Hossain, M. S.	Affective Computing Framework for In-Home COVID-19 Symptom Management Using Edge GPUs Architecture; Crafting DL libraries tailored for diverse IoMT gadgets, perfect for crafting health-oriented applications at the edge. These IoMT units are equipped to handle DL-based CNN, aided by edge TPUs or GPUs; developing a collection of Quality of Life (QoL) monitoring apps leveraging IoMT edge learning.	Journal - Internet of Things Journal	Q1	IEEE	2021

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S22	A Deep-Learning-Based Edge-Centric COVID-19-Like Pandemic Screening and Diagnosis System within a B5G Framework Using Blockchain [MH21]	Muhammad, G., & Hossain, M. S.	Edge-Centric AI-Enabled COVID-19 Screening and Diagnosis System Utilizing Beyond 5G Network with Blockchain-Based Secure Data Transmission	Journal - IEEE Network	Q1	IEEE	2021
S23	Deep learning empowered COVID-19 diagnosis using chest CT scan images for collaborative edge-cloud computing platform [SK22]	Singh, V. K., & Kolekar, M. H.	Proposing a novel deep-learning model for COVID-19 diagnosis that is readily deployable on edge devices	Journal - Multimedia Tools and Applications	Q1	Springer	2022

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S24	Edge deep learning for neural implants: a case study of seizure detection and prediction [LR21]	Liu, X., & Richardson, A. G.	developing Edge DL models for Clinical Neural Implants: A Study on Epileptic Seizure Detection; Utilizing three prevalent deep learning architectures (namely DNN, CNN, and LSTM) and enhancing these models for efficient deployment on hardware with limited resources.	Journal - Journal of Neural Engineering	Q1	Iop Science	2021
S25	Smart Health Monitoring for Seizure Detection using Mobile Edge Computing [ASE20]	Ali, Z. S. et al.	Proposing a deep learning method for epileptic seizure detection using mobile edge computing	Conference - International Wireless Communications and Mobile Computing (IWCMC)	B	IEEE	2020

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S26	Edge Intelligence: Federated Learning-Based Privacy Protection Framework for Smart Healthcare Systems [AMLR22]	Akter, M. et al.	Proposing a Three-Fold Federated Edge Aggregator Architecture for Privacy-Preserving Smart Healthcare Systems	Journal -Journal of Biomedical and Health Informatics	Q1	IEEE	2022
S27	Cognitive computing-based COVID-19 detection on Internet of things-enabled edge computing environment [LLAB$^+$21]	Laxmi Lydia, E. et al.	Enhancing COVID-19 Detection with Federated Deep Learning on IoT-Enabled Edge Computing: A SqueezeNet Approach	Journal - Soft Computing	Q2	Springer	2021

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S28	A wearable sensor-based activity prediction system to facilitate edge computing in smart healthcare system [Udd19]	Uddin, M. Z.	Investigating a system for predicting human activities through a multimodal approach, leveraging multiple wearable healthcare sensors. This involves employing Deep Recurrent Neural Networks (RNNs) to train on data sourced from the publicly available MHEALTH dataset, to model twelve distinct human activities.	Journal - Journal of Parallel and Distributed Computing	Q1	Elsevier	2019

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S29	Wearable IoT Smart-Log Patch: An Edge Computing-Based Bayesian Deep Learning Network System for Multi Access Physical Monitoring System [MSF+19]	Manogaran, G. et al.	Designing IoT-Enabled Wearable Patch with Edge Computing for Accurate Physical Activity Monitoring	Journal - Sensors	Q1	Mdpi	2019

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S30	Edge Computing Empowered Smart Healthcare: Monitoring and Diagnosis with Deep Learning Methods [WKCZ24]	Wang, K. et al.	Presents a FETCH framework that leverages fog computing to complement cloud computing for more efficient healthcare systems by using FogBus middleware to optimize resource allocation, latency, and power consumption in the processing of medical data.	Journal - Journal of Grid Computing	Q1	Springer	2024
S31	An effective training scheme for deep neural network in edge computing enabled Internet of Medical Things (IoMT) [PPG^{+}20]	Pustokhina, I. V. et al.	ETS-DNN: systems Effective Training Scheme for Deep Neural Networks in Edge Computing Enabled IoMT Systems	Journal - IEEE Access	Q1	IEEE	2020

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S32	Migrating Intelligence from Cloud to Ultra-Edge Smart IoT Sensor Based on Deep Learning: An Arrhythmia Monitoring Use-Case [SFFN20]	Sakib, S. et al.	Intelligent Ultra-Edge IoT Sensor for Arrhythmia Detection in Mobile Health Scenarios	conference - International Wireless Communications and Mobile Computing (IWCMC)	B	IEEE	2020
S33	B5G and explainable deep learning assisted healthcare vertical at the edge: COVID-I9 perspective [RHAG20]	Rahman, M. A. et al.	Distributed Deep Learning Framework for COVID-19 Management with Mobile Edge Computing	Journal - IEEE Network	Q1	IEEE	2020

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Study ID	Title and Reference	Authors Name	Major Contributions	Journal / Conf Name	Rank	Publisher	Year
S34	FedHome: Cloud-Edge based Personalized Federated Learning for In-Home Health Monitoring [WCZZ20]	Wu, Q., et al.	FedHome: A novel Cloud-Edge Federated Learning Framework for Privacy-Preserving In-Home Health Monitoring	Journal - IEEE Transactions on Mobile Computing	Q1	IEEE	2020
S35	Collaborative Federated Learning for Healthcare: Multi-Modal COVID-19 Diagnosis at the Edge [QAA^{+}22]	Qayyum, A., et al.	Edge Computing Empowered Intelligent Diagnosis of COVID-19: A Clustered Federated Learning Approach	Journal - IEEE Open Journal of the Computer Society	N/A	IEEE	2022