A systematic review on Artificial intelligence approaches for Smart Health Devices (#96023)

First submission

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2. **STUDY DESIGN**
3. **VALIDITY OF THE FINDINGS**
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- Clear, unambiguous, professional English language used throughout.
- Intro & background to show context. Literature well referenced & relevant.
- Structure conforms to PeerJ standards, discipline norm, or improved for clarity.
- Is the review of broad and cross-disciplinary interest and within the scope of the journal?
- Has the field been reviewed recently? If so, is there a good reason for this review (different point of view, accessible to a different audience, etc.)?
- Does the Introduction adequately introduce the subject and make it clear who the audience is/what the motivation is?

STUDY DESIGN

- Article content is within the Aims and Scope of the journal.
- Rigorous investigation performed to a high technical & ethical standard.
- Methods described with sufficient detail & information to replicate.
- Is the Survey Methodology consistent with a comprehensive, unbiased coverage of the subject? If not, what is missing?
- Are sources adequately cited? Quoted or paraphrased as appropriate?
- Is the review organized logically into coherent paragraphs/subsections?

VALIDITY OF THE FINDINGS

- Impact and novelty not assessed. Meaningful replication encouraged where rationale & benefit to literature is clearly stated.
- Conclusions are well stated, linked to original research question & limited to
- Is there a well developed and supported argument that meets the goals set out in the Introduction?
- Does the Conclusion identify unresolved questions / gaps / future directions?

supporting results.

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Support criticisms with evidence from the text or from other sources	*Smith et al (J of Methodology, 2005, V3, pp 123) have shown that the analysis you use in Lines 241-250 is not the most appropriate for this situation. Please explain why you used this method.*
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Organize by importance of the issues, and number your points	*1. Your most important issue* *2. The next most important item* *3. …* *4. The least important points*
Please provide constructive criticism, and avoid personal opinions	*I thank you for providing the raw data, however your supplemental files need more descriptive metadata identifiers to be useful to future readers. Although your results are compelling, the data analysis should be improved in the following ways: AA, BB, CC*
Comment on strengths (as well as weaknesses) of the manuscript	*I commend the authors for their extensive data set, compiled over many years of detailed fieldwork. In addition, the manuscript is clearly written in professional, unambiguous language. If there is a weakness, it is in the statistical analysis (as I have noted above) which should be*

improved upon before Acceptance.

A systematic review on Artificial intelligence approaches for Smart Health Devices

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Wearable technology, as an evolution of the Internet of Things (IoT), has played an essential role in the smart health sector. The ability to monitor and analyze patient real-time data provides a significant improvement in healthcare and quality of life. In this context, Machine Learning (ML) and Deep Learning (DL) are emerging as successful technologies because they are suitable for application to advanced analysis and prediction of healthcare scenarios. This work aims to systematically review and analyze the research landscape on ML and DL approaches applied to the smart health domain. The aim is to provide a clear understanding of current trends, findings, and challenges, thereby helping to guide future research and development in this rapidly evolving field. The search focused on articles related to “Artificial Intelligence”, “Smart Health” and “Wearable Devices” extracted from two main databases, IEEEXplore and ScienceDirect. Specifically, 46 articles were selected and reviewed to answer the four research questions along which our study is directed. In particular, the study focused on the ML or DL network architectures used, the scope of the application, the accuracy and reliability achieved, and the privacy and security aspects involved. A final discussion highlights research gaps yet to be investigated, as well as the drawbacks and vulnerabilities of existing IoT applications in the smart health sector.

A Systematic Review on Artificial Intelligence Approaches for Smart Health Devices

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ABSTRACT

Wearable technology, as an evolution of the Internet of Things (IoT), has played an essential role in the smart health sector. The ability to monitor and analyze patient real-time data provides a significant improvement in healthcare and quality of life. In this context, Machine Learning (ML) and Deep Learning (DL) are emerging as successful technologies because they are suitable for application to advanced analysis and prediction of healthcare scenarios. This work aims to systematically review and analyze the research landscape on ML and DL approaches applied to the smart health domain. The aim is to provide a clear understanding of current trends, findings, and challenges, thereby helping to guide future research and development in this rapidly evolving field. The search focused on articles related to "Artificial Intelligence", "Smart Health" and "Wearable Devices" extracted from two main databases, IEEEXplore and ScienceDirect. Specifically, 46 articles were selected and reviewed to answer the four research questions along which our study is directed. In particular, the study focused on the ML or DL network architectures used, the scope of the application, the accuracy and reliability achieved, and the privacy and security aspects involved. A final discussion highlights research gaps yet to be investigated, as well as the drawbacks and vulnerabilities of existing IoT applications in the smart health sector.

INTRODUCTION

The integration of artificial intelligence (AI) and wearable solutions has driven a significant transformation in the smart health industry. This dynamic synergy has captured the interest of both the scientific and industrial communities, promising revolutionary advances in healthcare and improved quality of life for people.

Specifically, Wearable technology plays a central role in this transformation collecting and transmitting data in real-time, and promoting a more proactive approach to healthcare. Miniaturized sensors embedded in wearable devices can detect motion data to monitor human movements Rastegari and Ali (2020) and physiological and behavioral data, including heart rate Rahman et al. (2020), blood pressure Chiang et al. (2021), patterns of sleep Shen et al. (2022), physical activitiesStaab et al. (2022), SpO2 Chou et al. (2020) and more. These data streams, along with patient records Sabra et al. (2018), lifestyle and environmental data Wu et al. (2022), provide an invaluable resource for both healthcare providers and individuals, offering insights into trends in health and enabling early detection of potential health problems. Additionally, some studies have leveraged Internet traffic from IoT devices Yue et al. (2020) and social interaction data Ware et al. (2022) to develop depression prediction techniques.

However, the process of collecting and transforming large amounts of raw data into useful information represents a significant challenge, mainly due to factors such as the risk of cyber-attacks and invasion of privacy Bi et al. (2022), along with issues related to data overload and real-time sensory data processing latency Gupta et al. (2021). Furthermore, the substantial volume and complex nature of the data generated by wearable devices introduces a multitude of complexities that require the application of sophisticated analytical tools to transform it into meaningful information, and this is where artificial intelligence plays a critical role.

These technologies are proving indispensable for extracting valuable patterns, predicting health trends, and facilitating personalized health interventions. Their ability to adapt and learn from data allows the development of robust models that can continuously improve their accuracy and efficiency.

Therefore, our research strives to provide a systematic review of the current landscape where ML and DL are being leveraged to unlock the full potential of wearable applications in smart health. The analysis of the scientific literature aims to provide a comprehensive understanding of the prevailing trends, findings, and challenges in this rapidly evolving field. In this sense the following objectives have been defined, addressing five main goals:

- analyze the most recent and relevant research accomplishments in the field of AI applied to smart health;
- investigate which of the two most well-known AI methodologies, Machine Learning (ML) and Deep Learning (DL), is primarily employed in the specific research topic;
- evaluate the accuracy and reliability achieved by AI-driven models in the smart health landscape. This assessment provides crucial insights into the real-world feasibility and efficacy of these technologies in improving healthcare outcomes;
- assess critical aspects related to security and data privacy;
- outlines the research gaps still to be investigated.

In summary, through our systematic review, we aim to contribute to the current state of the literature, exploring the research landscape regarding Machine Learning (ML) and Deep Learning (DL) approaches applied in the smart health sector, to highlight challenges and vulnerability. These architectures form the backbone of the smart healthcare ecosystem, enabling the development of predictive models and decision support systems Yin and Jha (2017). In this way, we intend to highlight what future research efforts in this field should be.

The document is structured as follows. In Section 1 we reported the related works, first analyzing the research papers that significantly influenced our study's focus on the applications of artificial intelligence in wearable devices in the smart health sector and then the recent systematic reviews, placing the focus on the contribution of our work. In Section 2, we discussed the context related to the research topic and its current development. In Section 3, we outlined the search methodology employed by providing a comprehensive explanation of the search queries and selected databases, the search and filtering process, as well as presenting the distribution of analyzed articles by year and location. In Section 4, we report the results of our research work by classifying the selected articles based on the research questions outlined in the previous section. Section 5 involves interpreting the results of our systematic review, discussing their implications, and analyzing any limitations or potential future research directions. Finally, Section 6 summarizes the conclusions of the research work.

1 RELATED WORK

In this section, we present the results of an analysis of research articles identified in the literature that address the topic studied. The analyzed research documents show different application areas, some clearly defined to focus on specific pathologies or healthcare applications.

The field of smart health encompasses a multitude of goals, each distinctly contributing to healthcare progress. These applications can be classified into primary domains which are “diagnosis and classification”, “prediction” and “monitoring”. Studies focusing on diagnosis and classification delve into the accurate identification of various medical conditions such as arrhythmia Cheikhrouhou et al. (2021); Yin and Jha (2017), type 2 diabetes Yin and Jha (2017), urinary bladder Yin and Jha (2017) and lung tumor pathologies Masood et al. (2018). These applications aim to improve the accuracy and efficiency of medical diagnoses, helping healthcare professionals provide better care to patients. Another critical aspect is the prediction of health-related risks and conditions. This includes predicting the risk of diseases such as COVID-19 Neog et al. (2022), heart disease Chakraborty and Kishor (2022)-Sarmah (2020), viral infections Skibinska et al. (2021), Parkinson's disease Goñi et al. (2022), diabetes Xiao et al. (2022); Ferdousi et al. (2021) and even exposure to an epidemic Ng et al. (2022). Other studies develop prediction systems for health conditions such as blood pressure Chiang and Dey (2019) and flat feet Kim et al. (2020). These predictive models enable both individuals and healthcare systems to take proactive measures for prevention and early intervention. AI-powered monitoring systems offer real-time insights that can help people and healthcare providers make informed decisions. The ability to continuously monitor vital signs and physiological parameters such as respiratory rate Shuzan et al. (2021), tidal volume Schoun et al. (2018), and brain oxygenation Chou et al. (2020) is vital for the management of chronic diseases and ensuring general well-being. Furthermore, a distinct set of research papers highlights the indispensable role of wearable devices that facilitate comprehensive health monitoring, cognitive assessment, and monitoring of conditions such as myotonic dystrophy type 1 Chapron et al. (2021). Numerous studies have emerged demonstrating the development of multi-objective systems that integrate monitoring, classification, and prediction capabilities, as they not only monitor various parameters and conditions in real-time but also classify and predict outcomes based on the monitored data Bellos et al. (2014); Prathaban et al. (2021); Sopic et al. (2018).

Therefore, the combined efforts in these different fields illustrate the multi-faceted potential of artificial intelligence and wearable technology to revolutionize healthcare diagnosis, prediction, screening, monitoring, and patient care.

Regarding the contributions of other recent systematic reviews related to artificial intelligence applied to smart wearable devices, or the healthcare sector, we have examined some of them to highlight their differences compared to the proposed investigation. For example, the Site et al. (2021) study focuses primarily on the application of machine learning algorithms in the analysis of data from wearable devices in eHealth, and the most notable limitation of this study is a significant lack of exploration of the use of Deep Learning (DL) techniques for smart wearable devices in the smart healthcare sector. The studies Ahmadzadeh et al. (2022) and Alam et al. (2018) do not adhere to the Kitchenham guidelines for systematic reviews Wu et al. (2022), as they do not offer details on the research databases used, the search queries performed, the exclusion and inclusion in the filtering process or the number of documents discovered. The study Mughal et al. (2022) delves into the use of wearable sensors for the management of pathological conditions underlining their usefulness, challenges, and results. The Alam et al. (2018) study, however, specifically focuses on the integral role of communication technologies in supporting IoT applications related to the healthcare sector. Both research papers do not investigate artificial intelligence methodologies, including Machine Learning (ML) and Deep Learning (DL), as they concern the analysis of data obtained from wearable devices in the field of smart health. Instead, the study Qaim et al. (2020) systematically examines energy efficiency considerations in the field of wearable devices integrated with the Internet of Things and incorporates the shortcomings identified in the previously mentioned studies.

This research study proposes a systematic review, according to the guidelines of the Kitchenham method Wu et al. (2022), to explore the research landscape regarding the application of artificial intelligence, with its ML and DL techniques, in the smart health sector.

2 BACKGROUND

2.1 Artificial Intelligence Techniques

Artificial Intelligence is a field of computer science that aims to develop systems capable of performing tasks that normally require human intelligence Winston (1984). These tasks include reasoning, learning, sensory perception, understanding natural language, and interacting with the surrounding environment. The goal of AI is to create machines and algorithms that can emulate or surpass human capabilities in specific domains.

It is divided into two large classes Wang and Siau (2019). The first represents Weak Artificial Intelligence, also known as specialized AI, which refers to systems designed to perform specific tasks without necessarily understanding or imitating human intelligence in a general way. Examples include search engines, recommendation systems, and gaming algorithms. The second is Strong Artificial Intelligence which aims to reach a level of intelligence comparable to human intelligence. In contrast to weak AI, strong AI should be able to tackle any intellectual task. However, currently, strong AI is still largely a future goal and subject to debate.

There are four main generic approaches, Machine Learning and Deep Learning, natural language processing, which focuses on the ability of computers to understand, interpret, and generate human language, and computer vision which is the ability of machines to interpret and analyze visual data, often used in applications such as facial recognition, robotic vision and medical image analysis Dargan et al. (2020). AI is an ever-evolving discipline with a growing impact on multiple industries, including healthcare, industrial automation, transportation, marketing, and many others.

More specifically, the application of Artificial Intelligence (AI) in medicine is revolutionizing the healthcare sector, offering opportunities to improve the diagnosis, treatment, and management of patients. The main application areas are medical diagnosis where machine learning algorithms, particularly convolutional neural networks (CNN), are used to analyze medical images such as X-rays, MRIs and computed tomography scans to identify abnormalities and aid in the early diagnosis of diseases like cancer; Clinical Decision Assistance, where machine learning algorithms are used to provide personalized recommendations to doctors, based on clinical data and test results, helping in choosing the most appropriate treatment options; treatment personalization where AI helps identify subgroups of patients with similar genetic or molecular characteristics or analyze historical patient data to predict treatment responses and optimize treatment protocols; and finally healthcare management and continuous monitoring, where AI facilitates the provision of remote medical care, allowing continuous monitoring of patients, management of chronic diseases and virtual medical consultancy, and introduces wearable devices that integrate with algorithms of AI can collect data on vital signs and report any anomalies, improving proactive health management.

2.1.1 Machine Learning

Machine Learning (ML) is a branch of Artificial Intelligence (AI) dealing with the development of algorithms and models that allow computers to learn from data and improve their performance without having been explicitly programmed Mitchell (1997). Instead of following explicit instructions, machine learning models draw insights from data so they can make decisions or make predictions based on new information.

The fundamental goal of machine learning is to allow computers to autonomously learn and adapt to new data and situations, continuously improving their performance over time. This is achieved by identifying patterns and relationships in the training data, which are then used to make predictions or decisions on previously unseen data.

There are three main types of learning in the context of machine learning: supervised learning, unsupervised learning, and reinforcement learning. In the first, the model is trained on a labeled dataset, where each input example is associated with a corresponding label or desired output. The goal is for the model to learn to map input features to desired outputs. Among the most used algorithms we find Support Vector Machines (SVM) which try to find the best hyperplane that separates the data into different classes in the feature space Noble (2006); the K-Nearest Neighbors (K-NN) which classifies a data point-based on the majority of labels of its nearest neighbors in the training set Peterson (2009); Decision Trees and Random Forests which recursively divide the data set into subsets based on decision criteria; and boosting algorithms that combine several weak models to create an overall stronger model. The idea is to iteratively train weak models, giving more weight to mistakes made earlier, so that the final model gives more attention to the more difficult cases. In unsupervised the model is trained on unlabeled data and tries to identify intrinsic patterns or structures in the data without having a specific output to predict Barlow (1989). The main goal is to identify hidden relationships or groupings in the data. Finally, with reinforcement learning the agent learns to make decisions by interacting with an environment. It receives feedback in the form of rewards or penalties based on actions taken, guiding the improvement of its strategies over time. Some examples of machine learning applications include facial recognition, machine translation, medical diagnosis, text classification, spam filtering, and many others. The advancement of computer technologies, accessibility to data and increasingly powerful computing capabilities have contributed to the growing importance and diffusion of machine learning in various sectors.

2.1.2 Deep Learning

Machine learning, which is basically a neural network with three or more layers, includes deep learning as a subset. These neural networks allow the system to ”learn” from large volumes of data by simulating the functioning of the human brain, although far from reaching its potential Deng and Yu (2014). Although a neural network with a single layer is small, it is capable of approximate predictions, while adding additional hidden layers can support the optimization and improve accuracy. Instead, for deep learning Deep neural networks (DNN) try to mimic the human brain by a combination of data inputs, weights, and distortion. These components cooperate to precisely identify, classify, and characterize features and information inside the data. A DNN is made up of several layers made up of interconnected nodes; each layer builds on the results of the one before it in order to refine and improve the final classification and prediction. Forward propagation is the term used to describe this elaboration process as it progresses through the DNN layers. A DNN's visible layers are the first and last layers, which designate the input and output layers, respectively. The neural network gathers data for the subsequent stages of the analysis in the first layer, known as the input layer, and elaborates the final prediction or classification in the last layer, known as the output layer.

Specialized architectures are convolutional neural networks (CNNs) O'Shea and Nash (2015) and recurrent neural networks (RNNs) Medsker and Jain (2001). CNNs can identify characteristics and patterns within an image, enabling tasks like detection and recognition. CNNs are largely utilized in computer vision and image classification applications. In 2015, a convolutional neural network beat a human in an object recognition challenge. RNNs are typically used in natural language recognition and speech recognition applications as they leverage sequential or time series data.

2.2 Smart Health

E-health refers, generically, to the various processes of digitalization of healthcare and, therefore to the creation of electronic infrastructures for the administrative and not just clinical management of each citizen's data, smart health focuses more on IoT devices, including smartphones, which implement those same processes and personalized models for monitoring and treating health conditions Tian et al. (2019).

Smart health is the basis of the so-called 4P medicine: Preventive, Participatory, Personalized, and Predictive. It is a medicine capable of preventing the disease based on the intersection of the different biological profiles of the person, through a simple blood sample and/or the processing of data from IoT devices Aversano et al. (2022a). A medicine capable of making each person no longer a "patient" but aware and involved in their state of health thanks to real-time communication with their doctors. But also to personalize diagnosis and treatment Aversano et al. (2021) based on the risk factors detected and the information received from the wearables and to predict the severity of the risk factors of pathology before it manifests itself.

Smart health serves to automate procedures and simplify bureaucracy, contain costs, reduce times, optimize flows, make people aware of their health condition through the transparency of data, immediately consultable, and develop "person-friendly" health paths. It is essential for monitoring the quality of air, water, and building safety.

Smart health allows you to be assisted almost everywhere, realizing the famous transition from expectant medicine to initiative medicine, or from an emergency model to a proactive model, of reticular, "care-intensive" assistance, which sees the hospital as a high-intensity center for acute pathologies, and the "low-intensity" territorial facilities as structures that manage chronic conditions, prevention and social-welfare services Aversano et al. (2022b).

2.3 Wearable devices

The term wearable devices refers to a wide range of intelligent devices that can be connected to other electronic devices such as smartphones, wirelessly or via Bluetooth technology, allowing not only the detection but also the storage and exchange of data of different like, immediately and often without the need for human intervention. Increasingly advanced, wearable devices are used for various purposes: from the detection of biometric signals, through sensors positioned on the skin, to quick access to online information Iqbal et al. (2021). Among these, we find wearable devices such as heart rate monitors, glucometers, or sphygmomanometers which are now able to offer a valid contribution when used in the healthcare sector. In fact, through sensors, actuators, and software connected from the device to a smartphone or tablet with the cloud, intelligent wearable devices worn by patients allow the collection, analysis, and real-time transmission of personal health data.

Wearable healthcare is based on the collection of real-time or continuous 24-hour data on a person's state of well-being and physical fitness Cho (2019). This data allows you to create a personalized health database. Anyone who wears a smart device capable of detecting health data can therefore use it to allow a healthcare worker to collect their data to obtain remote monitoring and to achieve health, fitness, well-being, and physical fitness objectives that are not necessarily related to the control of pathological conditions.

In healthcare, wearable devices such as healthcare smartwatches are often used to monitor patients' health conditions and related emergencies, allowing them to be recognized as soon as they occur. The use of wearable technology therefore creates the potential for a proactive approach to healthcare. This can help detect symptoms of an illness before they develop into larger problems and, therefore, can have dangerous health consequences. Even people with known pathologies can benefit from early identification of signs of possible anomalies.

A typical example of a smart (i.e. intelligent) device for health monitoring is smart patches Segev-Bar et al. (2015). These are thin stickers containing electronic components (including sensors and actuators with appropriate processing, energy storage, and communication capabilities) that collect a patient's vital signs: heart rate, body temperature, and more, and transfer them to appropriate apps for doctors and patients.

Another example is a mobile ECG monitor Baig et al. (2013). This device records the electrocardiogram via a wireless electrode that can be applied, for example, to the patient's chest or finger. The ECG data is sent to the cloud and, then, to a doctor for appropriate evaluation.

Therefore, wearable technologies can represent innovative and highly effective solutions for patient health, while also offering enormous potential benefits to healthcare workers and the entire healthcare system. But, to improve the usability and functions of the devices for practical use, issues such as acceptance by all users, security, ethics, and issues relating to the management of the big data generated still need to be addressed. from wearable devices. There are also elements of concern that arise from a large-scale wearable implementation, such as aspects of data privacy and security, but also supply chain management. When it comes to wearables and security, the medical Internet of Things opens the door to new attack vectors, including targeted malware and distributed denial of service threats. Therefore, to avoid privacy and security issues, it is necessary to establish robust authentication and authorization processes for collecting, sending, and analyzing data.

3 RESEARCH METHOD

We based our research approach on the principles outlined by Barbara Kitchenham in 2004 Kitchenham (2004) and consists of the following sequential phases:

- definition of relevant research questions;
- definition of appropriate search queries based on extracting keywords from search questions;
- selection of databases in which to search;
- definition of initial filtering criteria such as search time interval, quality of searched results, etc.;
- screening of titles and abstracts to exclude irrelevant and duplicate articles;
- definition of more in-depth eligibility criteria to apply them during the in-depth reading of the definitively selected documents;
- analysis of the remaining articles based on the research questions defined at the beginning.

3.1 Research questions and queries

The purpose of this study is to explore the state of the art in integrating artificial intelligence (AI) with Internet of Things (IoT) wearable devices in the field of smart health. In this regard, four research questions were defined.

The AI methodology used in the selected studies have been analysed to evaluate the complexity and depth of the model. Indeed, respect to their application with data collected from wearable IoT devices it is crucial the amount of data available. It is widely know that DL training often requires large amounts of data, while ML methods can work with smaller datasets. Therefore, in this study we also aim to evaluate which is the most suitable approach for wearable IoT applications in the field of smart health, addressing our first research question:

RQ$_1$: *Does the study use an ML or DL approach?*

Than the study focused more specifically to the DL approaches used, intending to evaluate which architectures are most common or suitable depending on the different application areas. Therefore, we address our second research question:

> **RQ**$_2$: *Which Neural Network architectures are used in IoT Smart Health considering the scopes of application?*

We also examined the performance of algorithms used in smart health applications. In particular, the accuracy and reliability of the algorithm result in the analysis, processing, and classification of data collected by IoT devices in the healthcare context were evaluated. Therefore, we address our third research question:

> **RQ**$_3$: *Which algorithms lead to better accuracy and reliability of Smart Health data collected from IoT device monitoring?*

Finally, health and medical data is highly sensitive and, therefore, its security and privacy are of paramount importance. Therefore, in order not to overlook the issues related to these approaches, we focused on the privacy and security issues faced in the collection and transmission of health data by IoT devices. Therefore, we address our fourth research question:

> **RQ**$_4$: *RQ4: What are the privacy and security issues taken into account while using health data collected from IoT devices?*

Once the directions in which to proceed to conduct the study were defined, the research questions mentioned above were transformed into a specific query, which was then used to examine the databases chosen and outlined in the following paragraph. The query used is shown below:

> **Q**: *(Wearable) AND (Artificial Intelligence) AND (Smart Health)*

3.2 Databases

To select the articles on which our research work focused, the following two main databases were used:

- IEEEXplore[1]: a digital library and research database for discovering and accessing journal articles, conference proceedings, technical standards, and related materials in computer science, electrical engineering, electronics, and related fields.;
- ScienceDirect[2]: which provides access to a large bibliographic database of scientific and medical publications from the Dutch publisher Elsevier.

The databases listed above were affected by the query described in Section 3.1.

3.3 Research and filtering process

The whole search and filtering process is depicted in Fig. 1. It can be noted that the process consists of three substantial phases. The first consisted of applying the query to the chosen databases, while the second involved initial filtering of the selected documents based on the defined inclusion (IC) and exclusion criteria (EC), reported in Table 1. Finally, the third phase consisted of the actual analysis of the studies considered for the review.

As shown in the Table, the search process involved selecting articles published in the year range from 2014 to 2022 (IC_2) from the databases listed in Section 3.2, using the input keywords consisting of the query (Q) defined in Section 3.1. This time frame was chosen because, before 2014, the literature lacked relevant publications regarding ML or DL approaches in smart healthcare. This first phase of the search produced a total of 228 articles, of which 107 came from IEEEXplore and 121 from ScienceDirect. The research work continued with the filtering process through (i) reading the titles, (ii) scanning the abstracts and (ii) removing duplicate documents, thus reaching a total of 105 selected articles. The selected studies had to fully meet the eligibility criteria in Table 1. In particular, they had to be written in English (IC_1), published in the period 2014 - 2022 (IC_2), they had to be focused on an Internet of Things scenario (EC_2

[1] `https://ieeexplore.ieee.org/Xplore/home.jsp`
[2] `https://www.sciencedirect.com/`

Acronym	Description of the criterium
Inclusion criteria	
IC_1	Studies written in English
IC_2	Studies published in the range 2014-2022
IC_3	Studies published in a press or in a journal
IC_4	Studies should use ML or DL for Smart Health in IoT
Exclusion criteria	
EC_1	Studies are literature surveys or systematic reviews
EC_2	Studies do not entail IoT
EC_3	Studies are not related to Smart Health
EC_4	Studies are not specifically focused on ML or DL

Table 1. Inclusion and exclusion criteria applied in the research process.

), had to be specifically focused on Deep Learning (DL) or Machine Learning (ML) approaches (EC_4) in the Smart Health domain (IC_3) and had to be neither a survey nor a review (EC_1). Furthermore, the search was limited to articles published or in press (IC_1), thus excluding conferences and preprints. This decision was guided by the quality standards we aimed for in our systematic review. We took into account the fact that preprints have not been peer-reviewed and that solid and valid conference contributions are usually published in journals in more detail. Therefore, this final filtering phase allowed us to retain a total of 46 articles to analyze through the defined research questions.

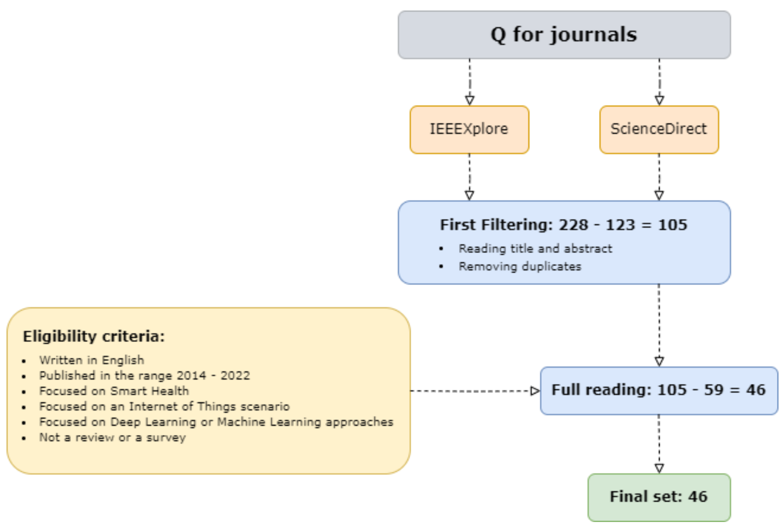

Figure 1. Research and filtering process for the paper selection

For completeness, Figure 2 presents the temporal distribution of the works definitively considered. This shows the years on the x-axis and the number of contributions on the y-axis, showing the total number of contributions with the blue bars, and the percentage with the orange bars. As can be seen from the figure, the number of articles addressing the topic of our research has become significant since 2017 and has increased over the years.

Furthermore, in Figure 3, we show the distribution of the articles considered per publisher, always reporting the name of the publisher in abscissa, the number in the ordinate axis. In particular, the blue bars take into account the number of papers published by the editor, instead of the orange ones the percentage. The analysis of the figure indicates the predominance of the articles of the IEEE publisher related to the topic of our research.

In figure 4 we refer to the distribution of the journals of IEEE editor, reporting the name of the journal in abscissa; furthermore, the blue bars consider the number of papers published by the journal, instead of the orange ones the percentage. The figure shows that our research topic is predominantly presented in the IEEE Access journal while the remaining articles are quite evenly distributed across various other journals

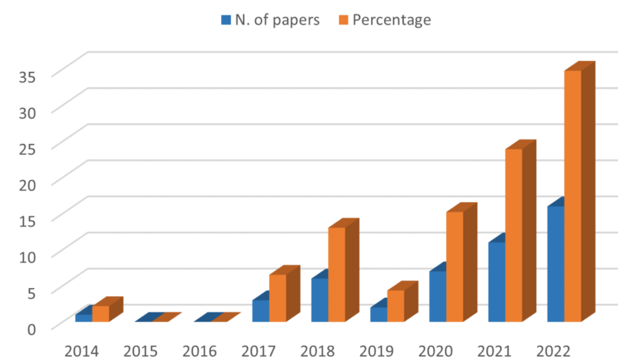

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Figure 2. Yearly distribution of the analyzed papers.

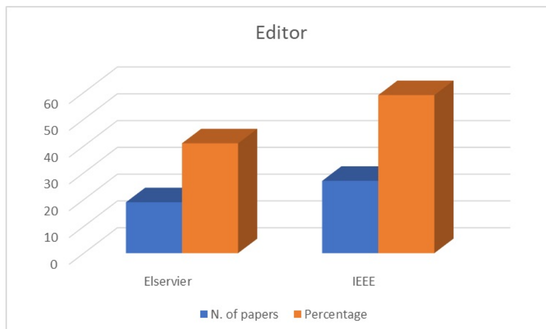

Figure 3. Distribution of the papers per editor

with some exceptions regarding journals such as IEEE Journal of Biomedical and Health Informatics, IEEE Internet of Things Journal, and IEEE Transactions on Biomedical Engineering.

4 RESULTS

In this section, we report the results obtained for each research question.

4.1 RQ1: Does the study use an ML or DL algorithm?

Different methodologies and approaches can be used to analyze health data. Among these, the best-known and most used in the literature are ML and DL algorithms and networks. There are the most disparate ML and DL techniques and there is also no shortage of customized implementations of basic algorithms, which makes the range of possible solutions truly wide.

For this reason, first of all, it is important to investigate which methodology is most used in the selected studies to determine the complexity and depth of the model with a distinction between ML and DL approaches or to investigate whether the study investigates both methodologies, therefore considering, in this case, the number of ML/DL Algorithms evaluated.

Figure 5 summarizes the absolute number of articles (in blue) and mass percentages (in orange) for each analysis method used in the study (ML, DL, or both algorithm types) plotted on the x-axis. It can be observed that the majority of articles (59.62%) concern ML methodology, followed by DL algorithms (25%). However, only in 8 studies (15.38%), the two approaches are used together.

In Figure 6 we report the distributions of the number of algorithms used in the selected articles: in Figure 6 a) we report the distributions of the number of ML/DL classifiers evaluated in the studies that only used the ML or DL approach, and in particular the distribution of the ML classifiers evaluated in the selected articles is highlighted in blue and that referring to the DL algorithms is highlighted in orange. On the other hand, in Figure 6 b) we show the distributions of the ML/DL classifiers evaluated in the studies that used both methodologies.

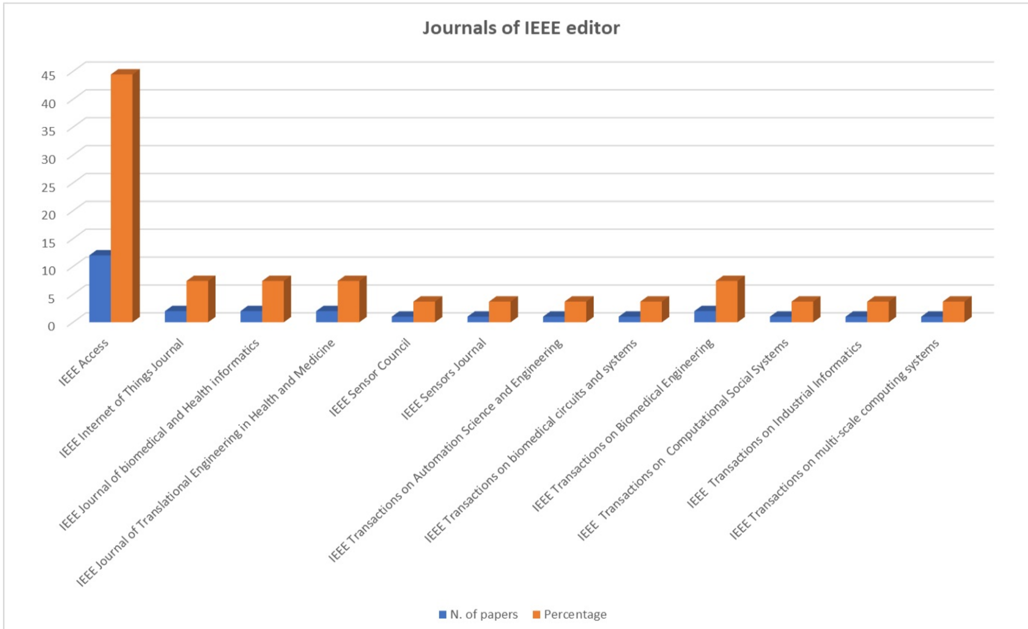

Figure 4. Distribution of journals of IEEE editor

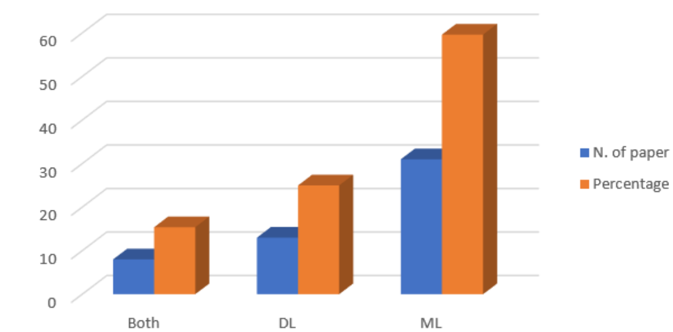

Figure 5. Distribution of the use of ML and DL techniques in the selected studies.

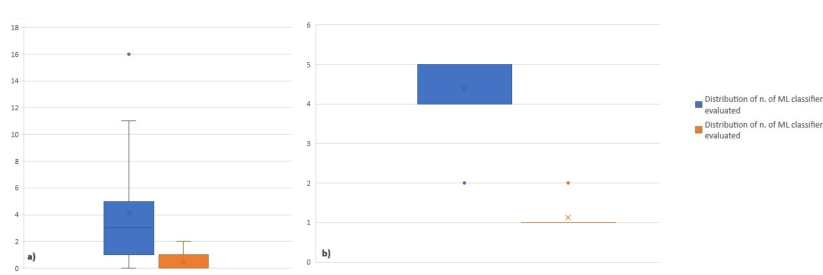

Figure 6. a) Distributions of the number of ML/DL classifiers evaluated in the studies b) Distributions of the number of ML/DL classifiers evaluated in the studies that used both methodologies

The analysis of the distributions of the number of ML/DL classifiers evaluated in the studies that used only of approach shows that in the majority of articles using ML algorithms, it is preferred to compare multiple classifiers of this type, at least more than 3 (median of the blue distribution). Instead, in studies where DL methodologies are used, it is preferred to use a single network selected according to the nature of the data. This choice is assumed to be made because DL algorithms require longer execution times and more computational memory than ML classifiers. Even in the case of articles that used the two approaches together, more ML classifiers are used than the DL approach which remains at the level of single network used.

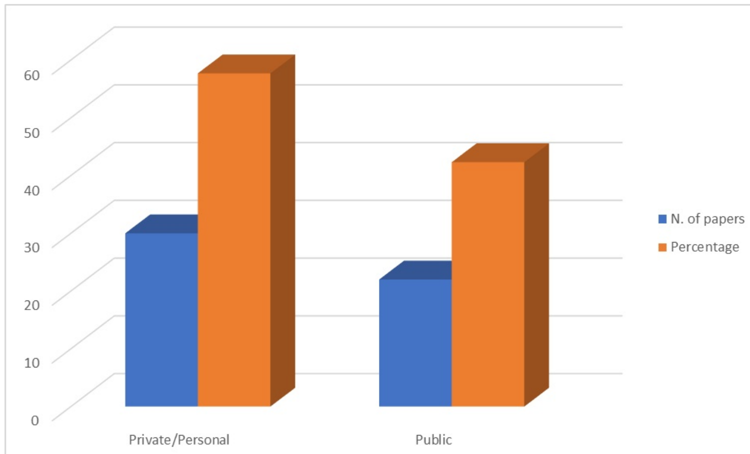

Figure 7. Distribution of the considered papers according to the data access policy

According to this research question, we also explored some aspects related to the data set used in the selected papers. Firstly we examine the possibility of accessing the data, specifically if the data set used is public or private/personal. Figure 7 displays the data access policy adopted by the authors. The larger number of the papers analyzed (58%) operate with private/personal data sets, while 42% of them analyze public data that in the majority of the cases are publicly available or can be released on request.

Relating to the nature of the data used in the considered papers, we also investigated the number of instances/patients involved in collecting the data. Additionally, we also scrutinized the number of features used to train the models used in the collected papers. In table 2 we disclose the results of this investigation. In particular, in it, we have reported in line with the confidence interval of the average number, the modal value, the minimum and maximum value assumed by the number of instances/patients involved in the data collection (first column), and the features used in the model training (second column).

Metrics	N. of instances/patients	N. of features
Mean	1588 ± 442,88	72 ± 19,99
Modal Value	40	6
Minimum	2	5
Maximum	42021	773

Table 2. Metrics relating to the analysis of the data used in the considered papers

Referring to the results obtained in table 2 we notice that for both analyses the minimum and maximum values differ greatly and for this reason, the mean and its relative confidence interval are extremely high; this is also the reason why we decided to study the modal value of the two distributions. In particular, taking this last value into account, we note that in general, the number of instances/patients in the papers is around 40 cases while the number of features used to train the models in the major of the papers is 6.

4.2 RQ2: Which Neural Network architectures are used in IoT Smart Health considering the scopes of application?

Neural network architectures play a significant role in IoT Smart Health by enabling the development of applications that improve health monitoring, diagnostics, and overall well-being of users. Furthermore,

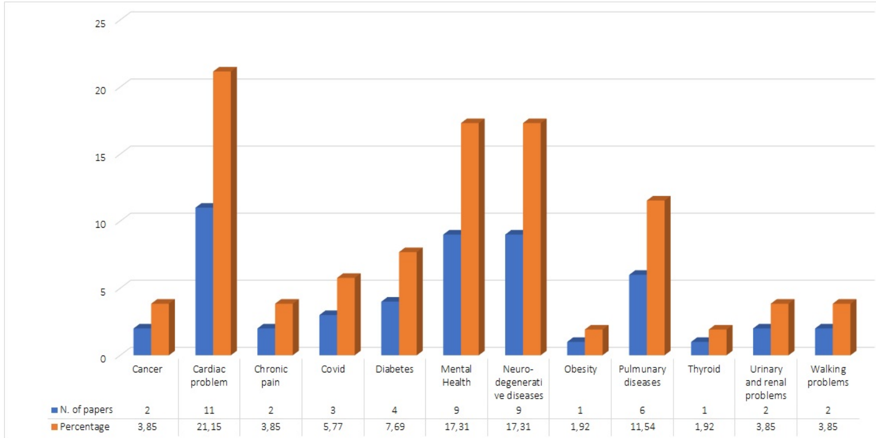

Figure 8. Distribution of pathologies analyzed in the selection of articles

DL architectures, together with appropriate data pre-processing and model optimization techniques, contribute to the advancement of IoT Smart Health applications, enabling early disease detection and better management of chronic conditions. In the documents analyzed, we found that there are some key neural network architectures used in IoT Smart Health concerning specific types of data:

- Convolutional Neural Networks (CNNs) are widely used for image-based diagnostics for example analysis of medical imaging data (X-rays, MRI, CT scans), and real-time video monitoring (e.g., for patient movement analysis). They help in identifying patterns, anomalies, and potential health issues from visual data.
- Recurrent Neural Networks (RNNs): are often used for time series analysis of health-related data, such as continuous monitoring of vital signs (heart rate, blood pressure)and patient activity tracking.
- Long Short-Term Memory Networks (LSTMs), an extension of RNNs, are valuable for processing and analyzing sequential health data, such as medical history, and time-stamped sensor data.
- Densely Connected Convolutional Networks (DenseNet) are a CNN architecture that connects each layer to every other layer in a feed-forward pattern. They are efficient for medical image analysis, especially when dealing with limited data or for transfer learning tasks.
- Dense Neural Networks (DNNs) are often used in IoT Smart health for remote patient monitoring. DNNs can analyze data from wearable devices, sensors, and other IoT-enabled medical devices to continuously monitor a patient's vital signs, detect anomalies, and provide real-time alerts to healthcare professionals for early intervention.

Concerning the pathology analyzed, we report in Figure 8 the distribution of the papers we considered according to the disease having been tackled.

In particular in Figure 8 the blue bars take into account the number of studies, while the orange bars take into account the percentage; the same figure also shows the table with the respective values. The results of this analysis show that in general, the most studied diseases are heart diseases (21.15%), mental diseases such as depression and panic attacks as well as neurodegenerative diseases such as Parkinson's, amyotrophic lateral sclerosis (ALS), and myotonic dystrophy (17.31%) and lung disease (11.54%).

In Figure 9 we have reported the distribution of the pathologies analyzed only with a DL approach. Also in this figure, we have displayed the number of studies in blue and the relative percentage in orange; at the bottom of the image we report the table of the relative values of both. This analysis shows that complex approaches such as DL are most used when dealing with heart and neurodegenerative disease data (20%), but also for mental health and lung disease data (15%). In particular, these diseases are the most difficult to diagnose because they present vast symptoms and therefore many characteristics that need to be managed during the analysis and classification of patients affected by them and all these aspects justify the use of complex techniques such as Neural Networks.

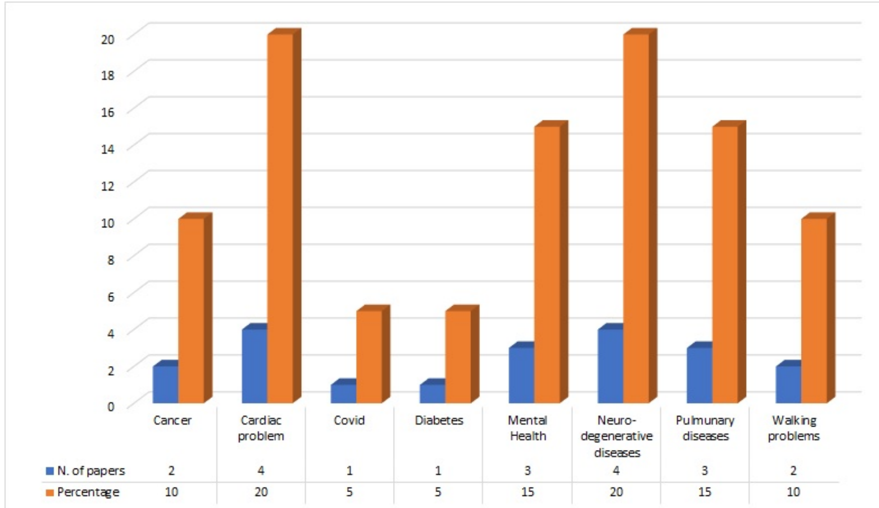

Figure 9. Distribution of pathologies analyzed with a DL approach

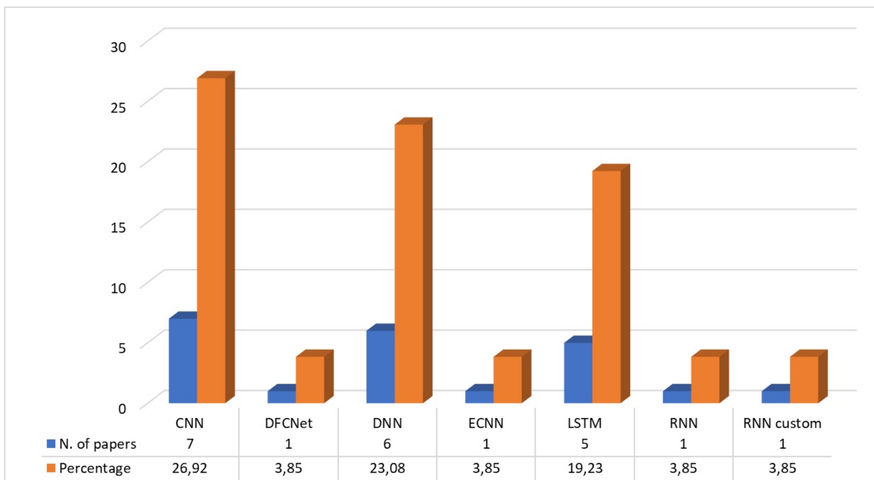

Figure 10. Number of papers and relative percentage, based on the type of Neural Network architecture

To understand which architectures are the most implemented in the case of medical data collected by IoT intelligent devices, we analyze the distribution of the most used DL approaches in paper selection. In Figure 10 we present the distribution of the type of neural network architecture used in the selected articles. In particular, the card numbers are shown in blue, while the percentages are considered in orange; furthermore, at the bottom of the figure, there is a table of the values assumed by the colored bars. The results show that the most used neural network architectures for IoT Smart Health problems are the Convolutional Neural Network, the Deep Neural Network, and the Short-Term Memory Network: in fact, these three different architectures alone cover almost 60% of the architectures used.

For completeness, to understand which Neural Network architectures are used in IoT Smart Health considering the pathology, we carried out a cross-analysis between the type of neural network and the pathology, the results of which are presented in Figure 11. The analysis shows that CNNs are the most used when dealing with clinical data relating to neurodegenerative diseases, mental problems, diabetes, heart problems, and cancer. Furthermore, DNNs are more used in the case of walking problems, lung diseases, and neurodegenerative diseases, while LSTMs are used when the data is related to heart problems, COVID-19, mental health, lung diseases, and walking problems.

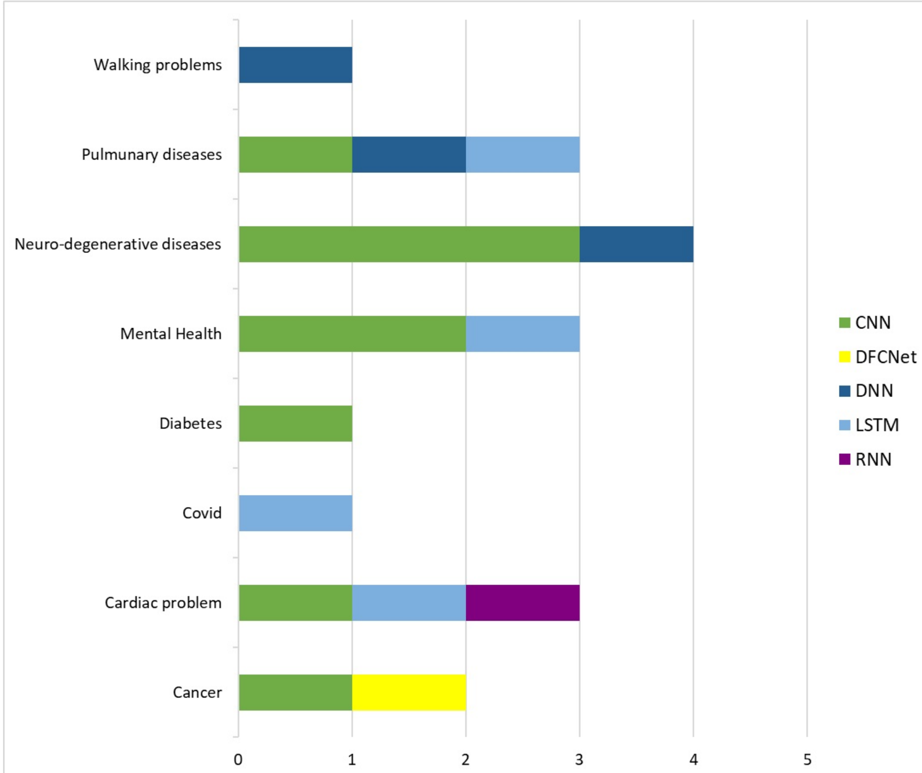

Figure 11. Distribution of Neural Network architectures based on the pathology analyzed by the different types of Neural Network architectures

4.3 RQ3: Which algorithms lead to better accuracy and reliability of Smart Health data collected from IoT device monitoring?

ML and DL algorithms play a vital role in improving the accuracy of the results produced and the reliability of healthcare data collected through IoT device monitoring. Algorithms can be trained using historical data to identify patterns and trends in healthcare data. Therefore, their application can be particularly useful for continuous monitoring of vital parameters such as blood pressure, heart rate, or blood sugar levels, or for long-term data analysis, allowing the identification of correlations between different parameters and risk factors. This can help develop personalized treatments and targeted preventive strategies, thus optimizing the effectiveness of treatments and improving patients' quality of life. For all these reasons, the ML or DL methodologies used to analyze the data must provide truly accurate results.

Consequently, we study the distributions of accuracy metrics obtained with the different approaches proposed in the selection of the analyzed documents to find out which algorithms bring better and more accurate results in the classification of healthcare data collected by IoT devices.

In this regard, we conducted a quantitative analysis, the results of which are reported in Figure 12, which shows the distribution of the values of the accuracy metrics reported in the selected articles with the use of the different approaches used. In the 46 studies analyzed, the minimum accuracy value obtained is 68% using multinomial logistic regression while the maximum accuracy obtained is 100% with Cubic SVM. On average, studies achieve an accuracy of 87% (confidence interval of the mean [79.80% - 96%]).

Furthermore, Figure 13 reports the averages of the accuracies detected in the different studies that use the ML algorithm or the DL network (expressed in abscissa). The three best classifiers in terms of average accuracy are, in decreasing order: Cubic SVM (100%), J48 (99%), and custom classifier (97%).

The first classifier, Cubic SVM, is a variant of Support Vector Machine (SVM) that uses a cubic kernel function to map data into a high-dimensional feature space. Using a cubic kernel function allows SVM to find more complex and nonlinear decision frontiers in feature space. This can be useful when the data is not linearly separable in the original space and requires a nonlinear representation to be accurately classified, as is often the case in medical/healthcare data.

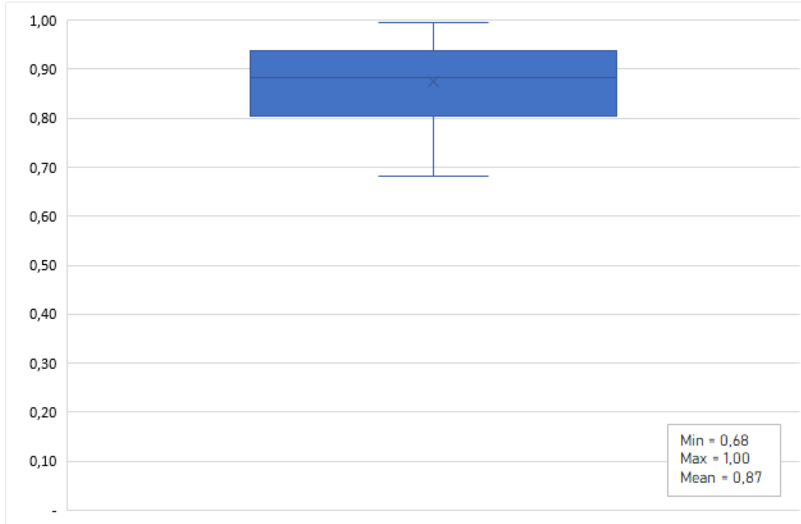

Figure 12. Distribution of values of accuracy metrics obtained with the approaches used in the selected papers

J48 is a widely used algorithm for creating decision trees. This algorithm requires a labeled dataset, meaning that each example in the dataset is associated with a class label. To select the best attribute, the J48 algorithm splits the dataset at each node of the decision tree allowing for better information gain; the data set is split to optimize the Gini index or gain ratio. The tree construction process continues until a stopping criterion is met. J48 is widely used due to its simplicity, interpretability, and effectiveness in a variety of industries, including the smart healthcare data space. Finally, a custom classifier is a

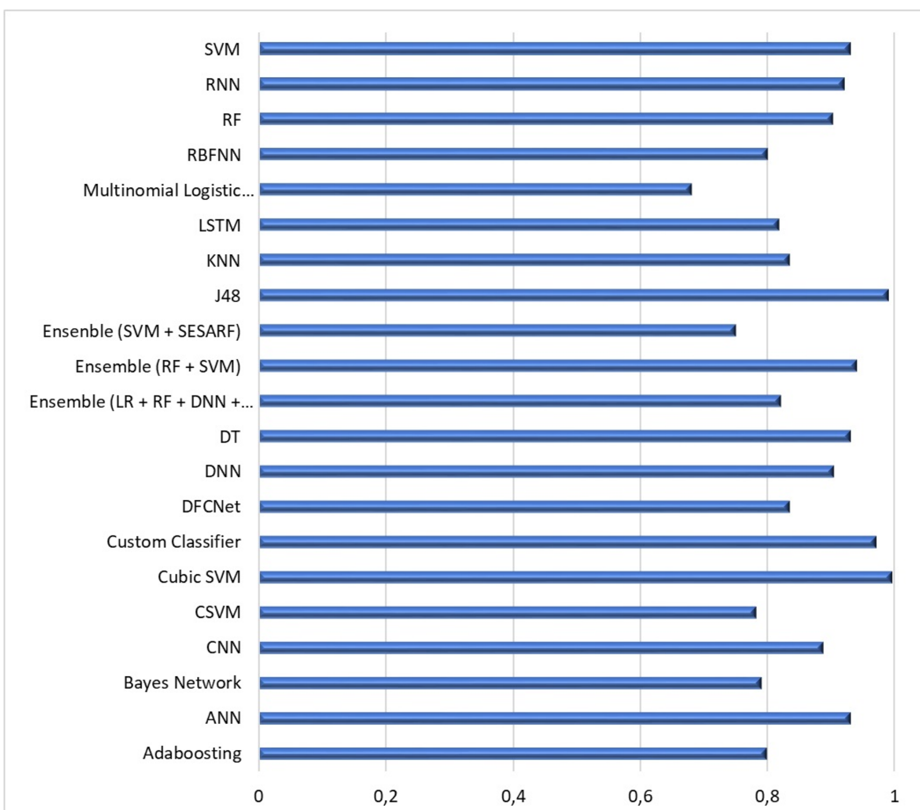

Figure 13. Average accuracy obtained by the approaches used in the selected papers

customization of an already existing algorithm, implemented concerning the classification objective. Customization, however, must be done thoughtfully and it is important to evaluate the performance of the customized model through appropriate validations and testing to ensure improvements and avoid unintended errors.

RQ4: What are the privacy and security issues taken into account while using health data collected from IoT devices?

The use of health data collected by IoT devices raises significant privacy and security concerns that must be carefully addressed to ensure the protection of people's sensitive information. For this reason, we also focused our analysis on this topic, evaluating in the selected documents whether privacy or security problems had been found and how these had been addressed during the phases of collection, transmission, and storage of health data by IoT devices.

First of all, we found that the two topics, privacy and security, were addressed in only 24% of the works analyzed. This means that less than one in three articles using health/clinical data questions whether the privacy of users using the devices is respected, considering whether sensitive data is recorded and whether storage techniques comply with data security standards.

In all the documents in which these issues were considered, the problems related to user privacy during the data recording phase by IoT devices were taken into account. Only 13.60% of the works also take into account the issue of data security addressed during the data archiving phase.

These studies also provide treatments aimed at solving these problems. In particular, problems relating to user privacy during the data recording phase(s) have been resolved:

- in 2.20% of cases considering only some characteristics extracted from the raw data stored and not using the starting data recorded by the device itself Ware et al. (2022),
- when the video recordings of the users filming their faces and voices are also included in the original data, in 4.30% of the works these recordings were eliminated from the analyzed data set Wu et al. (2022); Cai et al. (2018),
- in 2.20% of the other works, instead of recording user videos, a 'Radio Frequency Identification' (RFID) system was used, an automatic digital identification technology that allows the detection of objects, people, and animals, both static and moving, exploiting electromagnetic fields and not video recording Chen et al. (2022).

As regards the studies that take into account the issue of data security also during data archiving during and after data analysis, the main solutions adopted for this problem were:

- in 4.30% of cases the use of edge-fog architectures of the cloud Chakraborty and Kishor (2022); Sadhu et al. (2022),
- in 4.30% of the works encryption techniques were used to ensure that data collected from IoT devices is encrypted both during transmission and while stored in databases Sarmah (2020); Cheikhrouhou et al. (2021),
- in 2.20% of the papers high-security protocols of the storage clouds were adoptedYue et al. (2020),
- in the remaining 2.20% of the studies conduct regular security checks and assessments to identify vulnerabilities and risks in the cloud system, plus implement monitoring mechanisms to detect any unauthorized access or suspicious activity Rahman et al. (2020).

5 DISCUSSION

Overall, the analysis we conducted highlighted the following results:

- most of the research papers reviewed deal with ML methodologies rather than DL techniques, and only a small fraction of both;
- most articles using ML algorithms use multiple classifiers, while those using DL algorithms typically use a single network, and this pattern remains true even in cases where articles use both approaches;

- the most used neural network architectures for IoT Smart Health problems are (i) CNNs when dealing with neurodegenerative diseases [Prince et al. (2019), Chen et al. (2022)], mental problems Gupta et al. (2021), problems heart problems Cheikhrouhou et al. (2021), diabetes Ramazi et al. (2021) and cancer Masood et al. (2018)], (ii) LSTM when it comes to heart problems Chiang et al. (2021), covid Neog et al. (2022), mental health Jung et al. (2021), lung disease diseases Schoun et al. (2018) and walking problems Staab et al. (2022), (iii) DNNs are mostly used in case of walking problems Kim et al. (2020), heart diseases Wu et al. (2022), diseases pulmonary Wu et al. (2022) and neuro-degenerative diseases Prince et al. (2019);

- the minimum accuracy value obtained is 68% while the maximum accuracy obtained is 100% and on average the studies reach an accuracy of 87%;

- privacy and security issues were evaluated in only 24% of the works analyzed.

Our systematic review reveals a noteworthy emphasis on Machine Learning (ML) methodologies over Deep Learning (DL) techniques. This inclination can be attributed to several factors. ML algorithms, especially when dealing with traditional classification problems, are often more interpretable. Many researchers treat deep learning methods as an enigmatic system, lacking the means to justify its successful outcomes or make adjustments in instances of classification errors. Interpretability is crucial in healthcare, where clinicians and practitioners need to understand the reasoning behind AI-driven decisions.

In addition, training reliable and effective DL algorithms requires large sets of data. Even though there has been a recent surge in the availability of healthcare data, not all medical applications—especially those concerning rare diseases or events—are ideally suited for deep learning Ravì et al. (2017).

ML models usually require fewer computational resources compared to Deep Learning (DL) models, especially those with multiple layers. These DL models often necessitate substantial computing power and have extended processing times.

For what regards Deep Learning (DL) applications our research work highlights the most implemented architectures. Convolutional Neural Networks (CNNs), for instance, shine when confronted with problems involving image analysis since are adept at detecting intricate patterns in medical images, which are often pivotal in accurate diagnoses. Long Short-Term Memory Networks (LSTMs), with their sequential data processing capabilities, come to the forefront when tackling issues that involve time-series data. LSTMs can capture dependencies and trends in sequences of health measurements, enabling the prediction of deteriorating health conditions or the detection of subtle changes in a patient's well-being. This makes them invaluable in real-time monitoring and early intervention. Deep Neural Networks (DNNs), on the other hand, are prominently featured in health problems that demand complex feature extraction and data representation. DNNs are characterized by their depth and capacity to learn hierarchical representations, making them suitable for problems that involve multifaceted data sources and complex relationships. Despite exceptional performance offered, the high computational demands associated with Deep Learning (DL) models, can hinder real-time deployment in resource-constrained healthcare environments, where timely interventions are critical. Balancing high accuracy with practical utility and real-world applicability remains an ongoing challenge in smart health research.

Following all the aforementioned considerations, the adoption of Deep Learning (DL) techniques in a selection of research articles emphasizes their relevance in distinct healthcare contexts. As the volume of data grows, Deep Learning (DL) technologies can step in where human analysis might falter, enhancing the speed and intelligence of disease diagnosis. This can minimize ambiguity in clinical decision-making. Perhaps the ultimate challenge for deep learning lies in its ability to amalgamate data from various health informatics fields, paving the way for the next era of precision medicine.

A critical avenue for future research revolves around enhancing the privacy and security of health data, as these topics remain insufficiently explored in the literature. With the rapid development and integration of AI technologies into the landscape of smart health, as well as the widespread use of IoT devices for health monitoring, the protection of sensitive patient information has become an essential and paramount concern. One promising research direction involves the development of robust privacy-preserving mechanisms that can safeguard personal health data throughout its lifecycle, from collection and transmission to storage and analysis. Additionally, research efforts should focus on ensuring compliance with evolving data protection regulations and standards in the healthcare sector. By addressing these privacy and security challenges, future research can pave the way for the responsible and effective deployment of AI in smart health, ultimately benefiting both patients and healthcare providers.

6 CONCLUSIONS

Artificial intelligence in healthcare allows us to manage enormous quantities of data, finding connections between information that is apparently unconnected or so numerous that it cannot be analyzed otherwise. The system thus generates new concepts and new associations, for example by detecting, based on the repeated verification of images connected to the diagnostic data, that a certain conformation or color of the nevi corresponds to given tumor pathologies. It is evident, therefore, that the greater the number of data inserted in the learning phase or during the life of the system, the more accurate and precise the ability to create new connections, see hidden results, and reach conclusions that man would not be able to reach. arrived or would have arrived with extreme difficulty.

In healthcare, artificial intelligence finds space in sectors such as diagnostics, prevention, rehabilitation, telemedicine, robotic surgery, the development of new drugs and vaccines, the organization of services, or the definition of collective behavior models affecting the 'assistance.

The availability of wearable devices, capable of detecting important health parameters such as blood pressure, oxygenation, heart rate, or electroencephalogram, is also facilitating telemonitoring and remote assistance. The advantages are evident, allowing forms of control without changing habits or lifestyles and being able to acquire data from the context of the patient's daily life,

Therefore, the new frontier of wearable devices aims to exploit artificial intelligence not only to provide useful information for the present context, but to anticipate actions, or rather "predict" them to help people even more.

In this regard, in this study, we performed an in-depth systematic review of the application of ML and DL technologies to the advanced analysis and prediction of data derived from healthcare IoT devices. The main objective was to contribute to the current state of the literature by exploring the research landscape regarding Machine Learning (ML) and Deep Learning (DL) approaches applied in the smart health sector, to highlight challenges and vulnerabilities.

Our approach began with the definition of a query, which allowed us to select the studies present in the literature relating to the keywords Artificial Intelligence, Smart Health, and Wearable. We subsequently defined the research directions, defining four very specific research questions, which helped us through the definition of the inclusion and exclusion criteria, in the various document screening phases to reach the final set of 46 documents analyzed during our review.

The different analyses conducted first report whether the studies use ML, DL, or both models (i); which models are used specifically (ii); the accuracy and reliability of AI-based models in the smart healthcare landscape (iii); and evaluate important security and privacy issues related to data use (iv).

The results show that there is a more widespread use of ML techniques, rather than DL, but that in the case of DL the most used networks are CNN, DNN, and LSTM. The minimum accuracy value obtained is 68% while the maximum accuracy obtained is 100% and on average the studies achieve an accuracy of 87%. Finally, it is clear that very few studies consider the issue of data privacy.

Therefore, this review has helped to clarify several still unanswered questions on the topic we have chosen, demonstrating the need for further research in the near future to establish the use of ML and DL as a viable and mature strategy in the context of smart health.

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