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IoT-AI in Healthcare: A Comprehensive Survey of Current Applications and Innovations

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ABSTRACT

The convergence of IoT and AI technology has the capacity to revolutionize healthcare by facilitating the gathering of real-time data and employing sophisticated analytics for tailored medical solutions. This survey provides an in-depth examination of IoT-AI applications in healthcare, specifically focusing on wearable devices such as smart bands and wristbands, as well as health monitoring systems. We present the core principles of IoT and AI, examining their synergistic integration in healthcare environments. The taxonomy of IoT-AI-based healthcare systems is comprehensive and classifies them according to their architectural components, data processing algorithms, and application domains. The survey showcases distinctive achievements, including novel methodologies for combining data and making predictions, frameworks for improving patient monitoring, and inventive methods for delivering healthcare remotely. We offer a comprehensive examination of key challenges such as data privacy, interoperability, and regulatory compliance, and analyze their specific effects on the implementation and efficacy of IoT-AI healthcare systems. The comparison analysis encompasses measures such as system performance, accuracy, and user satisfaction, providing valuable insights into the strengths and limitations of different techniques. In addition, we analyze developing patterns and clearly outline future areas of study, such as the enhancement of stronger security protocols, the use of blockchain technology to ensure data integrity, and the progress in AI algorithms to achieve more precise diagnoses. Emerging trends such as Digital Twins and SLUC are identified as promising avenues for future research. In conclusion, this study provides a detailed framework that enhances the understanding of IoT-AI healthcare systems and offers practical insights for improving healthcare practices and guiding technology adoption.

1. Introduction

In today's world, there are many kinds of health issues due to the user's lack of personal health care. The human population has been dealing with a lot of health concerns lately, such as eating disorders, mental health illnesses, fitness issues, and more. A balanced diet enhances our energy levels and overall well-being. We can improve our health and fitness levels by following a regular exercise regimen and a balanced diet. Various software applications and websites are developed to collect user-provided health parameters and offer tailored health information and recommendations. For instance, some websites calculate daily caloric needs by using personal information such as height, weight, and goal weight to determine the necessary caloric intake for achieving a calorie surplus or deficit based on the user's goals. Software applications that track the dietary record of the user and recommend an appropriate dietary plan for the user by taking the data related to health from the user [1].

In a conventional medical system, hospitals featured a crowded waiting room, with many patients waiting in lengthy lines outside the waiting area with frustrated expressions to see their doctors. However, things began to change with the development of IoT technologies, healthcare mobile applications, higher network speeds, and the use of AI and big data processing methods in illness diagnosis and patient monitoring. Conventional medical services need well-trained practitioners and extensive testing equipment, forcing patients to visit hospitals frequently. Furthermore, it raises the cost of healthcare, which might become burdensome for middle- and low-income families. Many individuals purposefully postpone checkups to avoid unexpected medical expenditures. Another cause is that individuals typically have an incredibly hectic work schedule; as a result, they do not have enough time to attend medical appointments on time. As a result, a real-time and continuous health monitoring system might be quite valuable to them. In this case, an IoT-AI-based remote health monitoring system may play an important role because it offers an intelligent service that enables health monitoring in a variety of settings, including clinics, homes, workplaces, and so on. It also significantly improves human lives by lowering medical expenditures and other stresses. Furthermore, it accelerates the diagnostic and treatment procedures.

Smart wearable devices have emerged in the field of medical sciences for better monitoring of health-related parameters, providing necessary medical care for the user, and maintaining the quality of life [2]. These devices are used for detecting and monitoring various biosignals through trackers, recording daily activities linked to the user's gender, age, BMI, and physical activity behavior [3]. However, while wearables alone can collect a vast amount of data, the real value lies in the meaningful interpretation of this data. This is where AI/ML integration becomes crucial. AI/ML algorithms enhance the functionality of wearable devices by analyzing complex datasets in real time, enabling more accurate and personalized insights that static, pre-defined data cannot offer. For instance, AI/ML can be used to provide personalized dietary suggestions by analyzing a user's specific health metrics and comparing them with extensive datasets of healthy food items, rather than relying on generic dietary plans.

Moreover, this integration allows for proactive health management by identifying patterns and predicting potential health issues before they become critical, thereby facilitating timely interventions. Sensors like those measuring blood oxygen levels, body temperature, and heart rate can be coupled with AI/ML models to deliver tailored health recommendations that are continuously updated based on real-time data [4]. The necessity of this integration is further emphasized by its expanding applications beyond just workouts. For example, in sports, AI/ML-enhanced wearables are revolutionizing the way athletes' performance is monitored and evaluated, allowing for more precise physical assessments and tailored training programs [5]. Similarly, in mental health, wearables integrated with AI/ML can track physiological, movement, and biochemical signals to monitor anxiety, stress, and panic attacks, offering a more holistic approach to health monitoring [6]-[9]. In summary, the integration of AI/ML with wearable devices is not just an enhancement but a fundamental shift in how health data is utilized, transforming raw data into actionable insights that lead to better health outcomes.

Future projections indicate significant growth for the wearable device market. The prediction indicates that the growth rate of the industry will exceed 20% annually, resulting in a yearly revenue of over 40 billion EUR during the next five years and surpassing 150 billion EUR by 2028 [10].

Fig. 1 illustrates the increasing trend in the number of research papers being published annually in the field of IoT and ML applications for healthcare. Starting from 2020, there was a consistent output of papers, which dipped slightly in 2022 but rebounded strongly in 2023 with a significant rise in publications. The projected numbers for 2024 indicate a continued upward trajectory, albeit the number of papers published so far appears to be lower compared to the previous year, potentially because the year is still ongoing, and more papers may be expected to be published as the year progresses. The global implementation of IoT devices is increasing year by year. The Internet of Things (IoT) along with ML is offering solutions in many sectors, such as smart cities, smart homes, enterprises, health, and welfare [11], [12]. In the past ten years, there has been significant advancement in several fields such as sensors, micro-controllers, networking technology, computing instances, and societal requirements [13]. In recent years, the healthcare sector has experienced significant growth, mostly due to the integration of IoT devices. Experts project the worldwide healthcare Internet of Things (IoT) industry to reach a value of $188.2 billion by 2025 [14]. This trend highlights the growing interest and research activity in leveraging IoT and ML technologies to advance healthcare solutions, driven by factors such as the need for remote patient monitoring, predictive analytics, and personalized medicine. It suggests that the integration of IoT with ML in healthcare is an area of active exploration, with researchers continually contributing new findings and innovations to this rapidly evolving domain. The aforementioned development motivates researchers to utilize the IoT network in a wider range of domains.

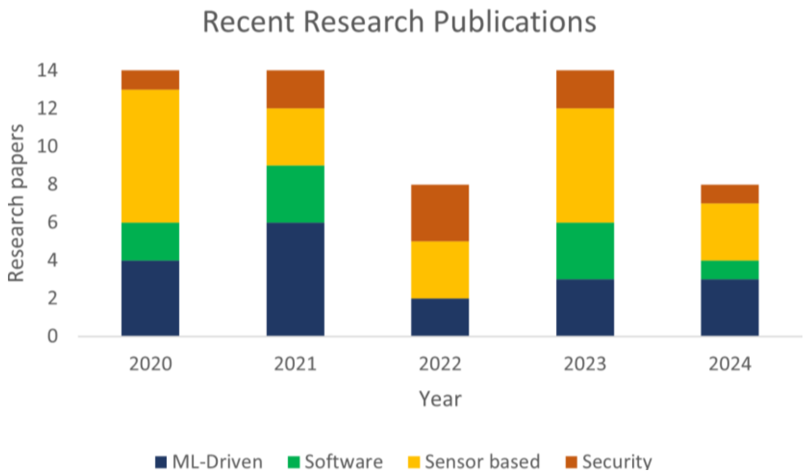

Fig. 1. Overview of papers published per year

Fig. 2 presents an outline of the IoT-ML-based uses in healthcare. It shows the whole process, from the sensors to the way the data is visualized. This paper gives a complete overview of IoT devices and ML approaches used in healthcare and describes network storage utilized to store large amounts of data for health services. We proposed an intriguing taxonomy that demonstrates IoT, communication, network storage and computing, ML, and healthcare applications.

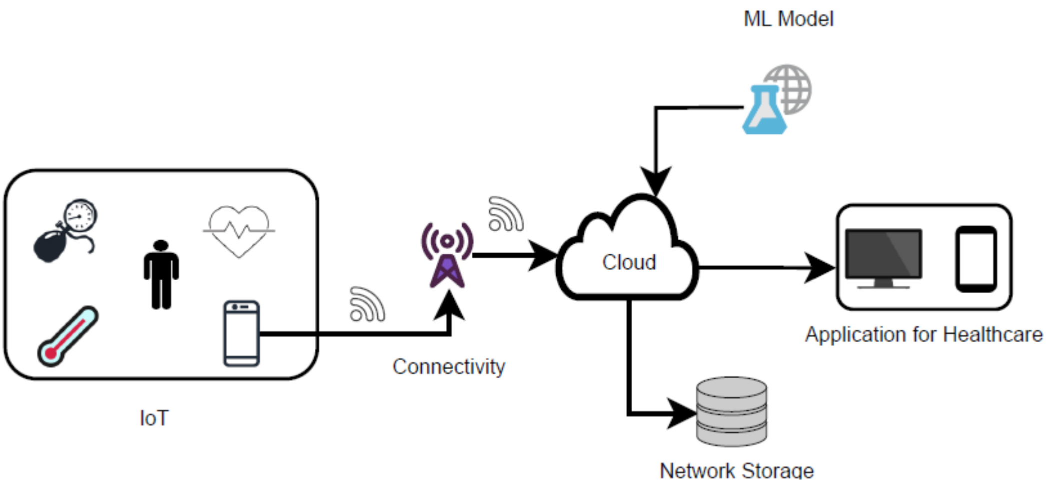

Fig. 2. Overview of the IoT-ML-based healthcare applications

Furthermore covered are the various communication technologies used in healthcare applications. Throughout the paper, our research contributions are evident in several key areas:

1.1. Comprehensive Literature Review and Categorization

We have conducted an extensive literature review that categorizes existing work into four main domains, addressing different aspects of the field:

- ML-Driven Solutions: These rely on machine learning to conduct predictive analytics and deliver individualized treatment.
- Software-Based Systems: This category focuses on developing and integrating platforms for data management and user interfaces.
- Sensor-Based Systems: These include continuous monitoring of physiological information using a variety of sensors and wearable devices.
- Security-Methods: These systems place a high priority on protecting confidential healthcare information and adhering to privacy requirements.

The selection of the four categories—ML-driven solutions, Software-Based Systems, Sensor-Based Systems, and Security Methods; was because they collectively represent the fundamental components required to build, deploy, and maintain effective IoT and ML systems in healthcare. By focusing on these areas, the literature review comprehensively addresses the technological, functional, and security dimensions critical to advancing the field. ML-driven solutions are central to predictive analytics and personalized care, making them essential for exploring intelligent decision-making in healthcare. Software-based systems provide the necessary infrastructure for data management and user interaction, forming the backbone of IoT-ML applications. Sensor-based systems are necessary for continuous monitoring and data collection, which are critical for real-time healthcare applications. Finally, Security Methods are indispensable for safeguarding sensitive medical data and addressing the vulnerabilities introduced by IoT integration.

This categorization facilitates the organization of research by highlighting specific technologies and challenges within each subject area, promoting a clearer understanding of their applications and progress.

1.2. Development of a Novel Taxonomy

We have developed a novel taxonomy for IoT and ML applications in healthcare, which provides a structured framework for understanding and advancing the field. Our proposed taxonomy outlines the crucial stages of an IoT-based healthcare application that utilizes ML to make informed decisions and relies on a cloud-based infrastructure for remote storage and computation. The taxonomy covers the entire workflow, starting from the hardware level and extending to the user-level visualization, centering on the phases involved in IoT-ML healthcare applications: IoT, communication, network storage and computing, and ML. This offers a fundamental understanding of IoT and ML-enabled systems in the healthcare industry.

1.3. Critical Analysis and Research Gap Identification

Our critical analysis of the literature offers a clear identification of strengths, weaknesses, and research gaps, paving the way for future research directions. We have carefully outlined both the outcomes and limitations of the research papers we reviewed, helping researchers understand the achievements and remaining challenges:

- High Accuracy vs. Challenges: While IoT and AI technologies have shown high accuracy in healthcare applications, they face limitations such as data acquisition complexities, computational demands, and privacy concerns. For example, LightGBM and DL models have achieved 99.23% accuracy in HAR systems but encounter challenges in data quality, processing power, and integrating multiple health metrics across systems.

- Emerging Technologies: Mobile health applications and sensor-based technologies offer insights into personalized health management but lack comprehensive cardiovascular risk assessment and accurate data integration. Emerging technologies like Digital Twins and SLUC show promise in predictive analytics but face model structure issues and ongoing privacy concerns.
- Integration and Scalability Issues: The integration of IoT with emerging technologies like THz systems and NB-IoT presents new opportunities but also introduces challenges in system interoperability, data security, and scalability.

Addressing these gaps is crucial for advancing the field and ensuring the effective and safe implementation of these technologies in clinical practice.

1.4. Proposed Future Research Directions

Based on the identified gaps and our critical analysis, we have proposed specific future research directions that address these challenges and suggest new avenues for innovation in IoT and ML integration in healthcare. These directions aim to push the boundaries of what IoT and ML can achieve in improving healthcare outcomes, enhancing patient care, and ensuring data security and privacy.

Fig. 3 illustrates the paper's structure. This paper is organized into four key sections, each designed to systematically address the complexities of integrating IoT and machine learning (ML) into healthcare systems.

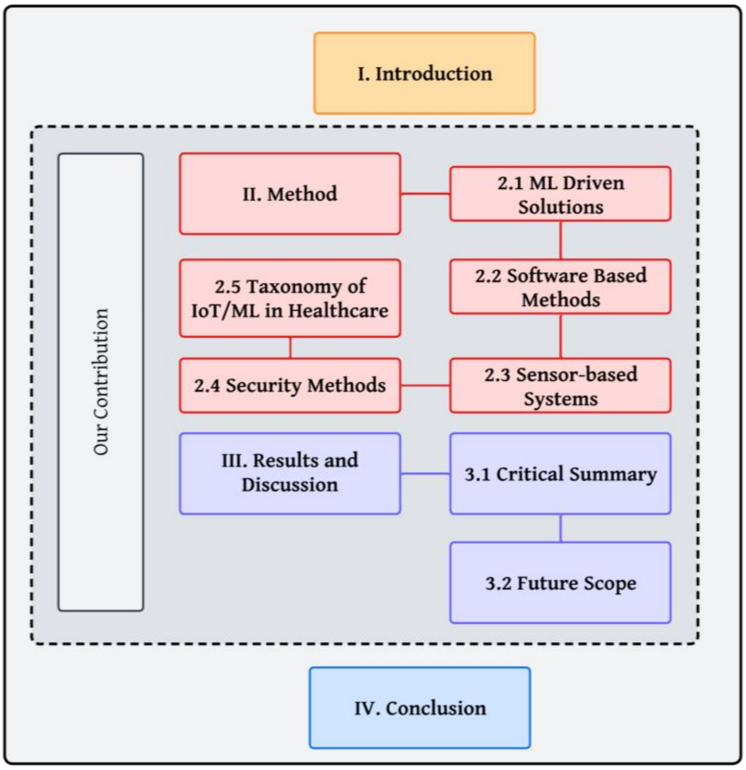

Fig. 3. Organization of our paper

- Introduction (Section I): The paper begins with an introduction that outlines the significance of IoT and ML in healthcare, providing an overview of the challenges and opportunities in this domain.
- Method (Section II): We divide this section into five subsections where we conduct a comprehensive review of the existing literature:
    - ML-Driven Solutions: This subsection delves into the application of various machine learning methodologies to healthcare IoT systems.

- Software-Based Methods: This subsection reviews software solutions that support IoT and ML integration in healthcare.
- Sensor-Based Systems: Here, we analyze the role of sensor technologies in healthcare IoT applications.
- Security Methods: We examine the security challenges and solutions pertinent to the deployment of IoT and ML in healthcare environments.
- Taxonomy of IoT/ML in Healthcare (Section III): A significant contribution of our research is the development of a novel taxonomy that categorizes the existing approaches, technologies, and solutions in IoT and ML as applied to healthcare. This taxonomy serves as a reference framework for both researchers and practitioners.

- Results and Discussion (Section III): We divide this section into 2 subsections
  - Critical Summary: In this subsection, we conduct a critical analysis of the surveyed literature, highlighting the strengths and weaknesses of current research and identifying gaps that need to be addressed in the future.
  - Future Scope: Based on the insights gained from the literature review and our taxonomy, we propose several future research directions. These recommendations aim to guide further exploration in areas that have the potential to advance the field.
- Conclusion (Section IV): The paper concludes with a summary of our findings, emphasizing the importance of continued research and development in the integration of IoT and ML in healthcare.

2. Method

This review of the literature aims to draw attention to the importance, methods, challenges, and advancements of earlier studies that use these tactics. To provide a proper and clear structure of the diverse range of technologies underlying in this domain, we have synthesized the research papers and divided them into 4 categories: ML Driven Solutions, software-based, sensor-based systems, and security-based approaches as shown in Fig. 4. In IoT smart wearable research for health assessment. Fig. 4. is a diagrammatic representation of the categories in which our survey is divided to help the readers understand the number of papers in each domain. We have specifically divided this research into four categories to help the researchers understand the different aspects of this domain and also to highlight the interdisciplinary nature of having different kinds of technology integrated into one domain spanning from hardware to software by also considering the security features and to highlight the importance of the technological advancement and development that need to be done in each distinct yet interconnected sphere of research and application. A critical analysis was performed comparing different algorithms used in ML models in software, sensors used in hardware, and different security challenges from different papers by creating a graph and also the number of researches done in each aspect of this domain shown in Fig. 1. According to prior researches, ML-driven solutions describe the use of different ML algorithms used to train the model to provide maximum accuracy in IoT systems for the prediction of health problems but doesn't specify what kind of algorithm provides maximum accuracy among all the algorithms used. Hence, our survey addresses this research gap and provides the details of the algorithm used to acquire maximum accuracy. Also, in the Software-based methods, the earlier research demonstrates the use of software applications in IoT devices and the services they provide for their users but it lacks any software having all features related to healthcare in one software. This gap is addressed in this survey to help the researchers in the future understand different kinds of features that could be added to the software. According to the earlier research done, Sensor-based systems represent the working of sensors and actuators that are used in healthcare but it doesn't correctly explain what kind of sensors and actuators are best suitable in comparison to other sensors and actuators. This survey addresses the research gap by explaining which sensors are best suitable for IoT-Ai in healthcare and also highlights the need for the advancements that are necessary for the development of sensors and actuators specifically designed for healthcare. Security-based approaches delineate the need for privacy and security for IoT systems for healthcare to avoid cyberattacks. It also mentions different security challenges but it doesn't mention different kinds of solutions that could prevent the potential cyber-attacks or features to protect the system from cyber attacks. In earlier research, in IoT-ML-based systems, the papers don't discuss the need for improvement in every aspect of the domain, they only discuss the specific aspects of this interdisciplinary domain and its uses in the healthcare field whereas our survey addresses this research gap and synthesizes every research in different research papers and provides a comprehensive survey of the use of IoT-ML in healthcare.

- The data extraction and synthesis process: After a thorough analysis of the research paper, we extracted the data based on the accuracy of the ML model used in the ML-based solution category, the software application and its feature developed in the software-based category, the sensors which are used in each paper in the sensor-based category and the types of security challenges that harm the software as well as the hardware in healthcare.
- Search methodology: The keywords and databases that are used to collect the research paper are listed in Table 1. These keywords are specifically used as they are more closely related to the domain of our research and we have searched in different databases to get relevant research papers from which only the databases mentioned in Table 1. Were used to collect authentic papers as other databases didn't provide us with satisfactory results.
- Quality of the research: Every research paper is collected and synthesized from the renowned publication mentioned in Table 1. so as to maintain the quality and authenticity of the research paper that is used to conduct this survey.

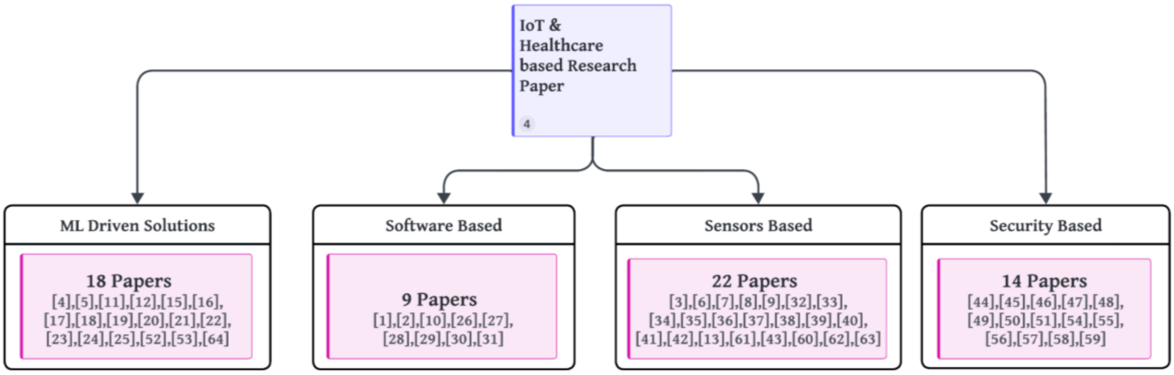

Fig. 4. Categorization of survey-based IoT-ML Healthcare

Table 1 provides a comprehensive list of research publications related to wearable devices, the IoT, and healthcare applications that we found using the keywords and database mentioned in the table in addition to the diagrammatic representation of the number of papers collected from each domain. Also, the papers have been collected belonging to the year ranging between 2019-2024, so as to consider the recent researches done in this domain.

Table 1. Recent publication Trends of IoT-ML-based healthcare systems

Categories	Publication	Citation	Year	Search Keywords	Database
ML Driven Solutions	MDPI	[4]	2023	diet and fitness healthcare IoT, sensors machine learning recommendations fitness assessment smart wearables Real-time monitoring	Digital library of IEEE Xplore Multidisciplinary Digital Publishing Institute Science Direct Springer Nature
		[5]	2021		
		[18]	2024		
		[20]	2022		
	Elsevier	[16]	2021		

Categories	Publication	Citation	Year	Search Keywords	Database
		[19]	2020		
		[24]	2023		
		[64]	2024		
	IEEE	[17]	2020		
		[23]	2020		
	Springer	[15]	2021		
		[21]	2023		
	Wiley	[22]	2022		
	Taylor & Francis	[52]	2024		
		[26]	2020		
	MDPI	[27]	2023		
		[1]	2023		
Software Based		[28]	2023	mobile applications digital health dietary assessment user clustering	
	IEEE	[29]	2021		
		[30]	2020		
	Elsevier	[31]	2024		
		[32]	2023		
	MDPI	[3]	2022		
		[35]	2023		
	IEEE	[36]	2021		
Sensor Based Systems		[38]	2020	smart sensors, BMI wearable systems wearable activity tracker Biosensors, Biosignals	
	Springer	[39]	2023		
		[37]	2020		
	Elsevier	[40]	2021		
		[41]	2024		
	Wiley	[42]	2024		
	MDPI	[44]	2023		
		[48]	2023		
Security Based		[45]	2021	Security, Privacy Blockchain Authentication	
	IEEE	[46]	2021		
		[47]	2020		
	Springer	[49]	2022		

Categories	Publication	Citation	Year	Search Keywords	Database
		[50]	2019		
		[55]	2021		
		[56]	2023		

2.1. ML Driven Solutions

In the research paper [4], S. K. Jagatheesaperumal et al. (2023) proposed an IoT-based framework for personalized health assessment and recommendations. The system uses IoT-integrated devices to collect health data such as pulse rate, BMI, body temperature, and blood oxygen level. It requires the collecting and analyzing of health parameters associated with different health indicators, utilizing ML algorithms like Catboost and RF to provide tailored diet and exercise recommendations and also compares this algorithm with RF and MLP classifiers. To facilitate engagement with the established framework, the system also incorporates an interactive web platform. The author of the research paper [15] Xingdong Wu et al. (2021) proposed a real-time health assessment system that utilizes wearables with IoT capabilities to track the health of Sanda athletes. These devices collect and transmit data to a server using a wireless communication relay network for continuous monitoring and analysis. PCA is utilized to de-noise and decrease the dimensionality of data. The system uses DL algorithms, such as GD, for real-time optimization and precise prediction throughout the transmission, monitoring, storage, and analysis of athlete data. In the survey [5] conducted by João Passos et al., along with his fellow researchers (2021) proposed an in-depth review of Wearable and IoT technologies in sports. It interprets that technologies depend on sensor systems that gather, analyze, and communicate pertinent data, including biomarkers and/or other performance indicators, which are essential for assessing how an athlete's condition is changing and, therefore, for enhancing their performance. It seeks to identify, condense, and debate the relevance of wearables and IoT technologies over fitness evaluation in recent studies that have employed them. It also describes how data taken from the wearable devices can be used and also uses CNN for giving a complete assessment of the athlete's physical whereabouts.

The authors N. S. Sworna et al. (2021) provided a comprehensive survey in the survey paper [16] on IoT and ML in healthcare applications sensing data using IoT sensors to visualize the data. It gives a detailed analysis of the IoT architecture and ML algorithms used for processing the data. It also describes different actuators, boards, and sensors used in the healthcare domain. It also discusses the communication technologies used to send the data over cloud for processing. The research paper [17] proposes a survey for the health domain conducted by F. John Dian et al. (2020) involving wearable IoT devices for health treatment, rehabilitation, and monitoring. It includes the development of smart systems for physiotherapy, stroke rehabilitation, and smart wheelchairs for disabled individuals. Additionally, it covers health monitoring wearables with bio-potential sensors, motion sensors, environmental sensors, and biochemical sensors for extensive health status insight. It has emphasized CIOT devices. Ayman Wazwaz et al. (2023) in their research paper [18] propose HAR architecture using edge devices, wireless, intelligent, and cloud computing that is both dynamic and intelligent distributed. It describes its application for model training, storage, and real-time predictions. Accelerometer and gyroscope metrics were used to identify activity from three places using wearable sensors and smartphones. The proposed system states the LightGBM algorithm's prediction accuracy was 99.23% during training with 18 features. It could handle varied conditions dynamically.

A research paper [19] proposed by Mwaffaq Otoom et al. (2020) presented an IoT-based monitoring and detection system for COVID-19 in real time to gather user symptom data for early coronavirus detection, treatment monitoring, and virus comprehension. To minimize mortality, early identification, follow-up on recovered patients, and disease knowledge are needed. It suggests eight ML algorithms: SVM, NB, Neural Network, and K-NN. These algorithms were tested on a dataset of genuine COVID-19 symptoms after choosing relevant symptoms. Five of these eight algorithms have accuracy above 90%. A systematic review conducted by, M. A. Makroum et al. (2022) suggested an automated system aimed to aid diabetic patients in making daily diet and exercise choices, analyzing meal content, assessing caloric value, tracking physical activity levels, and predicting blood glucose levels using wearable devices. It uses algorithms that include SVM, Bayes Classification, DT, K-NN method, Logistic regression, and AdaBoost. These algorithms were used for predictive analysis in diabetes management, automating the diabetic retinopathy diagnostic process so that patients may make daily food and exercise choices, and tracking daily activity levels with wearable devices [20].

On the other hand, S. S. Chopade et al. (2023) presented an IoT sensor and device integration survey for intelligent health monitoring. The system collects real-time patient health data using pulse rate, body temperature, and ECG sensors. This data is then transmitted to a control center for remote access and analysis. The system also incorporates technologies like edge computing and big data integration to enhance operational efficiency and minimize errors in healthcare monitoring [21]. Researchers, Fadi Al-Turjman & Ilyes Baali (2022) demonstrated in their research paper [22], the way WBAN uses ML algorithms for different applications. The system aims to leverage ML to increase the performance of WBAN networks by automating data collection and analysis, increasing healthcare system resilience and intelligence, lifestyle, sports, and entertainment domains. By incorporating cognitive capabilities into WBAN, the system seeks to address challenges related to power constraints, communication capabilities, and computation power in wearable IoT applications.

Another research paper [23] by researcher, A. Qayyum et al. (2020) developed the literature on ML/DL methods in healthcare into four main areas: prognosis, diagnosis, therapy, and clinical workflow. Next, develop a pipeline for ML for data-dependent healthcare applications and identify the multiple security and robustness vulnerabilities at each stage. A taxonomy of solutions for stable and vigorous ML/DL healthcare applications is presented. P. Kulurkar et al. (2020), along with other researchers proposed an IoT-based fall detection system using wearable sensors, a sophisticated IoT gateway, a Smart Gateway, and Cloud Services for real-time monitoring and accurate fall detection. It involves analyzing and reducing energy usage of wearable sensor nodes, gathering real-time data using wireless sensors, using an LSTM algorithm for fall detection, and MQTT broker for fall alert transmission [24]. A. Thamara et al. (2021) presented a survey about different machine learning algorithms with their applications in various domains and showed the advantages of machine learning techniques that help create efficient support infrastructure for medical fields and improve healthcare services [25]. IoT and ML provide tailored, real-time health evaluation and predictive analytics for better healthcare and sports monitoring. Table 2 has a complete overview of this category.

Fig. 5 outlines various ML and AI algorithms employed in different ML Driven Solutions research related to healthcare, fitness, and IoT applications. It serves as a quick reference to identify the specific algorithms used in each study. Fig. 6 represents the highest accuracy of the ML algorithms abstracted from all the ML-driven papers.

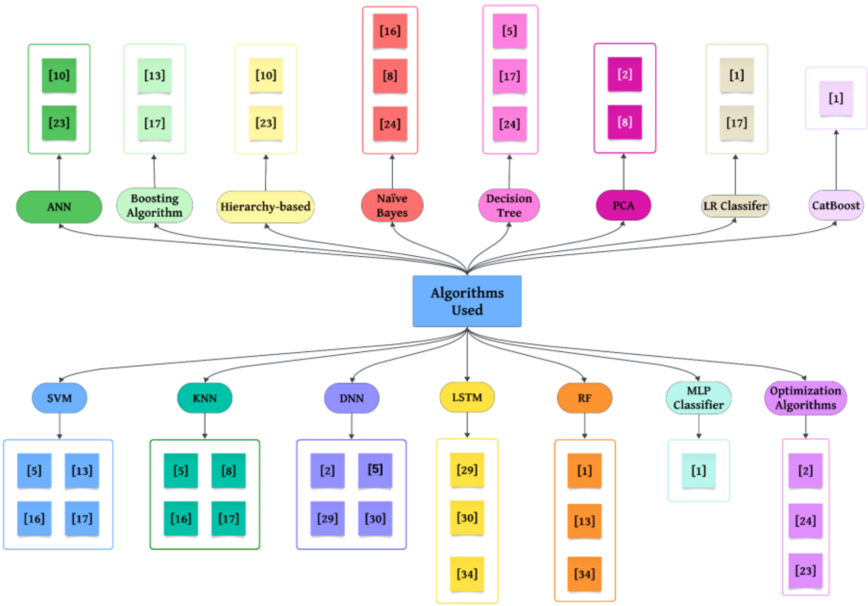

Fig. 5. ML algorithms and techniques used in ML-Driven research

Table 2. Summary of ML-Driven solutions research on IoT and wearable technologies

Literature	Components	Outcome	Disadvantages
S. K. Jagatheesaperumal et al., MDPI, 2023 [4]	Max30100 sensor, LM35 sensor, Arduino UNO, Flask web framework, AWS cloud	Health parameter acquisition and ML analysis for dietary recommendations.	Challenges in real-time data acquisition for personalized nutrition and fitness planning.
Xingdong Wu et al., Springer, 2021 [15]	ECG, blood oxygen level, frame module for general wireless sensors	IoT wearables and DL algorithms enable real-time health monitoring and disease classification.	Concerns about computation cost, and complexity.
João Passos et al., MDPI, 2021 [5]	waistband, chest band, calf band, upper-torso strap, bracelet	Biomarker collection and ML for cardiovascular assessment and fitness prediction.	This device majorly focuses on athletes only
N. S. Sworna et al., Elsevier, 2021 [16]	EEG, EMG, ECG, temperature sensor, oximeter	IoT-ML healthcare apps: monitoring, visualization, and sensor analysis for cardiac and stroke care.	Inefficient data management, high costs, test delays, and time constraints impede healthcare access.
F. John Dian et al., IEEE, 2020 [17]	bio-potential sensors, motion sensors, environmental sensors, ECG, adhesive hydrogel electrodes	Survey of smart wearable challenges in health, safety, and tracking, emphasizing CIOT devices.	Wearability issue: comfort and lightweight designs; safety: radiofrequency radiation exposure.
Ayman Wazwaz et al., MDPI, 2024 [18]	MPU6050, ESP32 microcontroller, Raspberry Pi version 3, cloud computing	HAR systems achieve 99.23% accuracy using LightGBM with 18 extracted and fused features.	Slower processing and increased active users affect edge request delivery times.
Mwaffaq Otoom et al., Elsevier, 2020 [19]	RFID, Bluetooth, IEEE 802.15.4, 6LoWPAN, NFC, heart rate, motion, image, audio, temperature, oxygen sensors.	Early COVID-19 detection and monitoring with ML algorithms at 90% accuracy to reduce disease impact and mortality.	Challenges in balancing data security owing to cyber threats and compromising security for vital situations.
M. A. Makroum et al., MDPI, 2022 [20]	activity trackers, mini ECG, glucose and blood pressure monitors, CGM devices, smart watches, bracelets	Overview of diabetes management technology and AI methods that improve quality of life.	Longitudinal studies address clinical variability and financial challenges in large-scale wearable deployment.
S. S. Chopade et al., Springer, 2023 [21]	ECG sensors, GPS module, RFID, Biosensors	IoT healthcare sensors generate data, edge computing enables efficient local processing.	Complexity in Data Processing, Security and Privacy Concerns
Fadi Al-Turjman & Ilyes Baali, Wiley, 2022 [22]	nano routers, EEG, PPG	Highlighting ML model deployment problems in critical WBAN networks.	Wearable devices in WBAN networks are constrained by limited power resources
A. Qayyum et al., IEEE, 2020 [23]	PPG	ML/DL techniques face security and robustness challenges, with solutions for secure healthcare applications.	Healthcare ML/DL models face complex challenges in security, robustness, privacy, and limitations.
P. Kulurkar et al., Elsevier, 2023 [24]	NUCLEO-L152RE, Raspberry Pi 3, 6LowPAN, extension modules using sub-2GHz RF link, STM42 Nucleo board	achieving high accuracy rates in fall detection, using the LSTM model to identify falls 99% rate.	Wearable sensors face energy inefficiency, causing unreliability and service interruptions.

2.2. Software Based Methods

A taxonomy for smartphone apps related to personalized workouts, guidelines for creating mobile applications for personalized workouts, adaptation of workout programs to the user, examination of the iOS app Store and Apple's ecosystem, and the application of AI/ML methods for generating solutions with training programs tailored to distinct user characteristics was devised in the research paper [26] by B. F. Tavares et al. (2020). The author Shiqi Chen et al. (2023) conducted an assessment if mobile apps can provide evidence-based, personalized fitness regimens. A thorough assessment was conducted on the app to determine if it was grounded in scientific evidence, incorporated a health screening process before participation, developed a risk profile for cardiovascular disease, focused on a specific chronic health issue, and structured the exercise regimen according to frequency, intensity, duration, and type, and specified special considerations—219 of 531 applicable applications qualified. A minimal number of the qualified apps were grounded in scientific evidence (0.5%) or included pre-activity health screening procedures (3.7%). Only 27.7% of them developed risk profiles for cardiovascular disease [27].

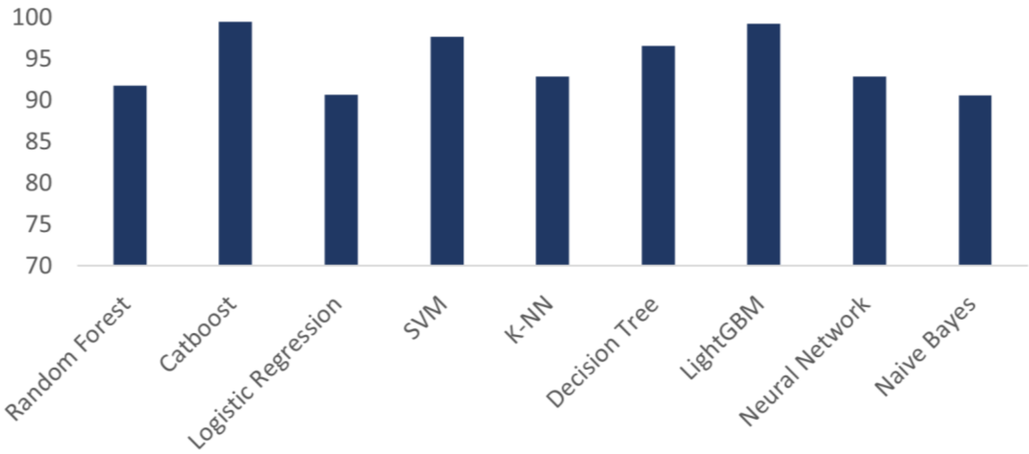

Fig. 6. Accuracy based on different ML techniques [4], [18], [19]

S. S. Mahal et al. (2023) proposed the smartphone application called the 'Diet DQ Tracker' was developed and validated to replace conventional methods of dietary data collecting and give real-time feedback and visualizations for diet diversity scores. The app minimized respondent–research strain and enabled economical and quick data gathering, with high respondent approval [1]. Ramin Ramezani et al. (2023) demonstrate the process by which a WearOS-based remote health monitoring system was developed. Integration with cloud services, connectivity through Bluetooth technology, embedded sensors for health monitoring, and features for feedback and interactive tasks [28]. A study conducted by Qiyun Zhang et al. (2021) in the research paper [29] addresses the challenge faced in securing the privacy of the user's sports locations and its information disclosure concerns by proposing SLUC which uses the SimHash technique to convert the location into binary values and clustering them based on the user's behavior and secures the user's privacy in the cloud system. This paper also explains various simulations used to test the PPICF system in terms of their performance in prediction accuracy.

A team of Human digital twins was made by B. R. Barricelli et al. (2020) and other co-authors which is an extension to SmartFit integrated for monitoring and managing the fitness activity of the athletes and increasing the capability of SmartFit. The Digital Twins predicts the twin performance measure of the user and in it, each twin tracks and collects the fitness measurement that describes the user's behavior like diet, sleep, and activity, and in the event of a non-optimal outcome, it proposes alterations in the athlete's conduct. It also takes the analyzed measurements and stores them in the historical data and is processed further to increase the knowledge of the digital twins and provide reliable and efficient predictions [30]. The research conducted by Rahul Pulimamidi (2024) through a qualitative, multiple case study approach, investigates the strategies and challenges healthcare organizations face in migrating from legacy systems to advanced eHealth systems. The study aims to understand how IT transformation can lead to cost-efficient, effective, and instant services for patients. It also emphasizes the importance of data privacy and security in the digital era of healthcare [31]. Integrating mobile applications, wearable technologies, and AI/ML in fitness and healthcare is advancing personalized workout regimens and health monitoring. However, challenges remain in ensuring scientific validity, privacy protection, and effective implementation of digital health solutions. Table 3 has a complete overview of this category.

2.3. Sensor-based Systems

Zhiyong Deng et al. (2023) presented a comprehensive assessment of advancements in wearable systems for health tracking, focusing on materials selection and system integration to promote precise, mobile, uninterrupted, and sustained health tracking. The most essential characteristics of health monitoring wearable devices are conformability, safety, and stability, therefore their skin contact must be safe, non-toxic, and comfortable. AI is also a great tool for wearable devices, which analyze sensory data to identify health issues [32]. Madhusudan B. Kulkarni et al. (2024) also reviews the recent advances in smart wearable sensors for continuous human health monitoring [33]. The work done by Sharzeel Saleem et al. provides an overview of smart wearable technologies and their applications in monitoring human health, including the challenges faced by manufacturers in launching these devices on the market [34]. The research conducted by Héctor José Tricás-Vidal et al. (2022) proposed a study that focuses on the utilization of wearable fitness tracker devices, such as those from Garmin, Fitbit, Polar, Apple Watch, or Nike FuelBand, for self-monitoring and recording of fitness and physical activity routines. The study utilized a multivariate analysis combined with an observational cross-sectional analysis design to examine the associations between the application of tracker devices and various health-connected factors, such as gender, BMI, and sedentary behavior. The study attempted to simulate the use of tracking devices to log daily activities based on the factors that had been previously identified as significantly related [3].

Table 3. Summary of software-based research on IoT and wearable technologies

Literature	Service Provided	Outcome	Disadvantages
B. F. Tavares et al., MDPI, 2020 [26]	provides a Gym workout planner daily to plan physical activities.	Enhanced activity processing for mobile training apps using static data due to sensor shortages.	Due to the lack of sensors only static value is considered.
Shiqi Chen et al., MDPI, 2023 [27]	provides cardiovascular risk factors that can offer evidence-based, personalized fitness plans.	Review of exercise mobile apps using cardiovascular disease risk factors; only 27.7% incorporate these variables.	Lack of evidence-based body image apps for chronic diseases and exercise principles.
S. S. Mahal et al., MDPI, 2023 [1]	Gather dietary information to assess diet diversity indicators.	It was a feasible and relatively accurate, Diet DQ Tracker. Convenience trumped 24-hour recall.	Traditional nutritional data collection methods are tedious error-prone, and difficult to input and analyze.
Ramin Ramezani et al., MDPI, 2023 [28]	Log management, Remote Monitoring and Configuration, Cloud compliance	Remote health monitoring system using WearOS, cloud services, Bluetooth, and interactive tasks.	Limitations in continuous operation, and challenges in ensuring patient data privacy, availability, and security.
Qiyun Zhang et al., IEEE 2021 [29]	Identify sport-related user data, ensure privacy, and analyze SimHash table convergence.	When categorizing people by particular risks, SLUC excels in accuracy, efficiency, and privacy.	Privacy issues and complicated QoS data's effect on prediction accuracy.
B. R. Barricelli et al., IEEE, 2020 [30]	SmartFit wearables and apps enable trainers to track athletes' behavior.	SmartFit's Digital Twins recognize feature changes that enhance athlete predictions and suggestions.	Missing and noisy data, imputed data model complexity, and training with more features take longer.
Rahul Pulimamidi, Elsevier, 2024 [31]	Remote patient monitoring, Real-time health data analytics	Enhance patient experience in e-healthcare.	Small sample size, lack of quantitative data, and potential biases

Two researchers Wei-Hsun Wang & Wen-Shin Hsu (2023) proposed a comprehensive, advanced system in the research paper [35] for managing long-term care services that combine AI with wearable IoT devices to provide comprehensive healthcare services to elderly individuals. RFID technology is used for precise monitoring and placement of senior citizens, along with check-in purposes and alerting caregivers based on location data. The backend server receives the gathered data and uses it for calculation, including the whereabouts of senior citizens. By using this data as reference models, AI, big data analysis, and DL methods are used to improve the standard of elderly care services. The author R. S. Bisht et al. (2021) proposed a review and analysis of a range of IoT devices that fall within the wearable device category. It evaluates the prospects of these devices, focusing on their hardware and software specifications, as well as their potential applications in healthcare systems and other fields. It specifies the criteria of wearable devices regarding their capabilities. These include fault robustness, little effort, unbiased usage, adaptability, basic use, and accurate measurements [36].

Another research done by Ningning Xiao et al. (2020) proposes an IoT-based smart bracelet monitoring system for monitoring the condition and changes in the heart rate of the user during sports. This bracelet collects the vitals from the user and is analyzed in the mobile intelligent terminal and is stored in the cloud platform and analyzed further. In case of any abnormal data, an alarm is sent to the mobile personnel to realize the heart conditions of the user. The algorithms used are the Digital Filter Threshold algorithm, and MT algorithm for estimating heart rate, feature point detection, and real-time monitoring of heart rate [37]. Yongpan Zou et al. (2020) developed iCoach, an inexpensive smart fitness glove with a ubiquitous inertial unit, for real-time monitoring, coaching, and evaluation of strength training workouts utilizing IMU data. The twofold adaptive threshold-based approach detects repeat start and end points, IMU sensor calibration and denoising, and standard template-based statistics computation. The system can accurately and reliably identify fifteen training programs, detect three typical non-standard behaviors, and evaluate training quality. The system's performance is measured by recognition accuracy, precision, recall, CPU resource occupancy, and energy usage [38].

A systematic review conducted by two researchers R. Jegan & W. S. Nimi (2023) demonstrates the progress made in creating energy-efficient wearable technologies designed to continuously monitor essential physiological indicators, integrating IoT for remote communication and support in the paper [39]. It examines the characteristics of physiological signals such as ECG, PPG, and EEG, the essential vital parameters, the significance of smart wearable technology, options for wearable gadgets, and the design factors to consider when developing wearable gadgets for the early identification of health disorders. The research paper [40] describes a thorough evaluation of wearable IoT medical devices, focusing on disease detection, monitoring, and curing, as well as discussing the framework of wearable gadgets proposed by Nico Surantha et al. (2021). The system architecture involves mobile gadgets and networks, wearable sensors, and medical cloud services. It emphasizes the development of compact and unobtrusive devices. Akshay Parihar et al. (2024) explore the structural requirements and role of IoT in healthcare, as well as the security and privacy issues that can hinder IoT's potential, and ways to overcome these issues [41]. Md. Motaharul Islam et al. (2024) propose an architectural framework that uses narrowband IoT technology and edge intelligence to enable real-time remote monitoring of patients in healthcare facilities. The use of NB-IoT provides extensive coverage, superior indoor penetration, and cost-efficiency, while edge intelligence enables rapid data processing and analysis [42]. Md. Milon Islam et al. (2020) proposed a smart healthcare monitoring system in an IoT environment that can monitor a patient's vital signs and environmental conditions in real-time [43]. Wearable IoT devices and AI integration in healthcare are enabling real-time vital sign tracking and analysis, while energy efficiency and seamless integration with existing healthcare systems drive innovation. Table 4 has a complete overview of this category.

2.4. Security Methods

In the research paper [44], Sanjit Thapa et al. (2023) described a proposed system that predicts customers' propensity to utilize WIoMT devices using two aspects security-related and product-related factors and five domains including performance, reliability, simplicity of use, perceived efficiency, security, and privacy perception. The desire to utilize WIoMT devices was most strongly correlated with perceived security and privacy. Quantitative approaches were used in an observational survey conducted at a specific time by using a questionnaire and the questionnaire consisted of two sections. The first section used demographic information to segment data and compare respondents. This section collected information regarding age group, gender, and level of technical proficiency in using computers. SPSS was used for statistical analyses, including regression analysis, to assess WIoMT device usage intention components. A research conducted by S S. Gopalan et al. (2021) in the paper [45] presents an overview and analysis of AI research on cybersecurity for healthcare IoT networks. A comprehensive 2014–2019 literature review is presented. This study discusses 18 insights from the surveyed works on healthcare IoT security, including numerical and experimental assessments. AI-based IoT security strategies for healthcare and related frameworks are also examined.

Table 4. Summary of sensor-based research on IoT and wearable technologies

Literature	Components	Outcome	Disadvantages
Zhiyong Deng et al., MDPI, 2023 [32]	Blood pressure, temperature, and heart rate sensor	Reviewing material and system integration for accurate, portable health monitoring.	challenges in maintaining data accuracy and privacy.
Héctor José Tricás-Vidal et al., MDPI, 2022 [3]	Wearable activity trackers	Tracker device use linked to reduced cardiovascular disease mortality risk from sitting.	Potential measurement errors and generalization challenges with new technology adoption.
Wei-Hsun Wang & Wen-Shin Hsu, MDPI, 2023 [35]	Stretchable substrates, Sensing material, flexible electrodes, and edge computing	IoT devices measure heart rate, temperature, blood oxygen, blood pressure, steps, activity, and calories.	Discomfort with traditional medical equipment and portable wearables.
R. S. Bisht et al., IEEE, 2021 [36]	cove, bioheart, with Bluetooth 4.2 LE, WiFi, GPS, NFC, Think Reality A3, Qualcomm Snapdragon XR1 platform	The survey highlights IoT wearables' flexibility, natural usage, distinct data, resilience, and accuracy.	High maintenance costs, frequent recharging, and security risks from network connectivity.
Ningning Xiao et al., Elsevier, 2020 [37]	ARM processor, step acceleration sensor mma9555lr1, pulse sensor, Bluetooth MCU, heart rate sensor son7015	Wearable system for real-time monitoring of vital signs during exercise.	Difficulty in accurately detecting R-waves due to noise and ECG artifacts.
Yongpan Zou et al., IEEE, 2020 [38]	Smart fitness glove, MPU9250 9-dof module, Micro-controller, Bluetooth 4.0 module	ICoach monitors strength training in real-time with high accuracy and under 90 ms reaction latency.	CPU consumption limits monitoring lower-body strength training exercises.
R. Jegan & W. S. Nimi, Springer, 2023 [39]	ECG, PPG, EMG, EGG, EEG, NFC, LoRa	Provides design tips for developing effective smart wearables for vital parameter monitoring.	Lack of discussion on factors like cost, user acceptance, or specific technical challenges.
Nico Surantha et al., Elsevier, 2021 [40]	PPG, 3 DOF magnetometer, 3 DOF gyroscope, 3 DOF accelerometer, and piezo sensor	Wearable IoT devices for illness detection, monitoring, and addressing existing and future development problems.	Reliable blood pressure monitoring, compact tremor control, and scalable user expansion are needed.
Akshay Parihar et al., Elsevier, 2024 [41]	Respiration sensors, blood glucose sensors, ECG sensors, pulse oximetry sensors, motion sensors	Enhanced patient monitoring and analysis, improved physician decision-making, remote vital sign monitoring	Lack of robust security and privacy standards
Md Motaharul Islam et al., Wiley, 2024 [42]	STM-32-based Nucleo boards, Quectel BG96 chipsets, and BP15 BLOW batteries of 20,000 mAh.	NB-IoT in healthcare includes extensive coverage, superior indoor penetration, increased capacity, and real-time monitoring	Data Security Challenges, Interoperability Complexity, and Scalability

M. A. Jan et al. (2021) proposed LightIoT as an efficient and highly secure method of transmitting data for medical infrastructure devices, creating secure sessions between communication organizations to ensure dependable data transfer using efficient hash algorithms and performing XOR operations. The technique is touted as robust, resilient to attacks on vulnerabilities of algorithms, and leads to decreased expenses in computation and communication compared to previous approaches. The experimental results validate the efficiency, showcasing its resilience against various attack scenarios and its low computational and communication overhead [46]. Another research paper [47] by M. A. Jan et al. (2020) proposes a low-cost two-way authentication system that efficiently utilizes computing, communication, and storage overhead. It is built on a server-client interaction framework and utilizes encryption techniques with shared keys. It is intended for large-scale I-CPS infrastructures. Symmetric encryption for establishing secure sessions and DTLS-enabled authentication approaches. These are used in data protection, privacy preservation, and secure data transmission in healthcare applications.

Mohit Kumar et al. (2023) highlight the integration of H-IoT with various technologies such as big data, blockchain, ML, deep learning, edge computing, and software-defined networks to enhance healthcare services. It addresses the critical challenges in H-IoT, including security breaches, real-time operational difficulties, energy consumption, and scalability. It proposes solutions to mitigate these challenges, suggesting the adoption of cryptographic measures and energy-efficient systems [48]. Khaled H. Almotairi (2022) explores the application of IoT in healthcare, emphasizing real-time delivery of diagnostic information and treatment. It discusses the potential benefits of IoT-enabled healthcare applications, including improved treatment and diagnosis. It addresses challenges such as security, privacy, and the high cost of IoT adoption in healthcare. It provides insights into the scope of IoT utilization in hospital management systems and future research trends in IoT-enabled healthcare infrastructure [49]. Advancements in healthcare IoT and AI are improving personalized care and data security, but challenges in privacy, efficiency, and integration persist, driving ongoing research and innovation in the field. Fig. 7 outlines various security challenges related to healthcare IoT applications. Table 5 has a complete overview of this category.

Table 5. Summary of security-based research on IoT and wearable technologies

Literature	Service Provided	Outcome	Disadvantages
Sanjit Thapa et al., MDPI, 2023 [44]	WIoMT devices monitor health and link to electronic health records.	Security and privacy were key factors influencing WIoMT device adoption and user trust.	Risks include real-time health data collection, security assessments, and balancing benefits.
S S. Gopalan et al., IEEE, 2021 [45]	Identifying a niche for AI cybersecurity in protecting healthcare IoT networks.	AI cybersecurity for healthcare IoT networks is a particular niche for researchers.	Healthcare data breaches and IoT cyberattacks might violate patient privacy and be life-threatening.
M. A. Jan et al., IEEE, 2021 [46]	Secures and transfers biological data using lightweight hash methods and XOR.	Initialization, pairing, and authentication for safe, lightweight healthcare data transport.	Data security, system architecture, resource restrictions, and lightweight authentication problems.
M. A. Jan et al., IEEE, 2020 [47]	Data collection aids decision-making, remote monitoring, healthcare security, cost-efficiency, and attack prevention.	HMM, healthcare privacy risk prediction, and lightweight I-CPS IIoT wearable authentication.	Resources, cybersecurity, payload size, and asymmetric algorithm overhead restrict healthcare wearables.
Mohit Kumar et al., MDPI, 2023 [48]	Cryptographic Platforms, Tele-Healthcare and Remote Monitoring	integration of Healthcare-IoT with ML, DL, and big data to enhance the healthcare services	Security breaches, real-time operational difficulties, energy consumption, and scalability
Khaled H. Almotairi, Springer, 2022 [49]	Real-time monitoring, secure storage, and device authentication via blockchain.	Prompt diagnostics and treatment for critical diseases.	Data privacy risks, high adoption costs, and ethical concerns in healthcare IoT.

2.5. Taxonomy of IoT/ML in Healthcare

This section provides a taxonomy for conducting research that is based on IoT and ML-powered systems for healthcare, which consists of five key elements: IoT, Network Storage, Communication, ML, and Application. The taxonomy's primary emphasis is on the application of ML and IoT in particular health domains, such as cancer, heart disease, and stroke (Fig. 8). IoT is the initial aspect of the taxonomy, which is widely employed in the medical field and encompasses a wide range of applications. Actuators, development boards, Sensors, storage, and communication are among the technologies used. IoT uses sensors to gather data from the surrounding environment. Medical sensors measure and monitor patients' pulse, the amount of oxygen present in their blood, blood pressure, blood sugar levels, body temperature, ECG, EEG, EMG, and other parameters. Actuators are employed to control changes in the environment. IoT also includes development boards. There are many kinds of development boards available for building the system to gather, process, and transmit data to various devices, including ESP32, Raspberry Pi, and Arduino.

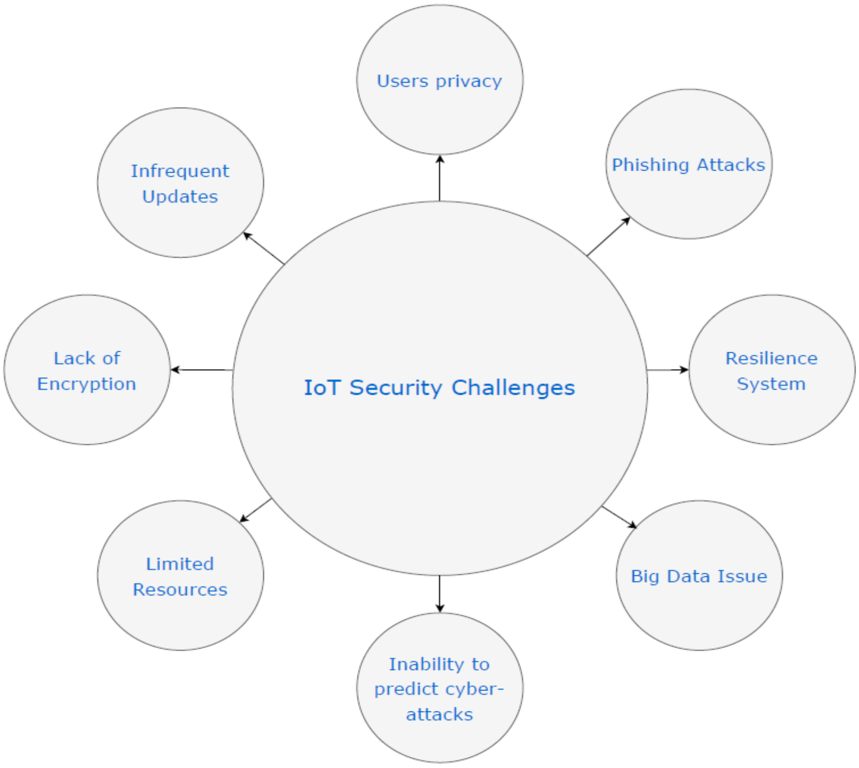

Fig. 7. IoT security problems [45], [48], [49]-[51]

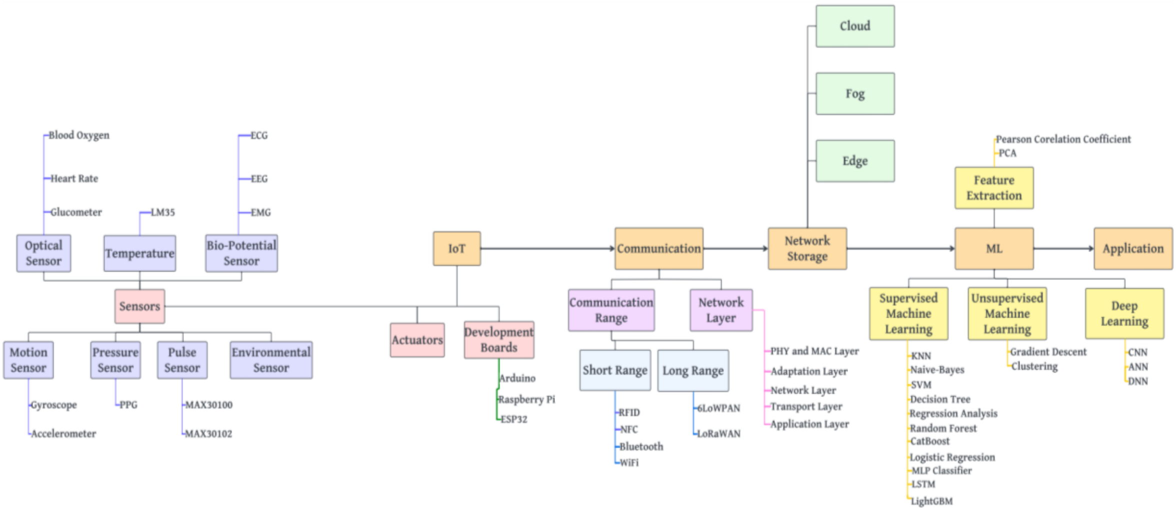

Fig. 8. IoT/ML healthcare taxonomy

The second element that we delineate here is communication. Using communication protocols, IoT architecture sends messages from the perception layer to the storage layer. RFID, NFC, WiFi, and Bluetooth are the most widely used low-power, short-range communication technologies. Hence, LoRaWAN and 6LowPAN are examples of long-range communication technology.

The network storage serves as the third component. This module serves as a makeshift data processing storage system. Big data analysis has become more popular as IoT-based healthcare systems progress. Cloud, edge, and fog computing are expected to be used to analyze and store large amounts of data.

The fourth component is the ML. Feature extraction methods and ML algorithms are utilized to detect diseases and keep track of physical states. The fields in taxonomy are categorized into analysis methodologies and feature extraction. Before incorporating sensor data into models, ML requires feature extraction. There are several feature extraction approaches, including PCA and PCC. In ML, there are two types of analysis techniques: supervised and unsupervised. There are various algorithms for supervised learning, including SVM, K-NN, RF, DT, and NB. Techniques for unsupervised learning include clustering and dimensionality reduction.

The fifth component is the application. Different applications related to healthcare are already discussed in Section 2.

3. Results and Discussion

3.1. Critical Summary

The integration of AI into IoT technology has revolutionized the healthcare industry. This provides real-time health monitoring, eliminates wires, and facilitates remote patient management. Bluetooth and NFC ensure seamless data transfer, making healthcare more proactive and efficient, as well as providing tailored and personalized health services. ML techniques like DL and LightGBM, which also aid in disease classification, provide users with real-time health monitoring and personalized suggestions [4], [5], [15]-[17]. These technologies attain a 99.23% accuracy rate in HAR systems, which shows their remarkable capabilities. However, it is important to note that the accuracy rates can differ based on the specific models and datasets used in each study, as in this study, LightGBM is used along with the extracted and fused features [18].

Despite these advancements, real-time health tracking and disease categorization face practical hurdles such as data collection complications, processing needs, and privacy concerns, which sometimes hinder their progress. Additionally, these technologies face difficulties with data acquisition, the complexity of computations, and the critical balance between data utility and privacy [19], [20]. They also improve early detection and prevention of health issues through continuous monitoring, enable more personalized treatment plans, and enhance remote patient monitoring, potentially reducing hospital visits. Better management of chronic conditions and improved athlete performance monitoring are additional benefits. This includes the use of wearable devices and AI/ML algorithms for continuous health monitoring and personalized care. It emphasizes the importance of predictive analytics for early detection of health issues, the development of software for data management, and the focus on security and privacy in healthcare IoT systems.

For multiple healthcare applications like cardiovascular evaluation, drowsiness detection, diabetic management, and early identification of COVID-19, ML models are applied [5], [20], [52]. Such applications provide useful insight into the potential of ML to provide increased effectiveness in therapy and enhanced accuracy in the diagnosis and also in detection of diseases, with some models achieving around 90% accuracy [19]. Some of the problems that come up with implementation are complicated data processing, the Wireless Body Area Network's (WBAN) limited power resources, and the need for large longitudinal studies to look at clinical variability [21]-[24], [53].

The proliferation of mobile health applications has introduced new paradigms in personal health management. However, a comparative analysis [27] revealed that only 27.7% of mobile apps for exercise incorporate cardiovascular risk factors. Some other applications, like the Diet DQ Tracker, provide improved convenience over the traditional 24-hour recall method [1], while some models still struggle to provide accurate data analysis and integration of different health metrics [26], [28].

Digital Twins and SLUC are used for analytics, which offers great potential for improving health predictions and recommendations [29], [30]. These tools provide efficiency in accurately categorizing individuals based on their health risks. Even though these tools provide high efficiency in accurate prediction, they still face data quality issues, intricate model structures, and the need to carefully balance predictive accuracy with user privacy concerns [31].

The use of WIoMT devices poses critical security and privacy concerns [44], [45], [48], [49], [54]. While these devices provide continuous health monitoring capabilities, they still face data breaches and privacy violations. IoT devices can provide real-time data, but the focus is often on operational efficiency rather than health outcomes. WIoMT specifically focuses on medical devices worn by patients, designed to monitor health metrics such as heart rate, blood pressure, and other vital signs, transmitting this data to healthcare providers for analysis and monitoring.

In IoT networks, the expectant network should improve security and flexibility to identify and prevent vulnerabilities like DDoS attacks [55]-[57]. Various new solutions, like lightweight authentication and HMM-based privacy risk prediction, have been proposed. Lightweight authentication employs symmetric encryption and a four-way handshake for efficient mutual authentication, minimizing overhead and mitigating DoS attacks. HMM predicts privacy leakage risks by analyzing usage patterns, allowing for timely data alterations when risks exceed a defined threshold [47], [58], [59]. Encryption and access control are used to protect sensitive data and ensure privacy in shared data. However, the limitations in the processing power of wearable devices and battery life remain a challenge for researchers in strengthening healthcare security [46].

Sensor-based technologies are quickly evolving, enabling various uses such as monitoring vital signs and tracking specific activities like strength training [32], [3], [60]. These devices offer continuous and flexible data collection, with some achieving impressive accuracy, such as ICoach's real-time strength training monitor with a reaction latency of less than 90 ms [38]. Nevertheless, they still encounter ongoing issues related to user comfort, battery duration, and measurement accuracy, especially in noisy environments or during intricate activities [35], [36], [37], [40]. One major constraint is the limited range; WiGig signals can only cover short distances, typically up to about 30 feet, and cannot penetrate walls, leading to rapid signal degradation over distance.

With the emerging advances in THz systems and the convergence of IoT, ML, and big data in the healthcare industry, there is potential to completely transform patient monitoring, clinical decision-making, and remote care delivery [41], [61], [62], [63]. Emerging technologies like NB-IoT provide extensive coverage and excellent indoor penetration, hence resolving some limitations associated with traditional wearable devices. However, NB-IoT primarily focuses on immediate benefits and operational efficiencies, such as improved data transmission and enhanced coverage. In healthcare, it may face challenges such as regulatory changes and cybersecurity threats. The integration of edge computing with NB-IoT is presented as a strategic approach to mitigate latency issues and enhance real-time data processing. Awareness of these technologies, including in rural areas, could be seen as a consideration for long-term applicability [42].

The process of integrating different systems poses new obstacles, including the need for data protection, ensuring interoperability between disparate systems, and ensuring that solutions can be scaled up effectively [42], [64]-[66]. Maintaining and sharing EHRs among multiple entities, such as nursing homes, presents challenges and incurs high costs of implementation. Cloud-based solutions involve complexities related to data migration, system compatibility, and ongoing maintenance [31].

To fully harness ML-driven healthcare solutions and assure their ethical, safe, and successful use in clinical practice, it is crucial to overcome these intricate hurdles as the sector progresses. The management ability of network and device automation to deliver healthcare to patients efficiently and effectively, independent of time and location, can be of great help in delivering patient well-being and care. Prevention of data misuse, strong encryption, and regular audits are necessary to ensure data security and prevent unauthorized access.

Fig. 9 is a visual representation of the critical summary, highlighting the key challenges associated with IoT and ML applications in healthcare. It encapsulates a variety of issues, including integration and interoperability, energy efficiency, personalization and adaptability, and privacy and security, among others. "Challenges in IoT/ML Applications for Healthcare" centrally connects these challenges, highlighting their interconnectedness in the implementation and scaling of IoT/ML solutions in healthcare. The diagram helps to understand how each of these challenges plays a role in the broader context of healthcare technology advancements, as described in the critical summary.

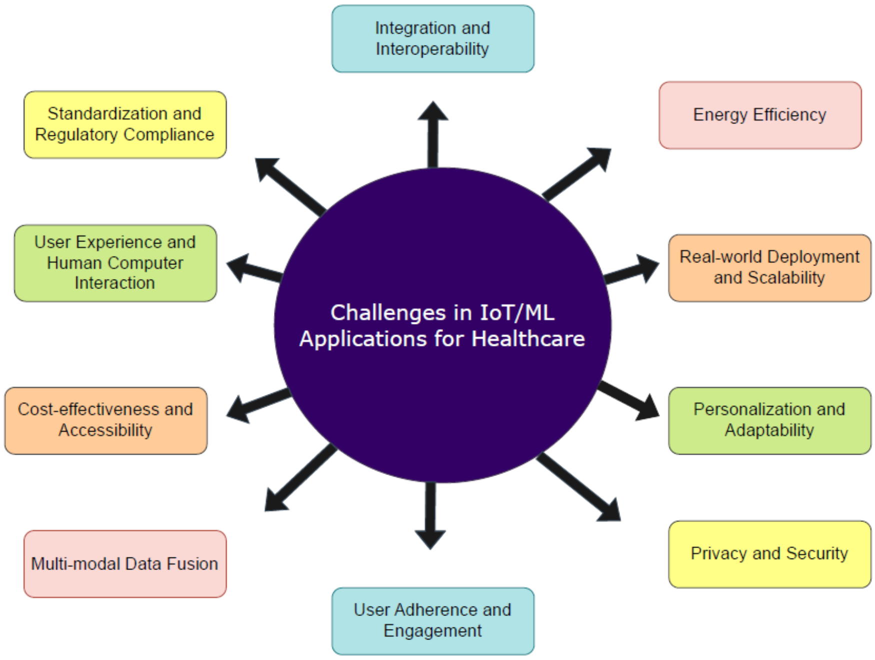

Fig. 9. Visual representation of critical summary

3.2. Future Scope

Creating compact, very precise, and dependable multi-modal sensors that can be included in wearable IoT devices is one of the future problems. Deciphering signals, combining data from many sources, and producing perceptive diagnoses based on different kinds of data need strong algorithms. It is crucial to have user-friendly interfaces that provide personalized health information. Standardized protocols are essential for ensuring secure data interchange, seamless integration of IoT devices, and interoperability amongst healthcare organizations. Crucial requirements include data privacy, legislation, user acceptance, and efficient data management systems.

4. Conclusion

In conclusion, this comprehensive survey provides an in-depth analysis of the convergence of IoT and AI technologies in healthcare applications by exploring the research done in every aspect of this interdisciplinary domain. As AI and IoT have grown in recent years, many researchers are interested in AI and IoT applications in healthcare, but there are various kinds of challenges in this domain that concern the authenticity of the use of IoT and AI in healthcare. IoT and AI can transform healthcare with real-time health monitoring of the patient, as well as help in remote monitoring the health of the patient and providing other tailored services. In some applications, ML approaches can identify diseases, recognize activities, and forecast health with 99.23% accuracy [18]. This accuracy was achieved by the LightGBM algorithm by utilizing 18 featured datasets, like UCI HAR and WISDM, and other datasets. Another study [4] suggests that the CatBoost algorithm, which employs the 70:30 rule for model training and testing, can also achieve comparable accuracy. Hence, the LightGBM and CatBoost algorithms have proved to be useful for having more than 90% accuracy in comparison with other algorithms, according to our study. Also, cloud storage is used for storing large amounts of data, which helps in real-time health monitoring in hospital management. We have also addressed some critical challenges that could potentially disrupt real-time services and provided recommendations for addressing these issues in the IoT-AI application. The challenges are categorized into 3 types: Technical, user-related, and regulatory challenges.

- Technical challenges
  - Data Privacy and Security: Data breaches of users have been a constant problem among applications. Because of this, users' health data and other personal information are

subjected to being leaked. So, this problem could be solved by developing advanced encryption systems and blockchain technology for securing data.

- Integration and Interoperability: The integration of IoT devices and ML models, which may be subjected to an update, may not be easily integrated, or the ML model may not always operate on different hardware platforms whenever necessary. To have seamless services without any issues, we recommend the creation of an open-source framework that facilitates interoperability across different healthcare IoT platforms.
- Resource Constraints: Issues such as Battery life, and user comfort have been a constant problem in wearables, so, to address that, we suggest focusing on the development of energy-efficient algorithms and methods to increase battery life.

- Regulatory challenges
    - Regulatory Challenges: Challenges to cope with the Pace of rapidly evolving IoT devices and developing new modules and algorithms is also a major task. We recommend establishing a multidisciplinary task force to develop guidelines that balance innovation with patient safety and data protection.
- User-related challenges
    - Ethical Implications: This survey highlights the gap in addressing the ethical methods of IoT and AI in the healthcare domain. To solve this problem, we suggest always taking care of the safety measures and also the long-term societal impacts.

According to the study, conducted by [27], despite the potential of mobile health apps only 27.7% of fitness apps include cardiovascular risk factors. Since cardiovascular risks are one of the major problems, we suggest creating an IoT-AI device focused on cardiovascular diseases so as to minimize the rate of delay in healthcare. Considering their continuous monitoring capabilities, wearable technologies struggle with user comfort, battery life, and measurement accuracy in real-world settings. By explaining the challenges faced in the security domain, we also highlighted various kinds of problems faced due to the security challenges faced by the model, such as phishing attacks, resilience systems, and infrequent updates leading the model to become vulnerable to cyber attacks, thus providing valuable insights in raising the security standard of the real-world models in health-care domains [49]. Researchers could prevent this by creating an AI algorithm that can detect attacks, add a firewall layer, and notify users to update IoT devices when needed. Another important issue that needs to be addressed is the societal impact or rejection of technology by society due to a lack of knowledge of technology or a lack of understanding of the importance of technology. AI in healthcare questions the ethical usage for health monitoring of the patients. To tackle this issue, we recommend carrying out experiments of the device as much as possible to check whether the devices are helping the hospital management in real-time and also guiding individuals about the need and usage of IoT-Ai applications. Another distinctive feature of work is the way we classified our research depending on ML-driven, software, sensor-based, and security approaches and researched them from the perspective of healthcare. This classification helps the user understand each aspect of one interdisciplinary domain and the research done in each part of this domain. We recommend focusing on specific research areas to increase the efficiency of IoT-AI use in the healthcare domain.

- Development of multi-modal data fusion techniques which can be used to integrate data from various IoT devices and enhance the features using this technique to provide more accurate and comprehensive health assessments.
- Conduct research on various kinds of other adaptive ML algorithms apart from the algorithms that are already made and try to create new algorithms to provide security and improve the long-term engagement between the IoT and the user.
- Research on the application of federated learning methods to tackle privacy issues and enhance the models on different distributed datasets.

- Conducting large-scale, longitudinal studies to assess the long-term impact of IoT and AI-driven healthcare interventions on patient outcomes and healthcare systems.
- Investigating the potential of edge computing in healthcare IoT to reduce latency and enhance real-time decision-making capabilities.

This highlights how the integration of IoT with AI enables remote patient health monitoring in the long term by increasing efficiency, reducing the manual workload of hospital workers, and alerting hospital management to any sudden spikes or variations in health data, thereby facilitating timely medical assistance and minimizing treatment delays in the future. The limitation of this study is that the technology has already been created and studied but this research could be much better in healthcare if it eliminated the discussed challenges in the future. Thus, by providing this comprehensive analysis, this survey serves as a resource for researchers, engineers, and other healthcare professionals to better understand the current landscape of the model and the future potential of IoT-ML-based systems by providing an in-depth description to improve by eliminating the challenges and providing more efficiency in personalized healthcare solutions. This survey's findings will help the researchers to understand the necessary solutions required to overcome the challenges so as to create a better healthcare system to be used in real time.

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Abbreviations List

IoT	: Internet of Things
ML	: Machine Learning
BMI	: Body Mass Index
AI	: Artificial Intelligence
MLP	: Multilayer Perceptron
PCA	: Principal Component Analysis
GD	: Gradient Descent
CNN	: Convolutional Neural Network
RNN	: Recurrent Neural Network
DNN	: Deep Neural Network
ANN	: Artificial Neural Network
HAR	: Human Activity Recognition
CIOT	: Contextual Internet of Things
ECG	: Electrocardiogram
PPG	: Photoplethysmography
SVM	: Support Vector Machine
K-NN	: K-Nearest Neighbors

NB	: Naïve Bayes
IMU	: Inertial Measurement Unit
DT	: Decision Tree
MT	: Movement Threshold
CPU	: Central Processing Unit
WBAN	: Wireless Body Area Networks
LSTM	: Long Short-Term Memory
MQTT	: Message Queuing Telemetry Transport
DL	: Deep Learning
AWS	: Amazon Web Services
PPG	: Photoplethysmography
RFID	: Radio-Frequency Identification
NFC	: Near Field Communication
CGM	: Continuous Glucose Monitoring
MCU	: Microcontroller Unit
EEG	: Electroencephalogram
EMG	: Electromyography
MPU	: Memory Protection Unit
ESP	: Electronic Stability Program
6LoWPAN	: IPv6 over Low Power Wireless Personal Area Network
ARM	: Advanced RISC Machines
GPS	: Global Positioning System
RF	: Random Forest
PCC	: Pearson Correlation Coefficient
LoRaWAN	: Long Range Wide Area Network
WIoMT	: Wearable Internet of Medical Things
SPSS	: Statistical Package for Social Science
IioT	: Industrial Internet of Things
HMM	: Hidden Markov Model
I-CPS	: Industrial Cyber-Physical Systems
DTLS	: Datagram Transport Layer Security
PPICF	: Privacy-Preserving Item-based Collaborative Filtering
SLUC	: Sport-Location-based User Clustering

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