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Efficiency, Research, and Healthcare Economics: (Vital Threat Detection System) ASystematic Review

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Abstract

Monitoring vital signs and detecting diseases like diabetes and cancer at an early stage are incredibly important for safeguarding patients' lives and ensuring a healthy environment. In this study, we present a comprehensive systematic review focusing on vital monitoring systems in diverse fields. We reviewed 85 articles spanning from 2019 to 2024. From the selected articles, our aim is to explore the frameworks and algorithms of vital signs monitoring, the latest techniques used in remote vital signs monitoring such as radar and smart watch, as well as the measurement of vital signs for heart rate and respiratory diseases. Also, we discuss the threats that may affect healthcare systems and how to secure against these threats. The findings emphasize the critical importance of acquiring continuous vital monitoring systems, which have immense potential for improving healthcare. These systems are crucial for early diagnosis and prediction of conditions that may negatively impact the patient's health. Additionally, it could be beneficial for doctors and healthcare staff by saving time and costs.

Keywords: Healthcare, Vital Signs, Monitoring, Techniques, Chronic Diseases,

Securing System

1. Introduction

Healthcare is a wide and complex field that includes a variety of services focused on maintaining and improving the health of individuals and communities. In addition to promoting general well-being, healthcare covers the prevention, diagnosis, treatment, and management of disease. Healthcare is evolving due to advances in technology. Therefore, the way medical services is delivered, improving efficiency, accuracy, and patient outcomes has changed.

Vital sign monitoring has spread beyond the realm of medicine and into many aspects of our daily lives. Originally, vital sign monitoring was performed in hospitals and clinics under careful medical supervision. Latest advances have resulted in cost reductions in monitoring systems, making these technologies more accessible and prevalent in fields such as telemedicine, emergency and wellness, and workplace safety. The integration of technology with the healthcare covers various areas: starting with electronic health records that facilitate accessing and sharing the patient's medical history, using telecommunication technology to provide remote consultant with patient via phone calls or videoconferencing and the emerging technology that has the major evolution of healthcare such as the wearable devices, artificial intelligence (AI) platforms, robots, systems with radars technologies, etc.

These technologies facilitate the work of medical staff by enabling them to detect patient's vital signs accurately and remotely and without touching the patients for special cases. Also, it provides continuous monitoring and tracking for patients' vital signs such as heart rate, oxygen level, blood pressure to assist in early diagnosis of any health issues, predicting the situation and optimizing treatment plan.

Although the integration of technology with healthcare has the potential to enhance patient care, increase efficiency, and reduce healthcare costs, it also presents challenges related to data privacy and security. Therefore, the use of technologies like block chain and Intrusion Detection Systems (IDS) aid in mitigating these risks.

The paper is organized as follows section 2 talk about methodology, section 3 is the literature review that consist of four parts: 3.1 is Frameworks and algorithms of vital signs monitoring, 3.2 latest techniques used in remote vital signs, 3.3 Measuring vital signs for specific diseases (Heart Rate and Respiration), 3.4 Securing of healthcare systems. Section 4 is the results of the paper and section 5 is the conclusion.

2. Methodology

This section aims to explain the method used in this review; we proposed a comprehensive review methodology and a holistic conceptual framework for Efficacy, Research, and Healthcare Economics: (Vital Threat Detection System) in diverse fields. Google Scholar was the used search engine for studies and research publication dated is predetermined which is from 2019 to 2024. First, seven keywords were selected as the search items including "Healthcare, Vital signs, monitoring, techniques, Chronic diseases, Securing system". Our broad keyword search initially found a large variety of papers. Employing a detailed review and process; titles, abstracts, and keywords were screened to choose a group of papers. To determine which papers were appropriate for this study, the whole texts of the selected publications were evaluated. The second stage was selecting 84 papers from highly ranked journals based on many factors such as eligibility, robustness, and the paper results. Fig.1 shows the count of published papers grouped by year.

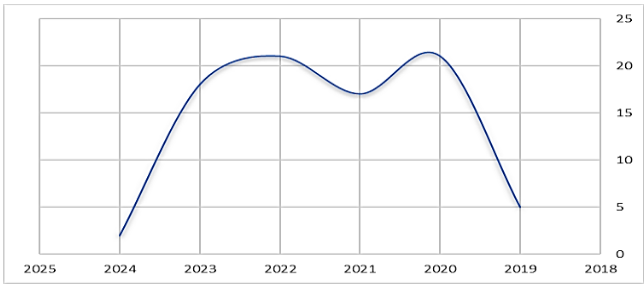

Figure (1): illustrates the count of published papers grouped by year

3. Literature Review

In this section, we aim to clarify the main concepts through readings and discuss related work in the field.

3.1 Frameworks and Algorithms of Vital Signs Monitoring

The need for a reliable and accurate monitoring system of vital signs is decisive for assessing patient health, diagnosing diseases, and preparing the appropriate interventions. This part discusses the different frameworks and algorithms that support modern vital signs monitoring systems. We will provide various technological procedures, spanning from traditional contact-based methods to advanced contactless solutions utilizing radar, cameras, and wearable sensors.

Paper [1] proposed a new method to improve accuracy, robustness, and timeliness of UWB (ultra-wide band) radar signal processing and to enhance vital signs extraction algorithms. This method used in emergencies such as wars, natural disasters such as earthquakes and tsunamis to detect human's location under these situations and extract their vital signs by UWB impulse radar to rescue them and save human life better and faster.

Paper [2] propose a device that can be a solution to the problem of measuring vital

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signs, especially the heartbeat rate and breathing rate, for patients with sensitive skin due to burns for example, especially in scenarios where there are many patients and limited medical staff. Without touching their skin, using an FMCW (frequency-modulated continuous wave) radar that sends electromagnetic waves to the patient's chest of several targets and detects the reflected waves.

Paper [3] presents a wireless healthcare system that uses FMCW radar technology for life detection and monitoring vital signs, such as breathing motion. The system enables accurate detection without the need for physical contact due to the use of radar technology, which can be particularly beneficial in the case of infectious diseases.

Paper [4] introduce the concept of "Smart Ambulance" which integrates cloud-based architecture and IoT to provide emergency medical services and Real-time monitoring of patient's vital signs during transit to ensure optimal care. Using fingerprint sensors guarantee secure and accurate patient identification and cloud-based infrastructure provide Real-time data analysis, scalability, and accessibility.

Paper [5] developed a V2iFi which is an intelligent system that accurately estimates respiratory rate, heart rate, and heart rate variability for in-vehicle vital sign monitoring using a COTS impulse radio mounted on the windshield. It detects driver's vital signs while driving and with the presence of passengers, which may enable the deduction of related health problems.

Paper [6] proposes a ViMo, is a remote vital sign monitoring system that can detect stationary/nonstationary users and estimate respiration rates (RRs) and heart rates (HRs) accurately. It consists of two main parts: an object detector to distinguish between moving individuals, stationary human subjects, and static objects, and a robust HR estimator that uses dynamic programming to resist random measurement noise and eliminate interference from respiration signals.

Paper [7] proposes vital signal detection using multiple radars to reduce signal fading from body movement, utilizing two adjacent radars with different line-of-sight to obtain correlated signals that improve signal-to-noise ratio in vital signal detection. Using different radars with varied line-of-sight (LOS) can obtain correlated signals which improves the signal-to-noise ratio in critical signal detection.

Paper [8] described a vital sign detecting system that uses a radiofrequency (RF) tags and radio-frequency identification (RFID) radar to monitor vital signs of detected subjects. To collect the vital signs of the identified individual, the RFID radar in the vital-sign detection system demodulates the reflected RF signal.

Paper [9] provides a low-complexity vital sign detection system that uses a phase discriminator, phase shifter, and variational pattern decomposition to accurately extract breathing and heartbeat frequencies.

Paper [10] presents a real-time non-contact vital sign detection system utilizing neural network-based detection, multi-object tracking, and direction of arrival (DoA) techniques. It achieves low error rates of less than 1 and 3 BPM for breathing and heart rate estimations.

This project [11] aims to develop a telehealth application framework that includes doctor consultation features as well as the capacity to remotely monitor a patient's vital signs. The application framework functions as a software foundation that may be converted into finished software. It also maintains consistency in the resulting product model throughout development. The application framework's analysis and design are based on Feature-Oriented Domain Analysis (FODA). FODA is often used to examine a single domain, but in this work, it was used to two distinct domains. Our research findings identify 14 core elements and 45 sub-components that must be integrated into the application architecture. The framework consists

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of 16 frozen and six hot areas that implement the Strategy, Observer, and Filter design patterns. These findings can help software developers create web-based Telehealth remote doctor consultations and vital sign monitoring.

This article [12] provides a summary of ML applications in two main healthcare areas: vital sign monitoring and activity recognition. Radar's most potential healthcare application is vital sign monitoring, which can forecast various chronic cardiac and respiratory disorders. Activity recognition is also a popular use, as failure to do activities might result in serious suffering. The article provides an overview of commercial radars, radar hardware, and historical progress in healthcare radars, followed by the use of machine learning for healthcare radars. The study then addresses how machine learning (ML) might overcome the limitations of standard radar data processing chains for healthcare radars. The essay also discusses some recent generative ML concepts utilized in healthcare radars. Among numerous noteworthy discoveries, it was observed that ML does not totally replace existing vital sign monitoring algorithms; rather, ML is used to overcome the constraints.

This study [13] introduces an edge-computing-based distributed interoperability architecture for smart healthcare devices, as well as a system that continuously monitors patients' vital signs and aggregates the findings for display in the nursing office or in the doctor's wallet. A healthcare setup was simulated to test the proposed method. The results were compared to a centralized authority-based system, and the proposed approach outperformed it in terms of reaction time, with the added benefit of employing local resources to ensure data interoperability. We employed deep learning techniques to learn patients' critical conditions from the vital signs monitoring database and predicted critical situations with 86% accuracy and 91% precision, allowing us to alert about critical patients. Our model achieved a sensitivity of 90% and a specificity of 72%. Thus, an excellent overall performance has been attained.

This study [14] Monitor vital signs to ensure patient safety, especially for older patients. The examination of heart rate and body temperature necessitates prompt service and handling. The issue at hand is the time it takes for doctors or nurses to provide diagnostic results, the manual system used by nurses to examine patients, and the limited number of medical personnel to handle the growing patient population. To address these issues, the researcher suggests developing a real-time monitoring gadget for patients' vital signs.

This work [15] aims to build a breathing and heart rate monitor. The author created equipment to detect respiration using a flex sensor and a heart rate monitor with the SEN11574 module. It helps diagnose diseases and determine the best medical treatment approach. One of the highest respiratory rates. Respiratory rate can indicate heart, nerve, and lung health, making it a significant measure.

Patients in critical condition are typically monitored by measuring their breathing rate. Heart rate is a crucial factor in the human cardiovascular system. An erratic heart rate might be a serious warning indication.

In [16] the worldwide health crisis has led to growing demand for healthcare technology development in Ambient Assisted Living during the past two years. COVID-19's contagious nature necessitates considering ways to alleviate its ongoing impact. Non-invasive measurement of vital signs, including heart rate, breathing rate, and SpO2, is crucial for assessing health condition, especially in frail and elderly patients. Remote photoplethysmography from facial video streams is a popular method for contactless vital sign monitoring. It eliminates the need for wearable sensors, which can be uncomfortable for the elderly, and can be performed with commercial or low-cost digital cameras. This work provides a new pipeline for estimating Heart Rate, Breath Rate, and SpO2 data, which may be integrated on the Raspberry Pi 4 as an elaboration unit. The pipeline offers algorithmic blocks to improve vital sign estimate inelderly patients, which can be challenging due to skin tone, wrinkles, folds, and moles. Our suggested pipeline is validated through quantitative evaluations on a dataset of solely elderly individuals over 65 years old. To validate against the current state of the art, tests were done on three common benchmark datasets featuring video of participants of varied ages. The pipeline demonstrated robustness inestimating vital signs in this study.

In [17] the future healthcare system will measure a patient's vital signs, transfer them to a smart device or management server, analyze them in real-time, and notify the patient and medical team. Internet of Medical Things (IoMT) .IT is integrated into patient monitoring devices (PMDs) and traditional measurement devices are being developed for healthcare information systems. The paper proposes a portable u-Vital system that includes a Vital Block (VB), a tiny PMD, and a Vital Sign Server (VSS) to store and handle vital signals. VBs collect real-time vital signs such as ECG, SpO2, NiBP, and BT and communicate them to a VSS via Wi-Fi or Bluetooth. An effective R-point detection technique has been devised for real-time and long-term ECG analysis. Experiments showed that the suggested portable u-Vital system can accurately measure, transmit, and analyze vital signs.

This study [18] compared the effectiveness of Self-InjectionLocking (SIL) radar, a continuous-wave radar system, with traditional electrocardiogram (ECG) measurements in monitoring respiratory rate (RR) and heartbeat rate (HR) during the COVID-19 pandemic. The research involved 31 hospital staff members, and data obtained from SIL radar and ECG were simultaneously collected and analyzed. Participants were categorized based on gender and body mass index (BMI), and the accuracy of measurements was assessed using mean bias errors (MBE) and limits of agreement (LOA) with a 95% confidence interval. The findings revealed that SIL radar accurately measured HR and RR, particularly for respiratory rates, across different BMI groups. Additionally, the study observed that measurements in male groups were more accurate than those in female groups. In summary, the non-contact SIL radar emerged as a reliable method for monitoring vital signs in a hospital setting during the COVID-19 pandemic.

This study [19] advocates for the implementation of a real- time remote patient monitoring system utilizing the Internet of Things (IoT) to ensure the accuracy of vital real-time signals. The proposed method employs the Message Queuing Telemetry Transport (MQTT) protocol to transmit vital real-time signals to a designated website. The primary objective is to efficiently read and analyze patients' vital signs while minimizing signal transmission latency.

This research paper [20] a new mobile agent-based intrusion detection system designed to secure networks of Internet of Medical Things (IoMT) devices within the healthcare industry. Utilizing a hierarchical and autonomous framework, this system employs machine learning and regression algorithms to detect network-level intrusions and anomalies in sensor data. By conducting simulations on different hospital network topologies, including wireless body area networks, the system proves to have high detection accuracy with minimal resource overhead, effectively addressing security concerns related to interconnected medical devices.

In [21] a system known as portable ubiquitous-Vital or u- Vital is proposed. This system consists of a Vital Block (VB), which is a compact patient monitoring device (PMD) that can get real-time patient vital signs and Vital Sign Server (VSS), which wirelessly transfers, evaluates, and maintains data. The VSS builds a database with the vital signs of the patients and uses a database lock to guarantee the security of the patient records. Through GUI clients, healthcare providers may access this data to track patients' health condition and provide reports as needed. Tests proved that the suggested portable u-Vital system is effective in measuring, transmitting, and analyzing vital signs.

Authors in [22] proposed a framework utilizing a Modified Deep Convolutional Neural Network (MDCNN) to assess heart disease more accurately. The patient's blood pressure and electrocardiogram (ECG) are tracked by the smart watch and heart monitor device that are connected to them. The received sensor data is classified as normal or abnormal using the MDCNN. Three datasets are used in the proposed system: Public Health, Framingham, and the Hungarian Heart Disease dataset. The findings show that the suggested MDCNN works better than other techniques, achieving an accuracy of 98.2%.

The purpose of this study [23] is to provide a novel identity management architecture for cloud computing and IoT based customized healthcare systems. The proposed system incorporates encrypted biometric characteristics, including PPG and ECG data to enhance accuracy and security. It integrates continuous biometric authentication with federated and centralized identity access mechanisms. Furthermore, homomorphic encryption strengthens the security of the framework. A machine learning model tested the framework using a dataset of 25 users in sitting position. The suggested fused-based biometric architecture successfully identified and authenticated all 25 individuals with 100% accuracy.

3.2 Latest Techniques Used in Remote Vital Signs

The technologies play potential role in healthcare evolving. It helps the field in many aspects such as digitization of patient's record, patient care, remote diagnoses, facilitating consultation, continuously monitoring, improving efficiency, and overall healthcare outcomes. In this part, the paper investigates papers that propose different technologies that provide vital sign detection such as heart rate, respiratory rate, blood pressure, and so on for different cases and issues. The technologies that make significant impacts are wearable devices, radars technology and sensors, artificial intelligence AI platforms, and robots.

Paper [24] develops a framework based on IoT and the Thing speak database to detect and monitor patient's vital signs signals, such as temperature, oxygen levels, and pulse rate, in real-time second by second. If any abnormal situation is detected, an LED warning will turn on and a SMS is sent to the patient's relatives or doctor by the GSM module.

Paper [25] proposes an electronic device for vital sign detection, integrated with Aphel, an artificial intelligence (AI) platform that includes humanoid robots, supporting patients and medical teams in hospitals. With this integration more health potential arises for research, diagnostic, and treatment options that were previously unthinkable. The device is in a prototype-level. It is a complex platform that integrates sensors, actuators, processing hardware, and software.

Paper [26] focuses on the estimation of vital signs in elderly patients using camera-based photoplethysmography. It is suggested to use a new pipeline integrated on Raspberry Pi4 to estimate SpO2, heart rate, and breath rate.

Paper [27] proposes a framework called ReViSe to measure human vital signs such as heart rate, oxygen level, blood pressure using a smartphone camera. Remote Photoplethysmography (rPPG) method used for collecting biometric data and deep learning-based neural network model for extracting face landmarks.

Paper [28] developed a smart watch application with embedded activity sensors and cellular connection and cloud-based data pipeline for medication intake monitoring and non-adherence. Smart watch application collects activity data and sends it to distribute data storage. Using a smart watch for medication intake monitoring embedded with sensors; offer a monitoring experience that is less intrusive than with other devices.

Paper [29] developed a wearable vital signs system by using Fiber-Bragg-Gratings sensor and a 180-nm CMOS image sensor process chip, capable of acquiring vital signs through reflecting light captured by a photodiode.

Paper [30] presents a photonic radar system for non-contact vital sign detection, achieving accuracy in detecting vital signs, by combining sensor-fusion architecture radar and LiDAR for improved results.

The research [31] aims to develop a vital sign monitoring system for home care patients that incorporates a smart watch as a data acquisition sensor device, a mobile application as a gateway that collects vital sign data and sends it to a web server, and a web application to remotely monitor vital signs and changes in their values. This system also intends to make it easier for patients and their families to communicate with doctors and nurses by displaying vital sign data and the danger of patient deterioration in the form of an Early Warning Score. The smart watch was chosen for its characteristics and inexpensive price, allowing for the creation of a low-cost vital sign monitoring system. Testing with the black-box method demonstrates that the system works properly and meets the anticipated functionality.

They present [32] a pipeline designed to improve the vitalsign estimation performance of mm Wave FMCW MIMO radars. The initial stage is to recognize human body parts and postures, which we do using trained.

Convolutional Neural Networks (CNN) to efficiently handle the flawed human form point cloud. The CNN architecture produces key points for various body sections and was trained using RGB picture reference and the Augmentative Ellipse Fitting Algorithm (AEFA). The next step is to use the chest information from the preceding estimated human posture to estimate vital signs. While CNN is originally trained to estimate human posture using frame-by-frame point clouds, vital signs are collected by beamforming toward the human chest. The numerical findings reveal that the spatial filtering enhances the estimation of vital signs in terms of lowering the cost.

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The purpose [33] of this study was to demonstrate the effect of vital sign observation frequency and alarm settings on alarms in a real-world dataset. Vital signs were obtained from 76 patients admitted to home healthcare programs utilizing the Current Health (CH) platform, which has a wearable that continually measures respiratory rate (RR), pulse rate (PR), and oxygen saturation (SpO2). Total alarms, alarm rate, patient rate, and detection time were calculated for three alarm rule sets designed to detect changes in SpO2, PR, and RR using four vital sign observation frequencies and four window sizes for the median filter of the alarm algorithms. Total alerts ranged from 65 to 3113. All alarm rule sets saw an increase in alarm rate and early detection as the observation frequency rose. The median filter window reduces alarms caused by natural changes in vital signs without reducing granularity.

In this study [34] Monitoring vital signs is critical for accurate diagnosis and maintaining patient health. Medical professionals monitor vital signs. The diagnosis of the patient's health state is still done manually. Medical staff must visit patients in each room, and equipment remains cable based. This type of vital sign assessment is not practicable due to the time-consuming diagnostic process. The proposed vital sign monitoring system design helps medical workers diagnose patients' illnesses. The vital sign monitoring system utilizes HRM-2511E sensor for heart detection, DS18b20 sensor for body temperature detection, and MPX5050DP sensor for blood pressure detection. Vital sign data processing utilizes a Raspberry Pi as a data delivery media for internet of things.

This work [35] proposes VitRad, a low-cost continuous wave (CW) radar system using 3D-printed high-gain horn antennas to detect human vital signs. The CW radar is made up of 3D-printed high-gain horn antennas, commercially available low-cost surface mounting devices, and monolithic integrated circuits. The CW radar system works at 5.8 GHz and collects backscattered I/Q data with a digital storage

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oscilloscope. (DSO). The data is processed using MATLAB to obtain vital sign information such as breathing and pulse rates. The proposed CW radar system for vital sign monitoring is proved to be effective in measuring respiratory and cardiac rates.

In [36] a non-contact bedside monitoring device with medical radar is intended to be used in clinical settings. Our earlier investigations created a monitoring system based on Medical radar monitors respiratory rate (RR) and heart rate (HR). Heart rate variability (HRV), which is used in advanced monitoring systems for prognosis prediction, is a more complex biological indicator than RR and HR. This work developed an HRV measurement filter and provided a method to determine the best cardiac signal extraction filter for HRV measurement. To separate the cardiac component from the radar output signal, digital filters must be used due to its tiny size compared to the respiratory component. The filter's properties determine whether HRV information is retained in the derived cardiac signal. Use a cardiac signal extraction filter that is not distorted in time and does not miss the heart component. We evaluated the interval between the R-peak of the ECG and the radar-cardio peak of the cardiac signal (R-radar interval). The R-radar interval refers to the duration between heart depolarization and ventricular contraction. We evaluated and compared a band-pass filter (BPF) with several bandwidths and a nonlinear filter called locally projective adaptive signal separation (LoPASS). The best filter was tested statistically by evaluating R-radar interval distribution and standard deviation. This monitoring device was evaluated on elderly patients at Yokohama Hospital in Japan.

In [37] Medical radar is a useful tool for monitoring vital signs without making contact. Radar's sensitivity and susceptibility to noise make it unsuitable for medical applications. Previous studies focused on recognizing vital signs from radar output, but mostly used high-quality signals in Laboratory environments. Maintaining high-quality signals is critical for radar applications. This study describes a medical radar-based vital sign monitoring system that analyzes signal quality, eliminates unsatisfactory signals, and extracts heartbeat and breathing signals using the support vector machine and singular value decomposition approach. We tested the system on 10 healthy people and compared their vital signs to those measured with a contact-type ECG equipment and breathing belt to assess its performance. Two evaluation steps were taken. We tested 10 subjects in a laboratory environment to assess signal quality. The results indicated that each subject archive had an accuracy range of 93.2% to 100%. We recovered vital indicators such as respiration rate (RR) and heart rate (HR) using signal quality classification. The results indicated RR and HR deviations of 0 to 1 bpm and 0 to 4 bpm, respectively. Furthermore, the technology was used in a real-world medical practice to continuously monitor the bedside of elderly patients in a hospital.

In this paper [38] Continuous monitoring of vital signs is crucial in neonatal intensive care units (NICUs). This work presents a non-contact method for monitoring vital signs using medical radar, including respiratory rate (RR), heart rate (HR), I:E ratio, and heart rate variability (HRV). Methods: A non-contact medical radar-based vital sign monitoring system with 24 GHz radar fitted in an incubator was created. The system uses a nonlinear filter to separate respiration and heartbeat signals from radar output, template matching to extract cardiac peaks, and an adaptive peak detection algorithm to estimate cardiac peaks over time. The laboratory test included nine healthy volunteers (five males and four females) aged 24 ± 5 years. We assessed the system's adaptability in NICU settings with three hospitalized infants, including two neonates. Results: In healthy subjects, the non-contact system and reference contact devices showed high agreement for measuring RR, HR, and inter-beat interval (IBI), with correlation values of 0.83, 0.96, and 0.94. Template matching and adaptive peak detection algorithms outperformed traditional methods, as expected. The suggested IBI was close to the reference Bland-Altman analysis, with a bias of 3 ms and 95% limits of agreement ranging from -73 to 67 ms, while the traditional IBI had a bias of 11 ms and 95% limits of agreement ranging from 229 to 207 ms. In the NICU clinical context, the conventional technique has an IBI correlation coefficient of 0.31 and a 95% limit of agreement of 91 ms. The proposed approach yielded correlation values of 0.93 and 21 ms. The suggested system for NICU monitoring uses a non-contact medical radar sensor. The signal processing approach combines cardiac peak extraction and adaptive peak identification algorithms, resulting in excellent flexibility in detecting IBI in varied applications.

In [39] With the Covid-19 pandemic, medical radar has emerged as a non-contact approach for patient monitoring. However, this radar is susceptible to external interference. Radar output signals from random body motions can drastically degrade the accuracy of vital sign detection algorithms. Additionally, algorithms should be designed for practical use. This paper introduces an enhanced 24-GHz radar signal quality classification model and a technique to increase the resolution of respiration rate (RR) and heart rate (HR) for short time interval signals. Lab VIEW software implements a real-time system for signal quality assessment and vital sign extraction. Signal quality categorization was examined using 10 healthy subjects' measured signals. The study found that using particular characteristics improves signal quality classification accuracy to 89.8%-100%. Real-time RR and HR extraction findings show significant agreement between radar measurements and contact-type sensors.

This report [40] presents our experimental results on monitoring human vital signals utilizing Novelda Xe-Thru X4M 202 impulse radio with ultra-wide band (IR-UWB) radio detection and ranging. Our results show that IR-UWB technology can monitor many human vital signs simultaneously. Thus, the general goal of this paper is to offer experiments that can effectively detect the human target's respiration and heart rate inside the IR-UWB RADAR range.

This study [41] evaluates the reliability of two wearable patch sensors (SensiumVitals and Health Patch), a bed- based system (Early Sense), and a patient-worn monitor (Masimo Radius-7) for continuous heart rate (HR) and respiratory rate (RR) monitoring in high-risk surgical patients during recovery. The observational study compares these devices with an intensive care unit–grade monitoring system (XPREZZON). Results indicate high accuracy for HR across all devices. For RR, Masimo Radius-7, Early Sense, and SensiumVitals demonstrate acceptable accuracy, while Health Patch overestimates RR. Data loss from wireless transmission varied across devices. The study suggests the potential value of wearable sensors for trend monitoring to promptly detect patient deterioration.

Wearable devices for continuous patient monitoring in general wards enhance safety, but experiences are not well understood. This randomized controlled trial [42] involving 90 patients in a Dutch university hospital assessed ViSi Mobile (VM) and Health Patch (HP). Semi structured interviews with patients, nurses, physician assistants, and medical doctors revealed 47 positive and 30 negative effects, along with 19 facilitators and 36 barriers. Key themes included early clinical deterioration identification and increased safety feelings. Both VM and HP were well- received, advocating for continuous vital sign monitoring in general wards. This study provides a valuable guide for future research and implementation in healthcare institutions.

This paper [43] introduces a Hybrid Intelligent Intrusion Detection System (HIIDS) for Internet of Things (IoT) applications in healthcare. Focusing on anomaly-based intrusion detection for securing cloud servers handling Electronic Health Record (EHR) data, the study utilizes the NSL-kDD dataset. Employing metaheuristic algorithms (PSO, GA, DE) for feature selection and supervised learning algorithms

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(kNN, DT) for classification, a hybrid approach is presented. Evaluation metrics include accuracy, execution time, memory usage, and CPU utilization. The GA-DT variant exhibits superior accuracy (up to 100%) in classifying DoS, U2R, R2L, Probe, and Normal classes with 8-10 features. The proposed HIIDS outperforms similar state-of-the-art works, and the paper concludes by designing an IoT-based healthcare architecture using the best-performing hybrid variant to detect and prevent malicious traffic.

This paper [44] addresses the challenges posed by the escalating network traffic and user data, emphasizing the critical role of intrusion detection systems in e-healthcare. The necessity for safeguarding patients' medical records, ensuring their security, confidentiality, and accuracy is paramount. Conventional artificial intelligence-based systems often grapple with outdated intrusion detection repositories, resulting in increased false positives and requiring frequent algorithmic retraining to accommodate new attack vectors. This leads to difficulties in securing patient records, rendering intrusion detection mechanisms frequently obsolete.

The study [45] provides an extensive examination of conventional approaches for monitoring cardio-pulmonary rates and explores the feasibility of substituting them with radar-based methodologies. Moreover, the research sheds light on the obstacles that radar-based vital signs monitoring techniques must address in order to be embraced in the healthcare sector. A proof-of-concept of a radar-based vital sign detection system is presented together with promising measurement results.

The study [46] highlighted the HEARThermo's ability to remind individuals to take additional temperature measurements using ear thermometers, thereby increasing compliance with temperature monitoring. This innovative wearable device, which offers a non-invasive and continuous monitoring solution, holds promise for use in the context of the COVID-19 pandemic.

The study [47] expands the utilization of millimeter-wave radar in the realm of healthcare. The findings indicate that the algorithms put forth successfully mitigate noise and harmonic interference, with the proposed algorithms achieving an accuracy of approximately 93% for both respiratory rate and heartbeat rate.

In this paper [48], a system for detecting and monitoring the health of elderly patients was developed on different environments. The methodology involves multiple key steps, beginning with the stages of task orchestration, which include microservices analysis, health device virtualization, intelligent task mapping and deployment on IoT devices.

Using biological sensors, the system identifies and alerts the authorities to worsening circumstances. Dataset generated by the E-PHMS contains 1440 instances. Round trip time, reliability, task drop rate, and latency performance measures are used to analyze the performance analysis of the proposed system. Findings indicate that the model could produce accurate solutions for crucial tasks in IOT environments.

In [49], authors aim to interduce an intelligent healthcare system with cloud and IoT integration technologies. The model combined deep learning algorithms with IoT-cloud technology to correctly identify COVID-19 from CT scan pictures. The model has been evaluated using two datasets: the Covid-Chestxray dataset and the Chex-Pert dataset. The findings show that the suggested approach provides 98.6% accuracy, 97.3% sensitivity, 98.2% specificity, and 97.87% F1-score.

3.3 Measuring Vital Signs for Specific Diseases (Heart Rate and Respiration)

Patients in critical condition are typically monitored by recording their respiration rate. Heart rate is an important physiological measure in the human cardiovascular system. An erratic heart rate might be a serious warning indication. Therefor people differ in the way of diagnosis depending on their status. In this section papers will be discussed based on background which is measuring vital signs for specific diseases such as respiration diseases or heart problems. Since we notice throughout our research that some researchers are studying Vital Threat Detection System with focus on some diseases or symptoms.

Paper [50] focuses on comparing the self-injection locking (SIL) radar with traditional electrocardiogram (ECG) in the efficacy and accuracy of monitoring respiratory rate (RR) and heartbeat rate (HR) during the COVID-19 pandemic.

The focus of the problem in this study [51] is exploiting cheap commercial BT/BLE smart watches as a component in a vital sign monitoring system for home care patients. The second problem is the proof of concept of using the National Early Warning Score (NEWS) as a method for monitoring the condition of home care patients in this monitoring system. The results of system testing are acceptable and in accordance with the needs of patients and medical personnel. Meanwhile, the results of validating the vital sign measurement by a smartwatch are not significantly different from medical equipment; the two- tailed P value equals 0.8236.

In [52] the worldwide health crisis has led to growing demand for healthcare technology development in Ambient Assisted Living during the past two years. COVID-19's contagious nature necessitates considering ways to alleviate its ongoing impact. Non-invasive measurement of vital signs, including heart rate, breathing rate, and SpO2, is crucial for assessing health condition, especially in frail and elderly patients. Remote photoplethysmography from facial video streams is a popular method for contactless vital sign monitoring. It eliminates the need for wearable sensors, which can be uncomfortable for the elderly, and can be performed with commercial or low-cost digital cameras. This work provides a new pipeline for estimating Heart Rate, Breath Rate, and SpO2 data, which may be integrated on the Raspberry Pi 4 as an elaboration unit. The pipeline offers algorithmic blocks to improve vital sign estimate in elderly patients, which can be challenging due to skin

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tone, wrinkles, folds, and moles. Our suggested pipeline is validated through quantitative evaluations on a dataset of solely elderly individuals over 65 years old. To validate against the current state of the art, tests were done on three common benchmark datasets featuring video of participants of varied ages. The pipeline demonstrated robustness in estimating vital signs in this study.

This study [53] addresses the need for automated monitoring of cardiac arrests in crowded emergency departments. It introduces and evaluates artificial neural network (ANN) classifiers, including multilayer perceptron (MLP), long-short-term memory (LSTM), and a hybrid model. The ANN models demonstrated superior performance (AUROC: 0.929 to 0.936) compared to non- ANN models, with the hybrid model showing the best results. Evaluation metrics, including sensitivity, specificity, and predictive values, underscore the effectiveness of ANN classifiers in predicting cardiac arrests within 24 hours. The hybrid ANN model, incorporating baseline and sequence information, exhibited the highest performance, surpassing traditional methods like the modified early warning score (MEWS). This study underscores the potential of ANN for early detection and improved surveillance in emergency departments.

This paper [54] introduces a Blockchain-driven framework for the early detection of diabetes within the healthcare sector. Leveraging machine learning classification algorithms, symptom-based disease prediction, and the interplanetary file system (IPFS), the framework ensures secure Electronic Health Records (EHRs) management. Utilizing wearable sensor devices, the system collects patient health data, which undergoes processing by a machine learning model in the EHRs manager. The results, combined with physiological parameters, are securely stored in the Blockchain with patient and practitioner approval. The proposed system addresses the urgent need for secure, efficient, and transparent management of patient health information, particularly in the context of diabetes, a prevalent and fast-growing chronic disease.

This study [55] explores the potential of using common devices like smartphones or personal computers for vital signs monitoring in COVID-19 patients. Their work demonstrates ML-enabled workflows for key indicators such as heart and respiratory rates, cough, blood pressure, and oxygen saturation. This approach presents a promising avenue for remotely managing patient symptoms, reducing the burden on healthcare professionals, and enhancing the effectiveness of home isolation strategies. They also address implementation challenges associated with deploying ML-enabled solutions for remote vital signs monitoring in the context of the ongoing pandemic.

In [56], researchers aim to develop a model to detect the lung cancer disease. Two algorithms were applied to the patient data: heuristic greedy best first search (GBFS) and random forest algorithms. The experiments showed remarkable results for the model. The dataset in this research sourced from the UCI machine learning repository this model is secure and aids in saving medical professionals' time and recourses by eliminating unnecessary manual labor. In future, the use of deep learning techniques can improve the diagnosis accuracy of lung cancer. It may be evaluated further using various disease datasets to provide a standard interface that can be used to launch a smart mobile application.

Authors in [57] suggested A home hospitalization system that combines cloud computing, fog computing, and (IoT). This system uses a mobile application and an environmental sensing equipment to monitor the hospitalization room's environment. Additionally, it gives the doctors access to a mobile application that lets them monitor patient health. The evaluation's findings indicate that patients as well as doctors find this method to be very acceptable. However, there is no video communication feature in the smartphone application.

ANAR and his colleagues [58] constructed a testbed for the enhanced healthcare monitoring system (EHMS), which gathers network traffic measurements and monitors patient biometrics. Two machine learning techniques—network and biometric metrics—are employed for healthcare intrusion detection to discover security issues. To assess the system's ability to recognize these security concerns, Man- in-the-Middle (MitM) attacks are simulated in a controlled setting. More than 16,000 records of both normal and MITM attack packets were assembled by the authors to generate a realistic healthcare dataset. The intrusion detection system's efficacy was enhanced by the combination of these two techniques.

Authors in [59] Automated diabetes risk prediction and management by using remote monitoring framework. To detect diabetes risks early, smart technology collects data from wearables and mobile devices. It logs user data and monitors health indicators like heart rate and blood pressure. The PIMA Indian Diabetes dataset used in this paper. The results demonstrate that performance metrics of accuracy, sensitivity, and specificity scores at 83.20%, 87.20%, and 79%, respectively. The primary constraints of this work stem from the limited breadth of the dataset and the small-scale testing of the system. Additionally, gender and ethnicity bias were introduced due to the dataset's specific inclusion of samples of women of Pima Indian heritage.

This research [60] proposes a framework for the Smart Healthcare Monitoring System for elderly people, which makes use of wearable sensors and a smartphone app. The system gathers patient physiological data in real-time from elderly individuals using wearable sensors (pulse, oxygen, etc.). The information is sent to a data repository, where it is kept and examined for anomalies. Any abnormality found in a patient's vitals will be immediately reported to the patient's doctors. The suggested system increases healthcare efficiency by offering a more convenient and dependable healthcare system that permits home-based monitoring.

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Authors in [61] propose Health Guard, which is an innovative security framework based on machine learning to identify harmful activity in smart healthcare system. To identify harmful activity in a SHS, Health Guard uses four distinct machine learning-based detection techniques: k- Nearest Neighbor, Random Forest, Decision Tree, and Artificial Neural Network. Twelve benign activities, comprising seven typical user activities and five others, were used to train the system using data gathered from nine databases for eight different devices. Also, three different threats have been used for evaluation. Findings indicate that Health Guard has a high degree of accuracy and F1 score in identifying different threats to the SHS.

To help and enhance patient prognoses for heart disease, enhanced deep learning assisted convolutional neural networks (EDCNNs) model have been proposed in [62]. In order predict and diagnose heart disease, the proposed EDCNN uses deep learning methods like as CNN and MLP for feature extraction and classification of ECG heartbeats. The UCI repository dataset was applied to conduct the experiment and obtain the findings. The procedure involves selecting features, preparing the data, and using convolutional blocks to extract and classify features efficiently. Test findings demonstrate that up to 99% accuracy may be attained.

Researchers in [63] developed an intelligent signal processing framework to eliminate the issues involved in remote vital sign detection. This framework utilizes Kalman filtering, K-means clustering, Singular Value Decomposition-Ensemble Empirical Mode Decomposition (SVD-EEMD), Convolutional Neural Networks (CNNs), and signal preprocessing. They conducted an experiment based on a single IR-UWB radar system. The experiment's findings demonstrate the excellent accuracy, stability, resilience, and real-time performance of the proposed approach. Additionally, it creates a more organized framework for deriving information about vital indicators from respiration and heart data.

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Researchers in [64] develop an application that uses the DCAlexNet CNN deep learning model to identify cardiac anomalies via ultrasound pictures. This application utilizes Kaggle or ANDI dataset for training samples. Data in two categories—numerical and pictures —are evaluated. Both RRF and DCAlexNet CNN algorithms, pictures were pre- processed and categorized. The MLP function allows text and picture datasets to be combined with features. The outcomes of the performance metrics show an F1 score of 99.34%, recall of 99.34%, sensitivity of 97.45%, and accuracy of 98.67%.

3.4 Securing of Healthcare Systems

Healthcare monitoring systems and patient data require protection against various types of threats. This section will review the different types of threats and how to deal with them to develop a secure and reliable environment for patients and the healthcare sector. Additionally, we will explore how modern technologies like blockchain and Intrusion Detection Systems (IDS) aid in mitigating these risks.

Paper [65] develops a secure monitoring system to continuously monitor patient's vital signal to prevent any progressive drop in his condition while underlying diseases being treated. If any situation arises while monitoring, a mobile phone alert is sent to the Physician through cloud API (Application Peripheral interface). For security issues, RFID smart cards used to read patients information and previous record and two-step authentication with OTP (one time password) and AES (Advanced Encryption Standard) used to secure access to patient's database.

This study [66] the emergence of the Internet of Medical Things ushers the healthcare ecosystem into a new digital era with numerous advantages, including remote medical support, real-time monitoring, and pervasive control. However, despite the benefits to healthcare, this development raises serious cybersecurity and privacy risks. This article focuses on the IEC 60 870-5-104 protocol, which is commonly

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used in industrial healthcare systems. First, we examine and assess the severity of IEC 60 870-5- 104 cyberattacks using a quantitative threat model based on Attack Defense Trees and the Common Vulnerability Scoring System v3.1. Next, we introduce an intrusion detection and prevention system (IDPS) that can automatically detect and mitigate IEC 60 870-5-104 cyberattacks. The proposed IDPS fully utilizes machine learning (ML) and software-defined networking (SDN) technologies. ML is used to detect IEC 60 870-5-104 assaults by analyzing 1) Transmission Control.

Protocol/Internet Protocol network traffic statistics and 2) IEC 60 870-5-104 payload flow statistics. On the other hand, automated mitigation is transformed into a multiarmed bandit issue, which is handled using a reinforcement learning method known as Thomson sampling and SDN. The evaluation analysis reveals the effectiveness of the proposed IDPS in terms of intrusion detection accuracy and automated mitigation performance. The suggested IDPS has a detection accuracy of 0.831 and an F1 score of 0.8258, while its mitigation accuracy is assessed to be 0.923.

In this research [67], they address the escalating security risks posed by the extensive integration of interconnected healthcare devices within the Internet of Medical Things (IoMT). The majority of IoMT devices lack resilience against internet attacks. Their work introduces a cyber- attack and anomaly detection model utilizing recursive feature elimination (RFE) and multilayer perceptron (MLP). The RFE method optimizes features through logistic regression (LR) and extreme gradient boosting regression (XGBRegressor) kernel functions. MLP parameters are fine-tuned via hyperparameter optimization, employing a 10-fold cross-validation approach for robust performance evaluation. The model achieved outstanding accuracy rates of 99.99%, 99.94%, 98.12%, and 96.2% on various IoMT cybersecurity datasets, including ECU-IoHT, ICU Dataset, Telemetry data, Operating systems' data, TON-IoT, and WUSTL-EHMS. Demonstrating its

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efficacy, the proposed method proves capable of countering cyber- attacks in healthcare applications.

This paper [68] addresses the growing challenges of cybersecurity in the security of things (SoT) paradigm for smart healthcare. To improve detection accuracy and overcome challenges, this study proposes a machine learning support system that combines Random Forests and genetic algorithms for feature optimization. Using the NSL-KDD dataset, the results demonstrate the effectiveness of the proposed method in achieving high detection rate (98.81%) and low false alarm rate (0.8%).

This study [69] presents an extensive examination of the latest cutting-edge measures employed to ensure the security of the Internet of Medical Things (IoMT) in Smart Healthcare Systems (SHS). It encompasses various aspects such as security, privacy protection, authentication, authorization, and the utilization of blockchain for secure data sharing. The review provides a comprehensive analysis of the advantages and drawbacks of existing solutions, ultimately offering valuable insights into potential opportunities and future research directions for the seamless integration of a secure IoMT in SHS.

This paper [70] discusses the growing susceptibility of hospitals to cyber and physical risks, highlighting the necessity for a system that can oversee, identify, and avert incidents immediately. The SAFECARE initiative strives to bolster hospital safety through the deployment of a Building Threat Monitoring System (BTMS). This suggested approach involves the use of sensors within hospital premises to relay occurrences, issues, and notifications, thereby protecting patient data and upholding adherence to European standards concerning ethics and confidentiality in healthcare provisions.

The research [71] presents an effective model for detecting multiple concurrent threats and determining their sources through real-time data and mobile-edge computing. This framework is structured hierarchically. Experimental findings confirm the accurate detection of multiple concurrent health security threats by the proposed framework.

The rise in cyber threats and vulnerabilities has been significant during the COVID-19 pandemic, as the world shifted towards increased technology usage. A solution to this challenge is presented in this work [72] in the form of IoT-Attributes and Threat Analyzer for Tracing Malicious Traffic in Smart Sensor Environment (IoT-ATATMT). This tool allows for the analysis of traffic from both normal and suspicious smart devices, using various machine learning algorithms to detect and protect against cyber threats in the e-healthcare system through a specially curated dataset.

The framework proposed in this article the article [73] aims to improve the security of IoT in healthcare by tackling the specific challenges faced by IoT devices. A new tool called IoT-Flock is introduced, which allows the generation of IoT datasets comprising both normal and malicious device traffic. By leveraging machine learning techniques, the framework enables the detection of cyber-attacks, with a particular focus on the healthcare sector. This approach takes into account the limited resources of IoT devices and offers context-aware security solutions for critical IoT applications.

In this study [74] introduce an approach called XSRU- IoMT, which utilizes explainable AI (XAI) to enhance transparent threat detection. By incorporating bidirectional simple recurrent units (SRU) and skip connections, XSRU- IoMT enables efficient training in recurrent networks. The integration of XAI further strengthens trust by offering interpretable explanations for predictive decisions. Through evaluation on the ToN_IoT dataset, the researchers demonstrate the superiority of XSRU-IoMT over existing solutions, positioning it as a promising option for real- world deployments in the IoMT network.

This paper [75] the authors present an innovative framework for categorizing intrusion detection methods in the context of IoT. This framework includes a comprehensive comparative analysis of various intrusion detection techniques, as well as a unique classification system for existing datasets that offers valuable insights into detection performance. Furthermore, the paper delves into the cybersecurity threats associated with the IoMT architecture and highlights the security requirements specific to IoMT. The authors also provide a thorough examination of the tasks performed within Cloud-Fog-Edge architectures and offer a classification of recent literature in this domain. Additionally, the legal and ethical security aspects of IoMT are discussed in detail. Lastly, the paper identifies the challenges faced in this field and proposes novel perspectives that warrant further investigation.

The study [76] presents IC-MADS, a new cross-layer trust calculation method developed to identify Man-in-Middle Attacks (MIMA) in IoT-enabled smart healthcare systems. Through simulation outcomes, it has been shown to be highly effective in preventing MIMA attacks, thus offering a potential solution to bolster security in IoT-based healthcare platforms.

In this paper [77], the authors focus on the detection of Denial of Service attacks carried out by TCP SYN flooding attacker nodes. They introduce a novel algorithm for Intrusion Detection System (IDS) aimed at identifying malicious activities within the Internet of Medical Things. The newly proposed method aims to reduce the frequency of attacks to safeguard data security and maintain the confidentiality of collected data. To assess the effectiveness of their approach, the authors conduct analytical evaluations and simulations to analyze the performance of their solution across various attack probabilities.

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The research [78] presents a new intrusion detection system that integrates particle swarm optimization and AdaBoost algorithms to categorize and identify malware-related data in innovative health app platforms. The results of the experiments show that the PSO-AdaBoost approach achieves better accuracy, precision, and recall in intrusion detection. This study emphasizes the potential of ML-IDSs in enhancing the security infrastructure of medical IoT devices and improving patient outcomes in the interconnected world of the Internet of Medical Things.

Sachin and his colleagues [79] examined the effect of implementing an app-based remote patient monitoring system (Huma Therapeutics) on the doctor's workload in a virtual ward designed specifically for COVID-19. An experimental prospective study was conducted from collected patients' data for one-month duration. Then, the clinical workload was comparatively evaluated between patients monitored solely by telephone (group 1) and those monitored via both mobile app and telephone (group 2). 56 patients were involved in the app-based virtual ward (group 2). The findings indicate a significant decrease in phone calls, resulting in a saving of 47.60 hours of work. However, one of the limitations that the experiment was conducted on a small sample.

In this article [80] ROMANY and his colleagues develop a heart disease and diabetes diagnosis model. This model combines AI and IoT for disease diagnosis to achieve better classification of the medical data and they use I Forest for outlier removal to improve the accuracy of diabetes and heart disease diagnoses.in addition, the model's weights and bias parameters are optimized by the use of CSO. Heart disease and diabetes datasets are used to evaluate the CSO- CLSTM model's performance, comparing its sensitivity, specificity, and accuracy. Results indicates that the model achieved the highest diagnostic accuracy of 96.16% and 97.26% for diabetes and heart disease, accordingly. However, one of the limitations is the CSO algorithm, which is considered a slow and less accurate search algorithm.

Faisal et al [81] interduce blockchain-based smart contract platform for monitoring patients' vital signs. This platform operates in four layers: the application layer, IoT blockchain service layer, the connectivity layer, and thehealthcare IoT physical layer. Hyperledger Caliper tool was used to evaluate the performance. Authors proposed new system with better sensors to collect data. Results indicates that the adoption of blockchain technology enhances efficiency and minimizes delay in contrast to the conventional healthcare system.

In [82], researchers aim to provide a blockchain-based secure healthcare 5.0 system they utilize federated learning to guarantee data privacy, blockchain technology for safe data storage, the RTS-DELM module for automated disease prediction, and (IDS) for thorough security evaluation. The system shows that the method is successfully improved for monitoring healthcare. However, the system's computing complexity is constrained by the increasing number of hidden layers, posing challenges for system efficiency.

This study [83] utilized a cost-savings analysis to calculate the anticipated cost savings associated with establishing continuous vital sign monitoring. For a period of one year, an experiment was created for a community hospital in the U.S. National databases and earlier research comparing the results of patients having continuous vital sign monitoring standard of care (periodic vital sign measures). Findings show that implementing continuous monitoring technology in medical-surgical units can improve patient outcomes and result in annual cost savings of approximately $6.8 million. However, there are some limitations in this study like the variations in patient demographics, including age and health status, may impact the precision of cost-saving predictions.

In [84] a proposed IoT-Cloud-based smart healthcare system for predicting dangers of heart disease. Therecurrent neural network's bidirectional LSTM combined with the fuzzy inference system (FIS) are utilized for the predicting role. Modules like the data acquisition/collection layer, data pre-processing layer, and illness prediction layer are provided in the proposed model. The Cleveland and Hungarian datasets from the UCI machine learning repository are taken into consideration for the experiment. This model outperforms existing prediction models with accuracy, precision, sensitivity, specificity, and F1-score of 98.85%, 98.9%, 98.8%, 98.89%, and 98.85%, respectively.

4. Findings

4.1 Frameworks and Algorithms of Vital Signs Monitoring

The COVID-19 pandemic has altered the worldwide landscape of the SHM Framework, emphasizing the importance of these systems at this challenging period. Several smart healthcare architectures prioritize wireless and mobile communications as critical need for the future (HoF). Evolving smart e-health requires new technologies, system designs, and computing paradigms. Smart healthcare systems address a range of needs, including dependency, low latency, mobility, energy efficiency, responsiveness, and security.

Effective and reasonable deployment of machine learning (ML) in SHM is crucial for future RPM and healthcare. Using complicated algorithms for data analysis in SHM can improve recommendations, reducing the risk of complications and allowing for early detection of acute consequences from chronic conditions. These studies aims to create ML and DL solutions for healthcare that utilize analytics, knowledge-driven learning, and logic-based inspection to close data-to-knowledge gaps. Tracking daily activities with IoT technology can improve the health and fitness of active individuals. Using a cloud-based machine learning platform enhances Big Data handling capabilities. The researches employed Azure, a cloud-based machine learning platform, for illness classification.

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4.2 Latest Techniques Used in Remote Vital Signs

Continuous monitoring of vital signs, including breathing and heart rate, is critical for early diagnosis and even prediction of conditions that may have an impact on the patient's well-being. There are two types of vital sign sensing techniques: contact-based and contactless-based. Traditional clinical methods of measuring these vital signs necessitate the use of touch sensors, which may be impractical for long-term monitoring and less convenient for repeating assessments. Wireless vital signs detection utilizing radars, on the other hand, has the distinct advantage of not requiring the attachment of electrodes to the subject's body, thereby allowing for greater freedom of movement and removing the chance of skin irritation. Furthermore, all of the aforementioned technologies utilized in vital health monitoring helped diagnose a larger number of patients in a shorter amount of time.

In addition, it eliminates the need for wires and limits patient access, particularly for toddlers and the elderly. This study provides a full analysis of established methods for monitoring cardio-pulmonary rates, as well as the possibility of replacing these systems with radar-based techniques.

4.3 Measuring Vital Signs for Specific Diseases (Heart Rate and Respiration)

The evolution of ubiquitous sensing technology has resulted in intelligent settings capable of monitoring and reacting to our daily activities, such as adjusting our heating and cooling systems, responding to our gestures, and monitoring the elderly. In this study, we investigate whether smart settings can remotely monitor our vital signs without the need to instrument our bodies. We introduce Vital-Radio, a wireless sensing device that detects breathing and heart rate without requiring bodily contact. Vital-Radio takes advantage of the fact that wireless signals are influenced by motion in the environment, such as chest motions caused by inhaling and exhaling and skin vibrations caused by heartbeat. The discussed studies shows that Vital-Radio can

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track users' breathing and heart rates with 99% accuracy, even if they are 8 meters away or in a different room. Furthermore, it can track numerous people's vital signs at the same time. We believe Vital-Radio will enable smart houses that monitor people's vital signs without body equipment and actively contribute to their residents' well-being.

4.4 Securing of Healthcare Systems

Based on the subjects covered, below are some recommendations for improving the security of healthcare IoT systems:

- Implement a strong healthcare IoT architecture. Design a safe and scalable architecture that includes all necessary components and linkages, taking into account data flow, device management, and interoperability.
- Provide secure data transmission. Use encryption and secure communication channels, such as Transport Layer Security (TLS), to protect data during transfer between IoT devices, gateways, and backend systems.
- Access control and authentication: Implement robust access control techniques, such as multi-factor authentication and role-based access control, to guarantee that only authorized users have access to healthcare IoT systems and sensitive patient data.
- Privacy Protection: Use privacy-preserving strategies such as anonymization, pseudonymization, and differential privacy to protect patient privacy while allowing for valuable data analysis and insights.
- Implement strong intrusion detection and prevention systems, as well as behavioral analytics and anomaly detection, to ensure ongoing monitoring and threat identification.

- Conduct regular security assessments and updates. Perform regular security assessments, penetration testing, and vulnerability scanning to detect and address any flaws or vulnerabilities in healthcare IoT systems. Keep your devices and software up to date with security patches and updates.
- Compliance with regulations: Keep track of important compliance requirements and regulations, such as HIPAA, GDPR, and medical device regulations, and ensure that healthcare IoT solutions meet these standards.
- Educate healthcare personnel, users, and patients on security best practices, phishing awareness, and strong passwords to reduce the likelihood of security events caused by human error or social engineering.
- Encourage collaboration and information sharing across healthcare organizations, regulatory authorities, and security communities to share knowledge, exchange threat intelligence, and stay up to date on evolving security threats and mitigation techniques.

5. Conclusion

This comprehensive review explored the expanding field of vital threat detection systems in healthcare, analyzing different frameworks, algorisms, and procedures for monitoring vital signs. This study demonstrates several key findings:

Achievements in Remote Monitoring: According to recent research knowledge, we can say there are advancements in remote vital sign monitoring procedures. There are many methods to achieve this progress like UWB radar, smartphone cameras, and IoT sensors. These advancements decrease the burden on healthcare providers by providing non-invasive ways that give continuous monitoring qualifications and enhancing patient accessibility.

Enhanced Diagnostics for Individualized Care: Developers are working on projects for providing specialized vital sign monitoring systems for specific diseases like diabetes, heart disease, and lung cancer. These systems analyze data and use specific algorithms to provide accurate diagnoses and personalized treatment options.

Harnessing Machine Learning for Advanced AI Applications: Thanks to integration of AI and machine learning algorithms, researchers developed techniques for data analysis, anomaly detection, and disease prediction. Studies clarified the potential of these systems in identifying risk factors, providing early intervention, and coming up with perfect results.

Building A Secure Environment: The increased amount of data within the healthcare system makes ensuring data security and privacy essential. Researchers created various methods for security measures such as blockchain technology, intrusion detection system, and access control mechanisms. These methods prevent cybersecurity threats from causing harm to healthcare data.

Challenges and Future Directions: Despite the impressive advancements, challenges persist in fields like algorithm optimization, data accuracy, and system compatibility. Future research should concentrate on overcoming these obstacles and finding novel strategies such as:

Composite Monitoring Systems: We can study the outcomes of using multiple techniques together like radar and camera-based methods. That could result in more comprehensive and accurate data.

Wearable Sensor Integration: Using AI technology can integrate wearable sensors and provide reliable data and individualized feedback.

Telehealth Applications: Enriching vital sign monitoring systems with telehealth technologies could expand access to care and promote management to remote patients.

Ethical Considerations: There must be updates and implementations about ethical issues related to algorithmic bias, data privacy, and equal accessibility to these technologies.

There Are Several Potential Research Gaps Emerge in The Field Of Vital Threat Detection Systems:

Integration and Interoperability: There are many separate systems available for tracking certain vital signs or illnesses, but little research has been done on how to combine these systems into a complete and compatible framework. This framework may offer a comprehensive picture of the health of patients and make it easier to identify any early risks.

Context-Awareness and Personalization: These features are frequently absent from current systems. To give more precise and customized risk assessments, future study may look at combining contextual elements such as patient history, lifestyle, and circumstances.

Cost-Effectiveness and Implementation: There hasn't been much study done on how affordable crucial threat detection systems are, as well as how they're really implemented in different healthcare settings. To assess the financial viability and potential obstacles to mass adoption, more research is required.

By addressing these research gaps, essential danger detection systems that are more modern, dependable, and easily available may be developed, eventually leading to better patient outcomes.

In general, vital threat detection systems have tremendous potential for improving healthcare by facilitating proactive and preventative care, enhancing patient outcomes, and saving healthcare costs. As research and advancements proceed, these systems can play a crucial role in shaping the future of healthcare delivery.

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