International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

Statistical Review of Health Monitoring Models for Real-Time Hospital Scenarios

Vonteru Srikanth Reddy[1], Kumar Debasis[2]
[1]VIT-AP University, School of Computer Science and Engineering
Amaravati, 522237, India
Srikanth.21phd7015@vitap.ac.in
[2]VIT-AP University, School of Computer Science and Engineering
Amaravati, 522237, India
Kumar.Debasis@vitap.ac.in

Abstract— Health Monitoring System Models (HMSMs) need speed, efficiency, and security to work. Cascading components ensure data collection, storage, communication, retrieval, and privacy in these models. Researchers propose many methods to design such models, varying in scalability, multidomain efficiency, flexibility, usage and deployment, computational complexity, cost of deployment, security level, feature usability, and other performance metrics. Thus, HMSM designers struggle to find the best models for their application-specific deployments. They must test and validate different models, which increases design time and cost, affecting deployment feasibility. This article discusses secure HMSMs' application-specific advantages, feature-specific limitations, context-specific nuances, and deployment-specific future research scopes to reduce model selection ambiguity. The models based on the Internet of Things (IoT), Machine Learning Models (MLMs), Blockchain Models, Hashing Methods, Encryption Methods, Distributed Computing Configurations, and Bioinspired Models have better Quality of Service (QoS) and security than their counterparts. Researchers can find application-specific models. This article compares the above models in deployment cost, attack mitigation performance, scalability, computational complexity, and monitoring applicability. This comparative analysis helps readers choose HMSMs for context-specific application deployments. This article also devises performance measuring metrics called Health Monitoring Model Metrics (HM^3) to compare the performance of various models based on accuracy, precision, delay, scalability, computational complexity, energy consumption, and security.

Keywords- health monitoring system, cloud computing, machine learning, performance.

I. INTRODUCTION

Health Monitoring System (HMS) design is a multidomain task that requires the modelling of sensor interfaces, data filtering and processing models, communication models, recommendation models, alerting methods, etc. These models are connected in a cascaded layered format, which assists in effective sequential operations. A typical HMS Model [1] that uses tiered layers can be observed in Fig. 1, wherein different body sensors are interfaced with processing devices, which communicate with Doctors, Medical Databases, Family Members, Emergency Departments, etc. The model uses different layers for designing an efficient HMS ecosystem and work efficiency even when the number of patients is high. This is possible via the use of a central repository of patient health records, along with their treatments, future health impacts, etc. Almost 75% of all illnesses in China are classified as chronic, according to the 2017 Ministry of Health Report on the State of Chinese Citizens Nutrition and Chronic Diseases. In addition, cardiovascular disease and diabetes together account for 85.5% of all deaths each year due to chronic illness [2, 3]. Online medical care often targets less healthy individuals and conditions. This is because of the high prevalence of less-than-healthy population subsets, the long-term nature of chronic diseases, the complexity of their aetiologies, and the high expense of treating them. Due to this, people have started paying greater attention to IoT-based health monitoring. China's ageing population and rising standard of living are largely to blame for the country's worsening health situation, which is reflected in rising rates of chronic illness. Effective, user-friendly, risk-free, and dependable healthcare facilities and services are desperately needed in China. It is necessary to create a health monitoring system to track a patient's status and vitals remotely in real-time [3, 4]. To address the issues confronting today's networks, organizations, and governments throughout the globe, researchers have developed a system known as the Internet of Things (IoT). Connects intelligent sensing devices and the Internet.

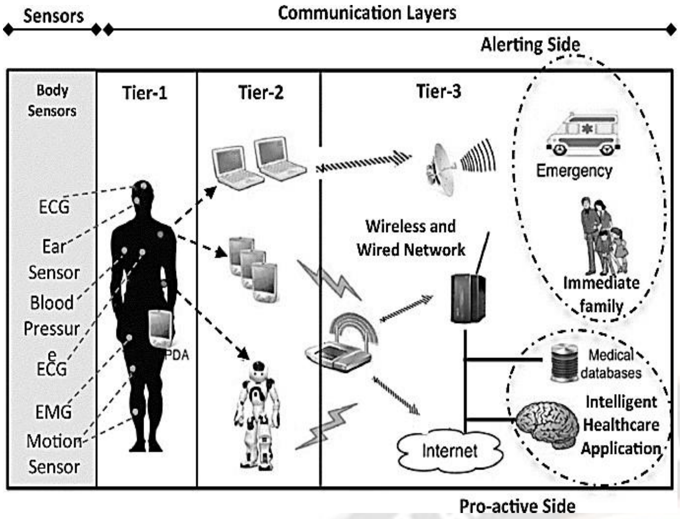

Figure 1: Design of a typical HMS Model [1]

The IoT has enabled a novel method of analysing data for many different purposes, using smart systems and intelligent objects. Figure. 1 shows that the core architecture of the IoT is consistent. Several potential uses for the Internet of Things have been proposed [4, 5]. Automation in agriculture, medicine, transportation, and the development of "smart cities" are all examples of such uses. Because of the vast nature of the Internet of Things, no one phrase exists that does its justice. Other services for the Internet of Things include: "a subset of the Internet that uses a wide variety of information sensors," as defined in [6]. These sensors can detect radio frequency identification (RFID), a global positioning system (GPS), infrared light (IR), heat (LHV), electricity (EHV), mechanical motion (ML), chemical composition (ChemBio), biological signatures (BioSig), and geographic location. Potential information sensors for the Internet of Things include radio-frequency identification technology, the Global Positioning System, infrared sensors, light, heat, and electricity.

"Health monitoring" refers to the continuous collection, using specialised monitoring equipment, of physiological markers crucial to a person's state of health and the impact factors linked with them. When people talk about "health monitoring" for different use cases. Sharing health data on people and populations is the last step in data-driven healthcare delivery. Improvements in health management coincide with a hastening of the emergence of new health risks and a narrowing of preventative and control measures. A growing number of studies worldwide are looking at the benefits of IoT-based health monitoring systems for humans. The evolution of human health monitoring technologies based on the Internet of Things is an area where China lags behind other nations. The remote collection of medical data like blood pressure and glucose levels is one of the many uses of telemedicine, a rapidly developing field (long-distance transmission). When linked to external wireless sensors, the agent system can track vital signs such as a person's core temperature, respiration rate, blood pressure, and heart rate.

A remote medical diagnosis system has been created using Internet of Things technology, including online consultation and video communication [7,8]. The system's principal function is to assist medical professionals in their pursuit of more precise diagnoses. To enable remote monitoring, Work in [9, 10] developed an electrocardiogram (ECG) monitor connected to the intelligent terminal of the Android system. To keep tabs on people's well-being, set up a network of connected devices connected to the Internet. This instrument can assess several physiological parameters, such as oxygen saturation, core temperature, and eye movement. Vital signs, including heart rate, electrocardiogram (ECG), temperature body, and respiration, were among the indicators measured by the Internet of Things-based healthcare monitoring system built in [11-13]. The absence of an interface is the technology's biggest drawback since it slows the viewing process. A non-invasive technique and device for monitoring heart rate were developed in [14, 15]. This technique uses a framework for real-time event monitoring to create dynamic IoT apps.

Work in [16-18] provides a technique for keeping tabs on one's pulse with nothing more than a portable electronic gadget. When their pulse rate was being tracked in the manner stated, the user interacted with the camera on the device. Research in [19, 20] designed a user-friendly programme for smartphones that they hoped would assist in the diagnosis of cardiovascular illnesses. The software records and keeps track of your typical heart rate. An analogue data monitoring strategy based on mobile technology has been developed for different scenarios. Bluetooth is also necessary for devices to transmit data, in addition to the Arduino platform, which is used for digital-to-analogue conversion. Safety devices take advantage of the IoT platform at the control, device, and transit layers. Internet Protocol (Ethernet) and wireless (Wi-Fi) connections transmit the data to the cloud storage service.

The monitoring systems for smart homes and the human heart are designed based on wireless sensor networks. The extraordinary connectedness of modern smart gadgets may be to blame for the meteoric rise of the Internet of Things. Since the healthcare industry increasingly depends on remote monitoring of patient severity, the Internet of Things (IoT) has come to the forefront. This technological advancement has influenced the fields of public health and workplace safety. With cloud-based solutions, the IoT might improve computing, processing, and storage in several ways. Processing and storing geographic data on a cloud platform is beneficial since it enables data sharing across many devices and application use. Because of this, analysing and storing geographical data

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

becomes more valuable. Several issues affect the human HMS based on the Internet of Things, such as increased user and dataset uploads, the lack of user guarantees, real-time performance, and inefficient data use. For this study, we create a human health monitoring system that relies on the IoT.

The device provides continuous and precise monitoring of The user's temperature, pulse, blood pressure, and heart rate are considered vital indicators. For health monitoring, this technology uses wireless sensors to gather vital data. Synthesising data and using IoT for processing, networking, and computing paves the way for real-time tracking. It has been shown that the suggested system can conduct tests with the same degree of accuracy and dependability needed to rectify flaws in the current health monitoring platforms. This article makes a valuable contribution to health management in the real world by advocating for using an Internet of Things-based system to track individual patients' vital signs. The development of standards and the enhancement of healthcare quality depend on this input.

A wide variety of similar HMS Models, their context-specific nuances, application-specific benefits, feature-specific challenge, and deployment-specific future research scopes are discussed in Section 2. It is observed that Blockchain Models, Machine Learning Models (MLMs), Encryption Methods, Hashing Methods, Bioinspired Models, and Distributed Computing Configurations have better QoS and performance in processing energy, scalability, security, and computational complexity. When compared to their counterparts. Upon referring to this article, researchers can identify the most optimum models for their application-specific use cases. Performance evaluation of these models in terms of QoS and security metrics is discussed in section 3. A novel Health Monitoring Model Metrics (HM3) that combines different performance metrics is proposed. These metrics incorporate different QoS and security measures, which assist in identifying optimally deployable HMS models for large-scale applications. Section 4 concludes this paper with interesting observations about the reviewed models and recommends methods to improve their performance under different real-time scenarios. The following are the main contributions of this paper.

- This article discusses some recent health monitoring models and compares them based on accuracy, precision, delay, scalability, computational complexity, security, and energy consumption.
- The article highlights the techniques that can be used in health monitoring models to enhance their performance in large deployments.
- The article discusses challenges that can be considered by researchers who are working to enhance the performance of health monitoring models.

II. BACKGROUND STUDY

Researchers propose various models to design efficient health monitoring systems shown in Figure 2. These models utilise IoT-based sensors, actuators, processing devices, and communication interfaces. This section discusses each model type in detail and evaluates their performance for real-time scenarios

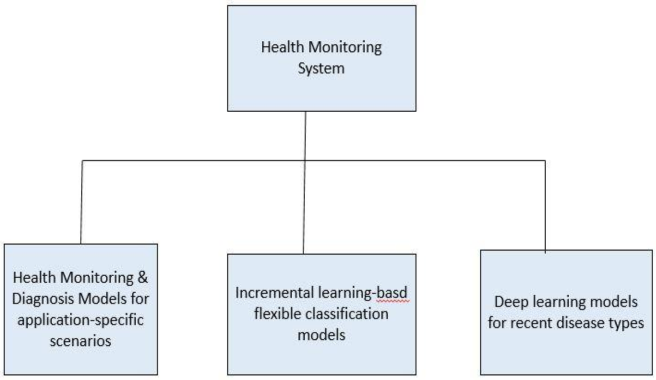

Figure 2: Health Monitoring System for different Models

A. Health Monitoring & Diagnosis Models for application-specific scenarios

The work discussed in this section is various IoT based systems and applications developed for healthcare monitoring, diagnosis, and management, including those for COVID-19 patients. Most of these studies involve using sensors, wireless communication technologies, cloud computing, and machine learning algorithms to acquire, process, and analyze health-related data in real-time.

Several studies focus on developing smart health monitoring systems for COVID-19 patients using IoT, such as systems based on wearable sensors and automated health monitoring systems. The studies discuss various aspects of these systems, including design, architecture, security, and privacy concerns.

Other studies describe the use of IoT in health monitoring applications for maternal and fetal care, ambulatory care, gait analysis, and ECG monitoring. They discuss the various IoT technologies and protocols used in these applications, including fog computing and cyber-physical systems.

In summary, these studies highlight the potential of IoT-based healthcare applications in improving patient care, diagnosis, and management while providing timely and accurate health-related data to healthcare providers. However, they also identify several challenges and limitations, such as privacy concerns, data security, interoperability, and standardization,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

which must be addressed to ensure the successful deployment of these systems in real-world scenarios.

For instance, work in [2] proposes using smart connectivity sensors with ResNet models to enhance data scanning and processing capabilities. The model is capable of achieving an accuracy of 98.6% in terms of monitoring patient health status and reporting alerts to doctors in real-time, which makes it useful for large-scale deployments. But the model is designed for CoVID-19-based patients and cannot be scaled for other diseases due to its internal design characteristics. To overcome this limitation, work in [3] proposes the use of Honey Badger Optimization (HBO) with Least Squares Support Vector Machine (LSSVM)for general-purpose applicability. The model is capable of achieving an accuracy level of 94.8% but can be used for a large number of health conditions. It uses a combination of different sensors Lm35 based, Temperature, ECG, Blood Pressure, Heart Rate, Pulse Oximetry, an Accelerometer for movement detection, and a Respiration Sensor, which are connected to an Arduino interface for real-time processing capabilities. Data from these sensors are processed via HBO Model, which optimises a fitness function that calculates error and can be calculated via equation 1,

$$f = \frac{1}{A} * \sum_{i=1}^{A} \frac{Act_i - Est_i}{Act_i} \qquad (1)$$

Here, Acti, Esti, and A represent actual output, estimated output, and the number of parameters predicted by the model, respectively, which assists in continuously improving prediction performance. The model showcases better accuracy when compared with Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM) Models, thus making it useful for highly scalable deployments. DT showcases an accuracy of 84.5%, RF achieves an accuracy of 82.1%, and SVM can detect health conditions with an accuracy of 89.6% under different real-time conditions. But these models are used for single-hospital deployments and cannot be extended to cloud-based Software as a Service (SaaS) applications. To overcome this limitation, work in [4] proposes a fog computing model depicted in Fig. 3, wherein the Cloud, Fog, and Things layers (CFT) are observed.

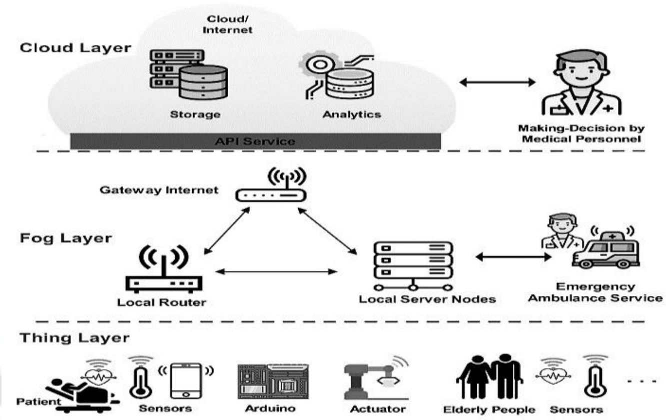

Figure 3. Fog-based HMS Model for large-scale deployments[4]

The model uses sensors, controllers, actuators, and other devices at the 'Things' layer. At the same time, emergency services, routers, and gateway nodes are connected to the cloud at the 'Fog' layer, which assists in deploying the model for multiple hospital environments. These environments are controlled using the 'Cloud' layer, which helps in storage and analysis operations. The model showcases an accuracy of 93.5% but can be deployed for large-scale real-time HMS applications. The efficiency of this model must be tested in different environments and was improved through the use of Context-Aware Learning (CAL) based Optimal Neural Network Model (ONNM) as discussed in [5], which proposes a design of Data Pre-processing (DP), Context-Aware (CA), and Decision-Making Modules (DMM). Due to context awareness, the models can identify real-time patient conditions, which are communicated with doctors via the DMM-based alert methods. It also proposes using Adaptive Grass Hopper Optimization (AGHO), which assists in continuously improving its context-aware performance. The model showcases an accuracy of 83.5%, which is higher than Back Propagation Neural Network (BPNN), k Nearest Neighbours (kNN), and Artificial Neural Network (ANN), which achieve an accuracy of 46%, 54%, and 75% respectively, under different real-time use cases. Work in [6] further extends this model via the design of a semantic-enabled context-awareness model (SECM) for monitoring health conditions. The model uses standard IoT ontologies, including Semantic Sensor Observation Service (SemSOS), Semantic Sensor Network (SSN), Coastal Environment Sensor Network (CESN), and Ontonym Sensor, to estimate time, location, connectivity, device information, and trajectory data for different IoT sensors. It combines data from these ontologies and segregates them into connected device knowledge, patient knowledge, and context-specific knowledge categories. These categories further improve configuration, risk anticipation, and notification rules for decision-making under normal and emergency conditions. The model showcases an accuracy of 83.5% with context awareness (CA) and 71.9% without

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

Normalized context awareness (NCA), which assists in deploying the model for various real-time applications.

Work in [7] proposes a specialised application-based HMSM for CoVID-19 patients, which uses sensors for Temperature, Oxygen Saturation (SpO2) and Pulse levels. These sensors are connected to a cloud, which assists in maintaining a central repository that is incrementally updated for continuous performance optimisations. The proposed model uses a Linear Regression (LR) classifier and achieves an incremental accuracy of 85.5% under different deployments. Similar applications are discussed in [8], which propose the use of IoT for child health information tracking, adverse drug reaction prediction, community-based healthcare services, wearable devices-based processing, and ambient assisted living for HMSM designs. The model proposes using blockchain for data storage and retrieval, which helps achieve and integrate immutability, transparency, traceability, and distributed computing capabilities. These models have large-scale applications, some of which can be observed in Fig. 4, wherein Rehabilitation, Wheelchair management, Asthma monitoring, Glucose level monitoring, etc., are depicted.

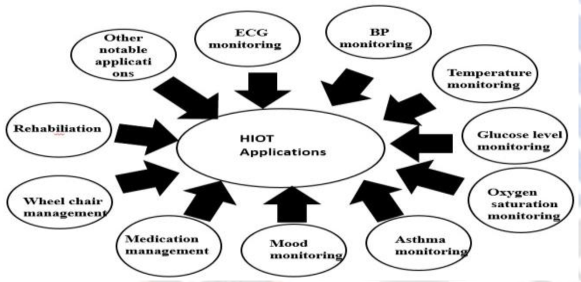

Figure 4. Different applications for Healthcare IoT devices [8]

The study showcases that blockchain-based healthcare models (BHM) are useful for multiple hospital-based use cases and can be scaled without security issues. But the model's QoS performance reduces to the increase in chain length, which must be handled using bioinspired computing techniques. BHM achieves an accuracy of 89.5%, which is improved via deep learning classification and processing models. Such a model applied to COVID-19 HMSM application is discussed in [9], wherein researchers have proposed the use of Convolutional Neural Network (CNN) with Fuzzy Logic (FL) to achieve an accuracy of 95.8% under different patient types. Modifying training and testing datasets must validate The model's performance on other health conditions. The model doesn't incorporate security measures and thus cannot be used for multitenant operations. To integrate such security techniques, work in [10] proposes the use of Lightweight Access Control (LAC) with Lightweight Secure Internet of Things (LS-IoT) and Attribute-based access (ABE) with Signal Strength Analysis (SSA) for real-time deployment applications. The model integrates edge computing with reliable data exchange protocols to improve security while maintaining better QoS levels. It can achieve an accuracy of 96.5% for real-time datasets, making it scalable for different applications. Its efficiency is higher than Portable Short Range Wireless Technology (PSRWT) which showcases an accuracy of 93.8% on the same datasets. To estimate its real-time performance, this model must be validated on application-specific datasets like CoVID-19, Heart Condition Detection using ECG, Brain Monitoring using Electroencephalogram (EEG), etc.

They propose a model that integrates remote patient health monitoring via ECG and Global Positioning System (GPS) based processing, which assists in alerting medical experts in emergency conditions [11]. The model uses a Naïve Bayes (NB) classifier, capable of low delay and high-efficiency alerts and can detect changes in ECG with 83.5% accuracy. These models must be validated for different applications. They can be extended via frequency-modulated continuous wave (FMCW) based communication circuits, as discussed in [12], which assist in long-ranged transmissions. These transmissions are controlled via equation 2, where the maximum transmission range of communication devices is calculated,

$$TR(x) = x * \sin\left[2 * pi\left(\frac{B}{T} * \frac{2d}{c} * t + f_0 * \frac{2d}{c}\right)\right] \qquad (2)$$

Here, x represents the input signal, B and T represent bandwidth and the period, and time for the signals, respectively, while d, f_0, and c represent the distance between communication entities, base communication frequency, and communication capacity of these entities, respectively. The model enhances communication range by 30% and can achieve an accuracy of 90.5% via radio-frequency with pre-filtering of received datasets. An application of such models is discussed in [13], wherein a 1-D Convolutional Neural Network (CNN) is used to perform Ambulatory Maternal and Fetal Monitoring via extraction of Fetal Heart Rate, Maternal Heart Rate, Maternal Oxygen Saturation, Maternal Temperature, and Material Blood Pressure levels. Due to this, the model can achieve an accuracy of 91%, which must be improved via bioinspired optimisations with augmented deep learning models and the use of real-time capturing and processing devices. Such a model that takes real-time data captured 3-lead ECG is discussed in [14], wherein a Central Processing Hub (CPH) is deployed for processing these signals. The CPH integrates Star and Mesh topologies for accuracy estimation under different real-time conditions. This model showcases an accuracy of 85.5%, which makes it useful for real-time deployments. A similar model that extends ECG classification performance via the use of photoplethysmography (PPG) sensors is proposed in [15], where Message Queuing Telemetry Transport (MQTT) is used for real-time data communication with central processing devices. The model

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

combines central storage with distributed computing to learn incrementally from collected readings. It also uses Advanced Encryption Standard (AES) for enhanced security, making it useful for various real-time deployments. The model showcases an accuracy of 95.5% under different use cases due to the integration of CNN for classification purposes. Wearable devices that support HMSM designs are also helpful for deploying large-scale learning models. Such a model is depicted in Fig. 5, and its description is discussed via the work in [16, 17] that proposes the use of Triboelectric Sensors that contain triboelectric nanogenerator (TENG) with ANN and cloud-assisted CNN (CA CNN) for large-scale deployments. The TENG ANN model achieves an accuracy of 98.4%. In comparison, the CA CNN model showcases an accuracy of 98.9% across multiple datasets, which makes it highly useful for the design of body-sensor-based classification applications.

Figure 5. Design of wearable sensors for HMSM deployments [16]

To improve the performance of these models, work in [18, 19] proposes the use of Particulate Matter with Deep Learning (PMDL) and Quality Assessment based on Sensor Disconnection and Saturation (QASDS), which assist in improving classification performance via multiple feature augmentation methods. The PMDL model showcases an accuracy of 75.8%, while QASDS achieves an accuracy of 98.2% under different HMSM applications. These models augment input feature sets by adding a more significant number of features, which enhances their real-time performance.

B. Incremental learning-basd flexible classification models

The work in this sub-section covers various aspects of IoT-based healthcare solutions. In [22], a flexible and pervasive IoT-based healthcare platform is presented for physiological and environmental parameters monitoring. [23] uses machine learning algorithms for the predictive monitoring of schizophrenia. A blockchain-based electronic health record servicing scheme for IoT is proposed in [24]. Smart health has been introduced as a novel paradigm for controlling the Chikungunya virus [25]. In [26] presents an IoT-based healthcare monitoring system that uses blockchain. In [27] focuses on long-term wearable social sensing for mental well-being. Efficient fine-grained access control and trustworthy data processing for remote monitoring services in IoT are discussed in [28]. Proposes architectural requirements for enabling health IoT ecosystems [29]. They use Improved Bayesian convolution networks for human activity recognition based on IoT data [30]. Secure data management in cloudlet assisted IoT enabled e-health framework in a smart city is presented in [31]. In [32] proposes an integrated solution for COVID-19 management using IoT, AI, robotics, and blockchain. In [33] presents a universal health management and monitoring system in resource-constrained environments based on IoT. An IoT used for health indexing method using heterogeneous neural networks is proposed in [35] and presents an insole optical fibre sensor architecture for remote gait analysis. Finally, [36] proposes an IoT-based unobtrusive sensing system for sleep quality monitoring and assessment, and [37] discusses IoT-associated impedimetric biosensing for point-of-care monitoring of kidney health.

Individual models are discussed in [20, 21], where the use of CNN (CNN) and Reinforcement Learning based Partial Confident Information Coverage (RL PCIC) is proposed for large-scale monitoring applications. FCNN achieves an accuracy of 85.6%, while RL showcases an accuracy of 98.5% under different monitoring scenarios. These models require larger computational power, which affects their real-time usability. To overcome this restriction, work in [22, 23] proposes a combination of ambient parameters with physiological parameters (AP3), which are processed via CNN, and the use of Linear Regression (LR) with Extreme Gradient Boosting (XGBoost) for development of low complexity, and high-speed HMS Models. These methods deploy feature selection directly on sensor data, which assists in reducing data dimensionality, thereby assisting in high-speed operations. The AP3 CNN Model achieves an accuracy of 91.8%, while LR and XGBoost showcase an accuracy of 86.5% under different real-time patient monitoring scenarios.

To improve security and add additional computing layers, researchers have proposed the use of IoT-Blockchain (BIoT) [24], Multisensory data aggregation with CNN classification (MDACNN) [25], Blockchain with CNN (BCNN) [26], Long-term Wearable Sensor Models (LWS) to achieve better Mental Wellbeing [27], and deployment of Microscopic Access Control with Trust Modelling (MACTM) [28] are discussed, which assist in the integration of data immutability, transparency, traceability, and distributed computing for a large number of applications. These models utilise machine learning to reduce the computational complexity of blockchain deployments by using smaller sidechains that can store department-level or patient-level information sets. Such a

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

blockchain-based model is depicted in Figure 6, which assists in visualizing hashing, encryption, distributed data exchange methods, and mining operations for different deployment conditions. These models are highly resilient against internal and external attacks but require higher computational power when compared with their linear data processing counterparts. The BIoT model can achieve an accuracy of 97.5%, MDACNN achieves 98.6%, BCNN achieves 98.2%, LWS achieves 90.5%, and MACTM achieves 99.1% under different deployment conditions. These models are extended further via the work in [29, 30], which proposed the use of IoT-Device Description Language (IoT DDL) with Q Learning (QL) and Improved Bayesian Convolution Network (IBCN) for deploying healthcare device monitoring processes. These models utilise real-time IoT data and process it using low-complexity and real-time methods to improve their usability and performance capabilities. These models use variance-based feature reduction, which assists in extracting high-density feature sets for better classification performances. The Model IOT DDL showcases an accuracy of 96.5%, while IBCN achieves an accuracy of 97.8% under different use cases. These models are used for context-specific applications and can be extended to larger deployments via the augmentation of training and validation datasets. These models must also be deployed for distributed computing applications via Cloudlets eHealth Framework (CEF) [31], multiple sensor interfaces with Multilayer Perceptron (MSI MLP) [32], Universal Health Management and Monitoring (UHMM) [33], kNN-based System [34], and use of Optical Fibre Sensors (OFS) for Remote Gait Analysis (RGA) via incremental and continuous learning (ICL) [35], which assists in designing HMSMs with high efficiency, and low delay characteristics.

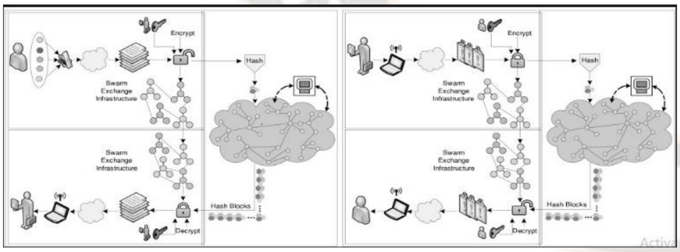

Figure 6 . Use of blockchain for high-performance and high-security HMSM deployments [24]

These models use data collected from different sensor interfaces to train and incrementally validate the performance of internal deep-learning networks. These networks are globally trained on central fog repositories via reinforcement learning, thereby assisting in continuous performance optimizations. The Cloudlet model is capable of large-scale deployments and showcased an accuracy of 83.5%, which can be improved by integrating RL or CNN Models with incremental transfer learning operations. Such operations are performed by MSI MLP, which achieves an accuracy of 91.3%. In comparison, UHMM showcases an accuracy of 89.5%, which is improved to 97.5% via the use of UTHI with HNN, which outperforms SVM (78.2%), kNN (76.8%), Decision Tree (DT) (82.5%), and RF (94.3%) under similar evaluation conditions. The OFS Model also achieves good accuracy levels of 89.4% under different health conditions.

Application-specific HMSMs are discussed in [36-38], which propose the use of Unobtrusive Sensing with Multilayer Feed-Forward Neural Network (US MNN), design of Molecularly Imprinted Polymer (MIP) with Electrochemical Impedance Spectroscopy (EIS) for kidney health monitoring, and Masked Region Convolutional Neural Network (MR CNN) for Smart Dental Health applications. The US MNN Model achieves an accuracy of 91.8%, EIS Model showcases an accuracy of 95.6%, and MR CNN achieves an accuracy of 94.5% when tested for multiple patient types. These models are helpful for application-specific deployments but cannot be scaled to design general-purpose health issues. Moreover, these models do not cater to security and privacy issues, which limits their usability for distributed computing applications. To overcome these limitations, work in [39, 40] proposes the use of Lightweight and Lattice-Based Authentication with Access Control (LAAC) and Lightweight with Secure Communication (LSCs) that assist in optimising model performance under different types of internal and external attacks. The LAAC model is capable of mitigating both storage and communication attacks.

In contrast, LSC mitigates network attacks like Replay, Client Forgery, untraceability, Mutual Authentication, De-Synchronization, Server Forgery, Gateway Forgery, Key Agreement, and Availability Attacks. These models must validate on large-scale network and can be improved via blockchain-based security methods. LAAC showcases a health monitoring accuracy of 95.8%, while LSCs achieve an accuracy of 93.5% under different healthcare environments.

C. Deep learning models for recent disease types

In this section, we cover different aspects of IoT-based healthcare applications. In [41] proposes a CNN-based health model for analyzing regular health factors in an IoT environment. In [42] presents an LSTM-based system that uses physiological signals and an IoT framework for healthcare and distance learning. In [43] introduces an IoT-based healthcare platform for patients in ICU beds during the COVID-19 outbreak. A COVID-19 diagnosis system based on machine learning and IoT in [44] in a smart hospital context. In [45] proposes an IoT-based clinical kit for collecting information related to COVID-19 through medical sensors. In [46] introduces an IoT-based smart health monitoring system for

COVID-19. In [47] presents a secure privacy-preserving data aggregation scheme for remote health monitoring systems. In [48] proposes a security-aware data transmission protocol for mobile health systems. In [49] introduces a modular platform for continuous monitoring and caretaker notification in the ICU. In [50] presents a smart healthcare framework for detecting and monitoring COVID-19 using IoT and cloud computing. In [51] proposes an efficient fine-grained access control and trustworthy data processing for remote monitoring services in IoT. In [52] introduces, interoperability and synchronization management of blockchain-based decentralized e-health systems. In [53] proposes a secure EEG signal transmission for remote health monitoring using optical chaos. In [54] introduces a physical layer security scheme for mobile health cyber-physical systems. Lastly, [55] analyses IoT-based healthcare applications over the last decades.

To improve this performance, work in [41, 42] proposes the use of CNN with Pearson Correlation Coefficient (PC3NN) and Long Short-Term Memory (LSTM) based model for high-density feature extraction under different healthcare applications. The PC3NN model identifies features with lower correlation and uses them to create a dense feature vector, while LSTM uses long ranged data sequences to obtain better classification performance with limited datasets. These models use incremental learning operations to integrate different disease types, which enhances their computational capabilities. The PC3NN Model achieved an accuracy of 94.1%, while LSTM achieved 95.8% for different datasets; thus, they can be used for real-time clinical applications. Specialised models for the identification of bed availability during pandemics [43], the use of ensemble classification models (ECM) for the diagnosis of diseases [44,45], and the use of generic IoT sensors for the collection of metadata are discussed by researchers. The evolving IoT architecture has enabled sensors, embedded devices, and other "things" to sense, process, and communicate in the smallest devices. In [46], the authors have proposed continuous cardiovascular health monitoring using an IoT-assisted ECG monitoring model with secure data delivery. The proposed ECG monitoring system integrates IoT sensors, Arduino boards, android phones, Bluetooth, cloud servers, and other devices to enable real-time categorization and ECG Signal Strength Analysis. The proposed IoT-assisted ECG monitoring system may improve the precision and dependability of unsupervised diagnosis.

Due to improvements in wireless communication and medical sensing technologies, the wireless body area network (WBAN) has become a crucial part of e-healthcare systems. WBAN [47] uses medical sensors to track a patient's well-being and sends the data to a distant medical server through a PDA (Privacy-Preserving Data Aggregation) or mobile device. Due to the limitations of a sensor network's power, storage, and computational capabilities, WBAN uses data aggregation to lower the communication overhead in real-time data transfer. Transferring crucial health information through WBAN may lead to serious data security and privacy difficulties. For remote health monitoring systems, authors provide a secure privacy-preserving data aggregation (SPPDA) technique based on bilinear pairing. The authors suggest the SPPDA approach to provide data integrity and authenticity in the WBAN by using the homomorphic characteristics of the ElGamal cryptosystem and the aggregate signature method. The Diffie-Hellman method protects data privacy, secrecy, and authenticity. While also guarding against replay and passive listening assaults. According to simulation findings and comparing computational costs with competing systems, PDA data aggregation and batch verification enable effective remote server computing by lowering communication and transmission overhead.

Wireless body area networks for remote patient monitoring (M-Health) technology make it possible to monitor a person's health status indicators from a distance. In [48], Zhang et al. used generalized signcryption, which uses a single key pair and a single algorithm. They described an M-Health data transfer protocol that uses certificateless generalized signcryption (CLGSC). An insider assault might compromise the CLGSC system's secrecy. According to [49], creative analysis methods may be used on physiologic data from the Intensive Care Unit (ICU). The authors created and put to the test ICU Real-Time Informatics System (IRIS) for physiologic monitoring, clinical judgment, and caretaker alarms in the ICU. The neurointensive care unit used the IRIS system to send EEG, ICP(Intracranial Pressure), and brain tissue oxygenation data to a server for analysis. Custom algorithms were used to detect elevated ICP, calculate Burst Suppression Ratios (BSRs), and find broken or disconnected EEG electrodes. The notifications were sent to hospital employees through a password-protected smartphone app. The deviation from normal ICP and brain tissue oxygenation values are correctly identified utilizing alarm throttling and user-defined thresholds. The technique successfully identified flawed EEG electrodes with 95% accuracy and reduced technicians' response delay by 93%.

The IoT is gaining popularity with each passing day [50]. IoT enables healthcare systems to make remote health monitoring easy. The amount of data produced by the healthcare sector is tremendous. The IoT has greatly increased the quantity of data it produces. Medical records must be carefully kept to be valuable. In this work, the authors used a cloudlet-based IoT e-Health framework. This e-Health framework makes real-time data access through cloudlets simpler. This framework helps store a lot of health data and answer customer inquiries faster. The health information is stored in the cloud. The authors

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

assessed the data transmission time, energy usage, query response time, data packet loss, and compared their outcomes with other cloud-based e-Health systems. The authors showed that their model was better than other cloud-based e-Health solutions.

The study in [51] indicates how IoT remote monitoring systems often use device-to-cloud networks. In remote patient monitoring (RPM) programs, devices with limited resources monitor a patient's health in a setting other than a clinical setting and transmit the data to the cloud backend of an authorized Healthcare provider for processing and decision-making. Since the measurements include patient information, access control and trustworthy processing are required. Even if this issue were solved in software using cutting-edge cryptographic techniques like attribute-based encryption and completely homomorphic encryption, it would be higher computing costs for clients and servers. The authors present secure and efficient remote monitoring (SRM), a reliable and effective remote monitoring framework, using the most recent hardware-based trustworthy computing technology, such as Intel SGX. The authors also provide a lightweight "heartbeat" mechanism for key revocation. The authors created a working prototype of SRM's framework, demonstrating that it offers more affordable user data privacy protection than other software-based alternatives.

E-health systems have gained popularity recently thanks to health monitoring technology and remote diagnostic services [52]. Managing the e-health ecosystem and protecting personal data are the two remaining obstacles. The first problem arises from data that is not aggregated, redundant, and often copied throughout various e-health service providers. The second problem arises from confidential data stored in centralized systems that can be breached, revealing crucial information. Blockchain technology enables the administration of massive decentralized corporate systems and data access and privacy protection.

In [53], authors used optical chaos to transport EEG data in remote health monitoring systems. The EEG signal is hidden before transmission by optical chaos produced by a semiconductor laser source. Using a 14-channel Emotiv headset, the EEG data is obtained, processed, and rescaled according to the experimental setup. EEG signals are combined with chaos via additive masking, making it simple to interpret. The investigation of EEG signal propagation is carried out by sending chaotic data over the optical fibre. Long-distance communication may be more secure by using this technique to regulate the linear defects in optical fibre. Suppose the transmission and receiving parameters are in synchronization. In that case, the transmitted signal can be removed from the identical chaos to recreate the EEG signal on the other side of the sender. The quality factors determine how well the system performs for various lengths of optical fibre cables.

In [54], the authors used the concept of Cyber-Physical Systems (CPS) to transmit medical information from mobile devices and biomedical sensors to an m-Health (Mobile-Health) server. The sensor network that gathers vital signals is the first level of a hierarchical mobile health system discussed in this paper. The mobile computing network that processes and routes data collected at remote locations comes next, and the back-end network that examines the data collected at remote locations and the patient's medical history is the last level. Using this architecture, a physical layer security mechanism is developed at the second tier. The mean end-to-end latency and safe transmission range are evaluated for short and long transmissions. This paper discusses the scenario in which the eavesdropper’s location is known and the scenario in which the location is unknown. According to the experiments conducted by the authors, transmitting to the closest neighbour involves the highest safe transmission distance and the least mean delay when the eavesdropper’s location is known.

The worldwide health sector has been transformed by wearable health monitoring devices [55] because they provide precise and fast information on physical tests, such as pain, heart rate, and blood glucose level, which help diagnose sensitive cardiac disorders. The Internet of Medical Things (IoMT) makes possible direct connections between doctors and patients, which links medical networks and equipment via the Internet. This article reviews IoMT and associated Machine Learning (ML) -based frameworks created or used between 2010 and 2019. These algorithms observe limbs, in addition, to managing rural healthcare, identifying e-health applications, monitoring health through mobile apps, classifying heart sounds, detecting driver stress, monitoring cardiac issues, forecasting heart attacks, and classifying breast cancer. The paper aims to present a precise image of the current IoMT environment to assist in detecting severe disorders, including cancer, heart attacks, and high blood pressure. The authors also consider the difficulties in implementing secure IoMT systems in the healthcare sector. The IoT-based health system offers patients and healthcare practitioners a variety of advantages, including quick diagnosis based on tracked health data. If data in the cloud is altered or deleted due to an external assault or a power outage, doctors may make an inaccurate diagnosis.

These models utilise deep learning techniques to integrate high-accuracy classification, low-delay identification, and high scalability operations under different scenarios. A statistical discussion of these models, along with their performance evaluation and comparison in terms of accuracy of health condition detection, precision, delay needed to monitor health conditions, security, and scalability are evaluated in the next

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

section of this text. Based on this discussion, researchers will be able to identify optimum models for their HMSM deployments.

III. STATISTICAL ANALYSIS

From the literature review, it was observed that existing models use some form of Machine Learning (ML), Blockchain, Incremental Learning, Cloud Computing, and Sensor specific optimization technique to improve their deployment performance. Thus, a comparison with these models would assist in the identification of optimum healthcare optimization techniques for various use cases. These models are compared in terms of accuracy of health condition detection (A), precision (P), delay needed to monitor health conditions (D), security (Se), Computational Complexity (CC), Energy Consumption (EC), and scalability (Sc) levels, which will assist readers in identifying optimum models for these application-specific and context-sensitive HMSM use cases. Values of accuracy and precision were available in their absolute formats, but delay, security and scalability were converted into fuzzy ranges of Low (L=2), Medium (M=3), High (H=4), and Very High (VH=5), which will assist in comparing these models with unified base performance ranges. This comparison is tabulated in Table 1 as follows,

Table 1. Performance comparison of different HMS models

Model	A (%)	P (%)	D (milliseconds)	CC (nano-seconds)	EC (watt hours)	Se	Sc
ResNet [2]	98.6	92.3	VH	L	M	M	M
HBO LSSVM [3]	94.8	86.8	H	M	L	L	M
CFT [4]	93.5	74.1	H	VH	L	L	H
AGHO [5]	83.5	61.1	VH	M	H	M	H
SECM CA [6]	83.5	80.0	VH	H	VH	L	H
LR CoVID [7]	85.5	90.0	H	M	H	L	L
BHM [8]	89.5	93.6	H	H	H	VH	H
CNN FL CoVID [9]	95.8	91.6	VH	M	VH	M	L
LAC LS-IoT [10]	96.5	89.9	VH	M	M	VH	H
NB ECG [11]	83.5	88.0	L	L	M	M	M
FMCW RF [12]	90.5	88.7	M	H	VH	H	M
1D CNN [13]	91	90.4	VH	H	L	M	H
CPH [14]	85.5	92.8	H	VH	VH	M	M
CNN MQTT ECG [15]	95.5	97.3	VH	H	L	M	H
TENG ANN [16]	98.4	90.7	VH	M	L	H	H
CA CNN [17]	98.9	90.7	VH	H	H	M	H
PMDL [18]	75.8	86.2	H	H	VH	H	H
QASDS [19]	98.2	93.8	M	L	VH	H	M
FCNN [20]	85.6	91.7	VH	VH	L	M	M
RL PCIC [21]	98.5	92.0	VH	M	VH	M	H
AP3 CNN [22]	91.8	91.6	VH	M	M	H	H
LR and XG Boost [23]	86.5	93.9	H	H	VH	M	H
BIoT [24]	97.5	97.8	VH	L	H	VH	VH
MDA CNN [25]	98.6	95.4	VH	L	L	M	H
BCNN [26]	98.2	95.6	VH	H	VH	VH	H
LWS [27]	90.5	95.0	M	M	M	H	M
MAC TM [28]	99.1	97.5	M	L	VH	H	H
IoT DDL [29]	96.5	92.3	H	L	VH	M	M
IBCN [30]	97.8	90.6	VH	M	VH	VH	H
CEF [31]	83.5	87.8	M	M	VH	H	VH
MSI MLP [32]	91.3	92.5	M	L	L	H	M
UHMM [33]	89.5	88.1	H	H	M	H	M
KNN Based System [34]	97.5	83.9	VH	L	H	M	H

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

OFS RGA [35]	89.4	92.0	H	VH	L	H	H
US MNN [36]	91.8	93.7	H	M	L	M	H
MIP EIS [37]	95.6	94.02	H	M	M	H	M
MR CNN [38]	94.5	94.3	VH	H	H	H	H
LAAC [39]	95.8	94.2	H	H	M	VH	VH
LSCs [40]	93.5	94.2	H	VH	L	VH	H
PC3NN [41]	94.1	93.2	VH	VH	M	VH	H
LSTM based System [42]	95.8	93.3	VH	VH	VH	M	H
ECM [44]	90.5	92.9	H	M	VH	M	M

The comparison of the models based on accuracy is shown in Figure 7. Based on both figures, it can be observed that MAC TM [28], CA CNN [17], ResNet [2], MDACNN [25], RL PCIC [21], TENG ANN [16], QASDS [19], and BCNN [26] have better accuracy. Thus, they can be used for applications that require high accuracy. These models utilise ML Methods to augment feature sets, which assists in improving the classification performance for different disease types

The comparison of the models based on precision is shown in Figure. 8. Based on both figures, it can be observed that BIoT [24], MAC TM [28], CNN MQTT ECG [15], BCNN [26], MDACNN [25], LWS [27], and MIP EIS [37] have better precision. Thus, they can be used in applications that require high precision. These models utilise ML Methods to augment feature sets, which assists in improving the classification performance for different disease types

The comparison of the models based on delay is shown in Figure. 9 Based on the figures, it can be observed that NB ECG [11], kNN based System [34], FMCW RF [12], QASDS [19], and LWS [27] have a lower delay. Thus, they can be used in applications that require immediate results. These models utilise feature selection and reduction methods to augment feature sets, which assists in improving their classification speed for different disease types.

The comparison of the models based on security is shown in Figure. 10. Based on both figures, it can be observed that BHM [8], LAC LS-IoT [10], BIoT [24], BCNN [26], IBCN [30], LAAC [39], LSCs [40], and PC3NN [41] are more secure. Thus, they can be used in applications that require more security. These models utilise optimised security and blockchain techniques to secure the network against internal and external attacks.

The comparison of the models based on the scalability is shown in Figure. 11. Based on both figures, it can be observed that BIoT [24], CEF [31], and LAAC [39] have higher scalability. Hence, they can be used for highly scalable applications. These models utilise machine learning methods to augment feature sets, which assists in improving their scalability for all healthcare applications.

The comparison of the models based on energy consumption is shown in Figure. 12. HBO LSSVM [3], CFT [4], SECM CA [6], TENG ANN [16], FCNN [20], MDA CNN [25], MSI MLP [32], USMN [36], and LSCs [40] have lower energy consumptions. Hence, they can be used in applications that require energy consumption to be low.

The comparison of the models based on the Computational Complexity is shown in Figure. 13. Based on both figures, it can be observed that Res Net [2], NB ECG [11], QASDS [19], BIOT [24], MDCNN [25], MACTM [28], and IoT DDL [29] have low computational complexity. Hence, they can be used in applications that require computational complexity to be low

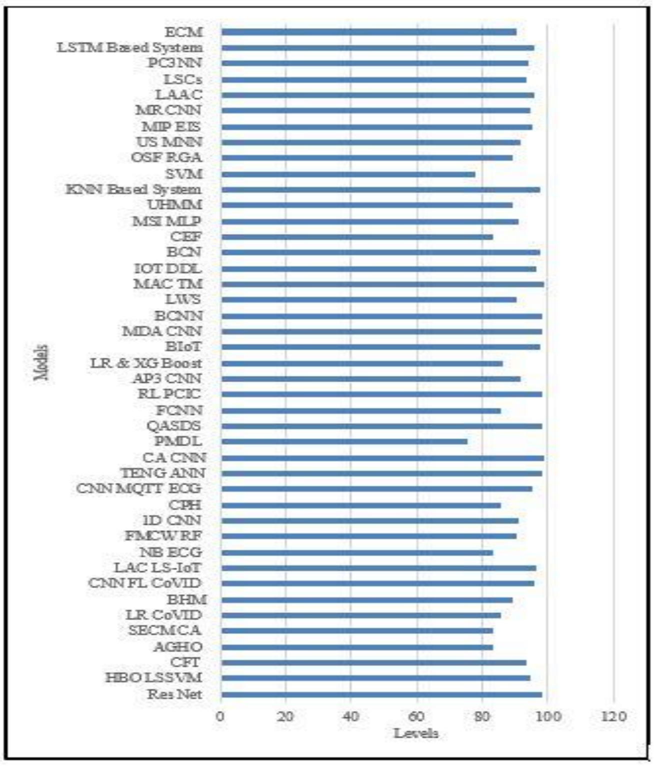

Figure 7. Comparison of Accuracy of HMSM Deployments

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

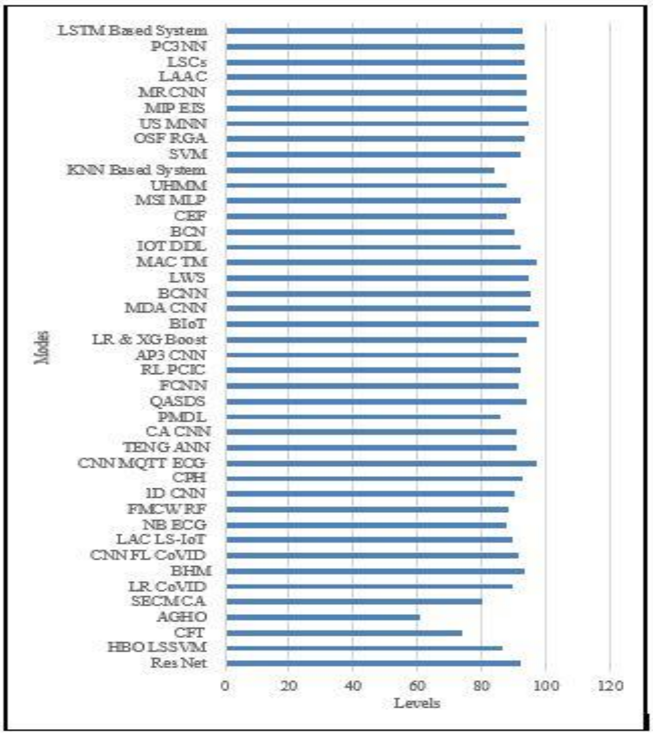

Figure 8:Comparison of Precision of HMSM Deployments

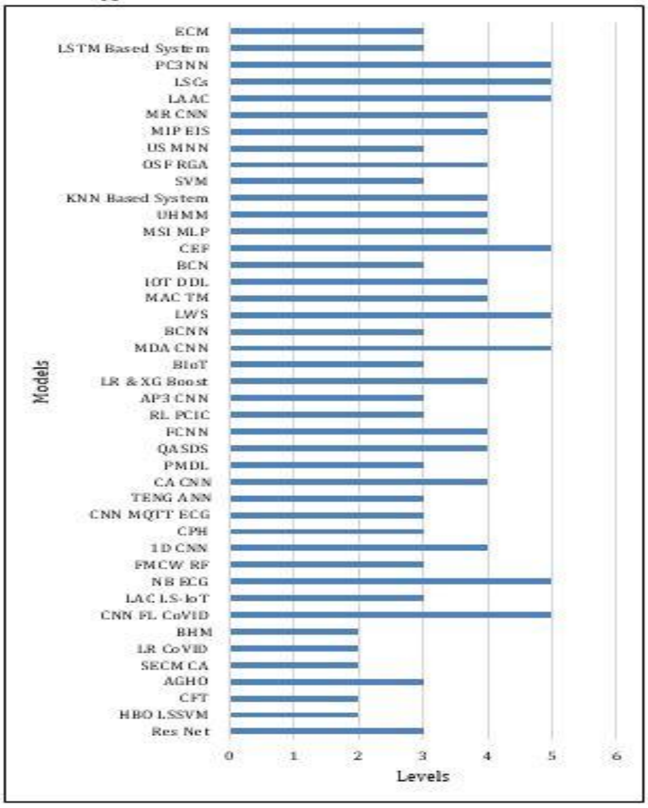

Figure 10. Comparison of Security of HMSM Deployments

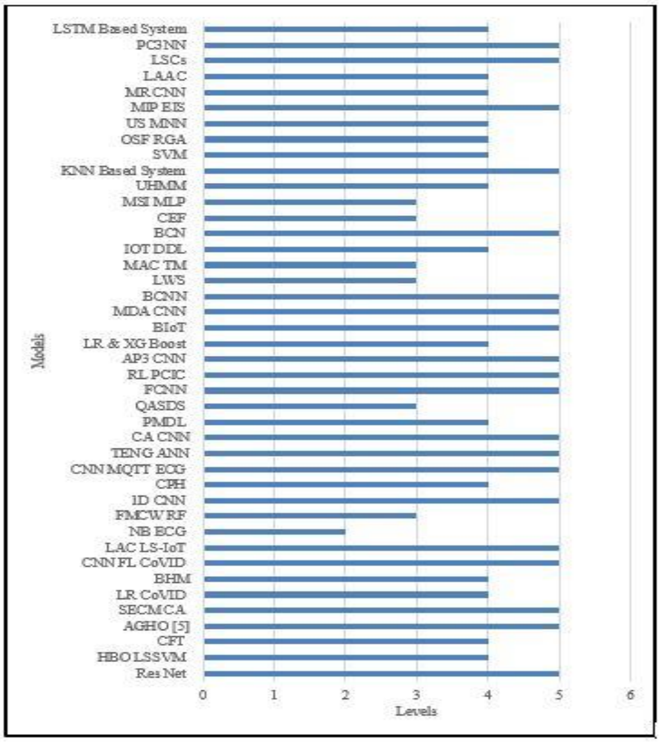

Figure 9. Comparison of Delay of HMSM Deployments

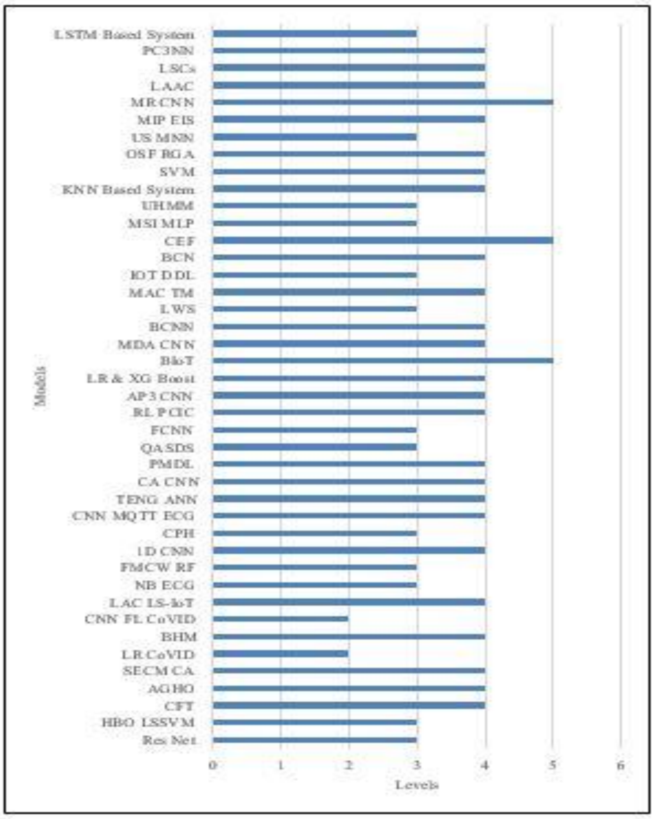

Figure 11. Comparison of Scalability of HMSM Deployments

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

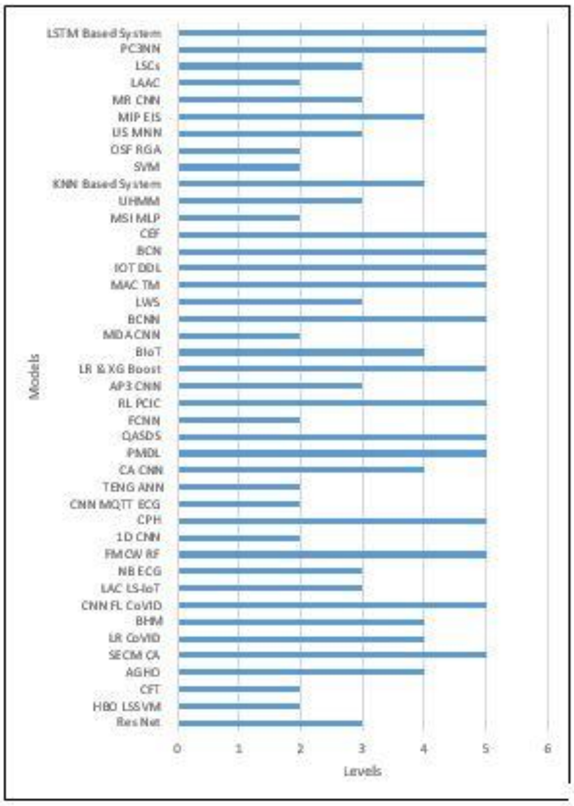

Figure 12. Comparison of Energy Consumption of HMSM Deployments

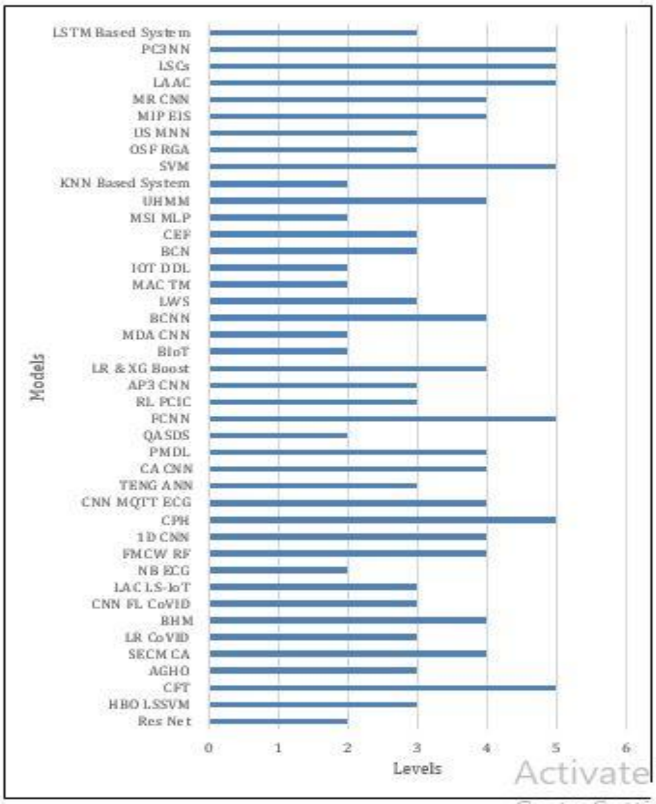

Figure 13. Comparison of Computational Complexity of HMSM Deployments

We used accuracy, precision, delay, scalability, security, energy consumption, and computational complexity for comparing the health monitoring models. Hence, these parameters were used to frame a Health Monitoring Model Metrics (HM3), as shown in Equation 3 below.

$$HM^3 = \frac{A+P}{200} + \frac{5}{D} + \frac{Se}{5} + \frac{Sc}{5} + \frac{5}{Ec} + \frac{5}{Cc} \qquad (3)$$

Here, A and P are used directly, while D, Se, Sc, Ec, and Cc are used after converting the quantisation levels into numerical values (L=2, M=3, H=4, and VH=5), which assisted in the identification of the real-time performance of these models under clinical scenarios the HM3.

The comparison of the models based on different HM3 values is shown in Figure. 14. Table 2 shows the comparison of all the models in a tabular format. It can be observed that NB ECG [11], QASDS [19], KNN Based System [34], CNN FL COVID [9], MAC TM [28], IoT DDL [29], and MSI MLP [32], have better overall performance, and thus must be used for HMSM deployments that need high accuracy, high precision, low delay, high scalability, low computational complexity, low energy consumption, and high security. These models must be validated for context-specific application simulations, which will assist in deploying them for different HMSM use cases.

Table 2. Comparison Table of different HMSMs based on HM3

Model	HM^3
Res Net [2]	7.6
HBO LSSVM [3]	7.6
CFT [4]	5.5
AGHO [5]	6.1
SECM CA [6]	6.1
LR CoVID [7]	7.9
BHM [8]	6.3
CNN FL CoVID [9]	8.0
LAC LS-IoT [10]	6.3
NB ECG [11]	8.9
FMCW RF [12]	7.3
1D CNN [13]	5.7
CPH [14]	6.6
CNN MQTT ECG [15]	5.8
TENG ANN [16]	6.2
CA CNN [17]	6.1
PMDL [18]	6.3
QASDS [19]	8.7
FCNN [20]	5.8
RL PCIC [21]	6.8
AP3 CNN [22]	6.3
LR and XG Boost [23]	6.5
BIoT [24]	7.2

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

MDA CNN [25]	7.0
BCNN [26]	6.4
LWS [27]	7.4
MAC TM [28]	8.3
QL [29]	8.3
IBCN [30]	6.8
CEF [31]	7.0
MSI MLP [32]	8.0
UHMM [33]	6.5
KNN Based System [34]	8.1
OFS RGA [35]	5.7
US MNN [36]	6.4
MIP EIS [37]	7.0
MR CNN [38]	6.1
LAAC [39]	6.0
LSCs [40]	5.7
PC3NN [41]	5.7
LSTM Based System [42]	6.1
ECM [44]	7.4

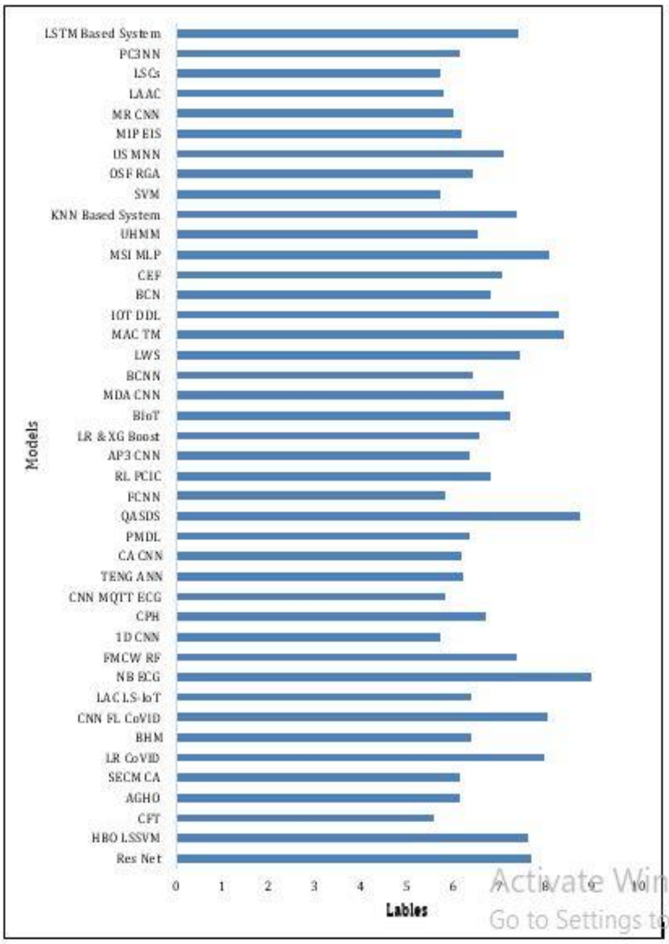

Figure 14. Comparison Chart of different HMSMs based on HM3

IV. CONCLUSION AND FUTUREWORK

This document discusses the characteristics of different Health Monitoring System Models (HMSMs) and devises performance measuring metrics to compare the performances of all the models. These models utilise Machine Learning Models (MLMs), blockchain models, bioinspired models, sensor interfaces, cloud-based interfaces, etc., to monitor patient health effectively. Based on the evaluations using the performance measuring metrics, it was found that the models MAC TM, CA CNN, Res Net, MDACNN, RL PCIC, TENG ANN, QASDS, and BCNN have better accuracy. The model's BIoT, MAC TM, CNN MQTT ECG, BCNN, MDACNN, LWS, and MIP EIS were found to have better precision. The model's NB ECG, kNN Based System, FMCW RF, QASDS, and LWS were found to have less delay. In terms of scalability, the models BIoT, CEF, and LAAC were found to perform better. The model's BHM, LAC LS IoT, BIoT, BCNN, IBCN, LAAC, LSCs, and PC3NN were found to perform better in terms of security.

Sidechains, secret sharing, bioinspired modelling, and Q-Learning can be included in IoT-based HMSMs in the future, which will allow researchers to improve the performance of these types of systems. The researchers also have the option of merging these models for different HMSM applications. Doing so would assist further in estimating the scalability of these applications in real-time deployments. The following challenges can be considered by researchers who are working to enhance the performance of health monitoring models.

- **Development of Advanced Health Monitoring Systems:** The development of advanced health monitoring systems that can continuously monitor vital signs such as heart rate, blood pressure, and temperature in real time hospital scenarios is a promising area of research. The development of non-invasive and wearable sensors that can collect accurate and reliable data could revolutionise the way we monitor patients in hospitals.

- **Artificial Intelligence and Machine Learning:** Artificial intelligence and machine learning algorithms can be used to analyse the vast amount of data collected by health monitoring systems. These algorithms can detect patterns and anomalies in the data, providing healthcare professionals with valuable insights into a patient's health status.

- **Internet of Things (IoT)**: The Internet of Things (IoT) is a rapidly evolving technology that connects devices and systems over the Internet. IoT can be used to create a network of sensors and devices that can monitor a patient's health status in real time. This technology can be used to provide remote monitoring, enabling healthcare professionals to monitor patients even when they are not physically present in the hospital.

- **Telemedicine:** Telemedicine is a rapidly evolving field that uses technology to provide healthcare services remotely. Telemedicine can be used in real-time hospital scenarios to provide remote monitoring and diagnosis of patients. This technology can be used to improve patient outcomes and reduce healthcare costs.

- **Wearable Devices**: Wearable devices such as smartwatches and fitness trackers can be used to monitor a patient's health status in real time hospital scenarios. These devices can collect data on vital signs such as heart rate, blood pressure, and temperature, and transmit this data wirelessly to healthcare professionals for analysis.

- **Blockchain Technology**: Blockchain technology can be used to store and secure health data collected from health monitoring systems. This technology can ensure the privacy and security of patient data, enabling healthcare professionals to access and analyse the data without compromising patient privacy.

- **Big Data Analytics**: Big data analytics can be used to analyse the vast amount of data collected by health monitoring systems. These analytics can detect patterns and anomalies in the data, providing healthcare professionals with valuable insights into a patient's health status. This technology can be used to improve patient outcomes and reduce healthcare costs.

- **Cloud Computing:** Cloud computing can be used to store and analyse health data collected by health monitoring systems. This technology can provide healthcare professionals with real-time access to patient data, enabling them to make informed decisions about patient care.

REFRENCES

[1] Albahri, A. S., Albahri, O. S., Zaidan, A. A., Zaidan, B. B., Hashim et al.,” Based multiple heterogeneous wearable sensors: A smart real-time health monitoring structured for hospitals distributor”, IEEE access, vol. 7, pp. 37269-37323, 2019.

[2] N. Nasser, Q. Emad-ul-Haq, M. Imran, A. Ali, I. Razzak et.al, “A smart healthcare framework for detection and monitoring of COVID-19 using IoT and cloud computing” Neural Computing and Applications, pp. 1-15, 2021..

[3] G. Premalatha and V.Thulasi Bai, “Wireless IoT and cyber-physical system for health monitoring Using honey badger optimized least-squares support-vector machine,” Wireless Personal Communications, vol. 124, no. 4, pp. 3013-3034, 2022.

[4] V. K. Quy, N. V. Hau, D. V. Anh and L. A. Ngoc, "Smart healthcare IoT applications based on fog computing: architecture, applications and challenges," Complex and Intelligent Systems, vol. 8, no. 5, pp. 3805-3815, 2022

[5] D. Kavitha and S. Ravikumar, "IOT and context-aware learning-based optimal neural network model for real-time health monitoring," Transactions on Emerging Telecommunications Technologies, vol. 32, no. 1, pp. 1-19, 2021.

[6] A. Rhayem, M. B. A. Mhiri, K. Drira, S. Tazi and F. Gargouri, "A semantic-enabled and context-aware monitoring system for the internet of medical things," Expert Systems, vol. 38, no. 2, pp. 1-33, 2021.

[7] M. M. Khan, S. Mehnaz, A. Shaha, M. Nayem and S. Bourouis, "IoT-based smart health monitoring system for COVID-19 patients, " Computational and Mathematical Methods in Medicine, vol. 2021, pp.1-11, 2021.

[8] B. Pradhan, S. Bhattacharyya and K. Pal, "IoT-based applications in healthcare devices," Journal of Healthcare Engineering, vol. 2021, pp. 1-18, 2021.

[9] S. S. Vedaei, A. Fotovvat, M. R. Mohebbian, G. M. Rahman, K. A. Wahid et al., "COVID-SAFE: An IoT-based system for automated health monitoring and surveillance in post-pandemic life," IEEE Access, vol. 8, pp. 188538-188551, 2020.

[10] G. Xu, "IoT-assisted ECG monitoring framework with secure data transmission for health care applications," IEEE Access, vol. 8, pp. 74586-74594, 2020.

[11] G. G. Warsi, K. Hans and K. Sunil Kumar, "IOT based remote patient health monitoring system," In 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), Faridabad, IEE, India, pp. 295-299, 2019.

[12] M. Mercuri, G. Sacco, R. Hornung, P. Zhang, H. J. Visser et al., "2-D localization, angular separation and vital signs monitoring using a SISO FMCW radar for smart long-term health monitoring environments," IEEE Internet of Things Journal, vol. 8, no. 14, pp. 11065-11077, 2021.

[13] J. A. L. Marques, T. Han, W. Wu, J. P. Vale Madeiro, A. V. L. Neto et al., "IoT-based smart health system for ambulatory maternal and fetal monitoring," IEEE Internet of Things, vol. 8, no. 23, pp. 16814-16824, 2020.

[14] N. Pathak, S. Misra, A. Mukherjee and N. Kumar, "HeDI: Healthcare device interoperability for IoT-based e-health platforms," IEEE Internet of Things, vol. 8, no. 23, pp. 16845-16852, 2021.

[15] T. Wu, F. Wu, C. Qiu, J. M. Redoute and M. R. Yuce, "A rigid-flex wearable health monitoring sensor patch for IoT-connected healthcare applications," IEEE Internet of Things, vol. 7, no. 8, pp. 6932-6945, 2020.

[16] Q Zhang, T. Jin, J. Cai, L. Xu, T. He et al., "Wearable triboelectric sensors enabled gait analysis and waist motion capture for IoT-based smart healthcare applications," Advanced Science, vol. 9, no. 4, pp. 1-13, 2022.

[17] H Yu and Z. Zhou, "Optimization of IoT-based artificial intelligence assisted telemedicine health analysis system," IEEE Access, vol. 9, pp. 85034-85048, 2021.

[18] M.J. Diván, M. L. Sánchez-Reynoso, J. E. Panebianco and M. J. Méndez, "IoT-based approaches for monitoring the particulate matter and its impact on health," IEEE Internet of Things Journal, vol. 8, no. 15, pp. 11983-12003, 2021.

[19] G. Narendra Kumar Reddy, M. S. Manikandan and N. N . Murty, "On-device integrated PPG quality assessment and sensor disconnection/saturation detection system for IoT health monitoring," IEEE Transactions on Instrumentation and Measurement, vol. 69, no. 9, pp. 6351-6361, 2020.

[20] A. Hussain, K. Zafar and A. R. Baig, "Fog-centric IoT based framework for healthcare monitoring, management and early warning system," Ieee Access, vol. 9, pp. 74168-74179, 2021.

[21] Mohammed Wasim Bhatt, Sparsh Sharma, "An IoMT-Based Approach for Real-Time Monitoring Using Wearable Neuro-Sensors", Journal of Healthcare Engineering, vol. 2023, Article ID 1066547, 10 pages, 2023. https://doi.org/10.1155/2023/1066547.

[22] M. Haghi, S. Neubert, A. Geissler, H. Fleischer, N. Stoll et al., "A flexible and pervasive IoT-based healthcare platform for physiological and environmental parameters monitoring," IEEE Internet of Things, vol. 7, no. 6, pp. 5628-5647, 2020.

[23] L. C. Huberts, R. J. Does, B. Ravesteijn and J. Lokkerbol, "Predictive monitoring using machine learning algorithms and a real-life example on schizophrenia," Quality and Reliability Engineering International, vol. 38, no. 3, pp. 1302-1317, 2022.

[24] P. P. Ray, B. Chowhan, N. Kumar and A. Almogren, "BIoTHR: Electronic health record servicing scheme in IoT-blockchain ecosystem," IEEE Internet of Things, vol. 8, no. 13, pp. 10857-10872, 2021.

[25] S. Rani, S. H. Ahmed and S .C. Shah, "Smart health: A novel paradigm to control the chickungunya virus," IEEE Internet of Things, vol. 6, no. 2, pp. 1306-1311, 2018.

[26] M. Vahdati, K. Gholizadeh HamlAbadi and A. M. Saghiri, "IoT-Based healthcare monitoring using blockchain," in Applications of Blockchain in Healthcare, vol. 83, pp. 141-170, 2021.

[27] S. Yang, B. Gao, L. Jiang, J. Jin, Z. Gao et al., "IoT structured long-term wearable social sensing for mental wellbeing," IEEE Internet of Things, vol. 6, no. 2, pp. 3652-3662, 2018.

[28] Y. Chen, W. Sun, N. Zhang, Q. Zheng, W. Lou et al., "Towards efficient fine-grained access control and trustworthy data processing for remote monitoring services in IoT," IEEE Transactions on Information Forensics and Security, vol. 14, no. 7, pp. 1830-1842, 2018.

[29] Jackson, B., Lewis, M., González, M., Gonzalez, L., & González, M. Improving Natural Language Understanding with Transformer Models. Kuwait Journal of Machine Learning, 1(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/152

[30] W. Lindquist, S. Helal, A. Khaled and W. Hutchinson, "IoTility: architectural requirements for enabling health IoT ecosystems," IEEE Transactions on Emerging Topics in Computing, vol. 9, no. 3, pp. 1206-1218, 2019.

[31] Z. Zhou, H. Yu and H. Shi, "Human activity recognition based on improved Bayesian convolution network to analyze health care data using wearable IoT device," IEEE Access, vol. 8, pp. 86411-86418, 2020.

[32] S. Sengupta and S. S. Bhunia, "Secure data management in cloudlet assisted IoT enabled e-health framework in smart city," IEEE Sensors, vol. 20, no. 16, pp. 9581-9588, 2020.

[33] F. Firouzi, B. Farahani, M. Daneshmand, K. Grise, J. Song et al., "Harnessing the power of smart and connected health to tackle COVID-19: IoT, AI, robotics, and blockchain for a better world," IEEE Internet of Things, vol. 8, no. 16, pp. 12826-12846, 2021.

[34] M. Zheng and S. Bai, "Implementation of universal health management and monitoring system in resource-constrained environment based on internet of things," IEEE Access, vol. 9, pp. 138744-138752, 2021.

[35] Ruben Enrique Cañón-Clavijo, Carlos Enrique Montenegro-Marin, Paulo Alonso Gaona-Garcia, Johan Ortiz-Guzmán, "IoT Based System for Heart Monitoring and Arrhythmia Detection Using Machine Learning", Journal of Healthcare Engineering, vol. 2023, Article ID 6401673, 13 pages, 2023. https://doi.org/10.1155/2023/6401673.

[36] M. F. Domingues, N. Alberto, C. S. J. Leitão, C. Tavares, E. R. de Lima et.al., "Insole optical fiber sensor architecture for remote gait analysis—An e-health solution," IEEE Internet of Things, vol. 6, no. 1, pp. 207-214, 2017.

[37] J. Y. Kim, C. H. Chu and M. S. Kang, "IoT-based unobtrusive sensing for sleep quality monitoring and assessment," IEEE Sensors, vol. 21, no. 3, pp. 3799-3809, 2020.

[38] S. N. Prabhu, C. P. Gooneratne, K. A. Hoang and S. C. Mukhopadhyay, "IoT-associated impedimetric biosensing for point-of-care monitoring of kidney health," IEEE Sensors, vol. 21, no. 13, pp. 14320-14329, 2020.

[39] L. Liu, J. Xu, Y. Huan, Z. Zou, S. C. Yeh et al., "A smart dental health-IoT platform based on intelligent hardware, deep learning, and mobile terminal," IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 3, pp. 898-906, 2019.

[40] D. S. Gupta, S. K. H. Islam, M. S. Obaidat, A. Karati and B. Sadoun, "LAAC: Lightweight lattice-based authentication and access control protocol for E-health systems in IoT environments," IEEE Systems, vol. 15, no. 3, pp. 3620-3627, 2020.

[41] M. A. Jan, F. Khan, S. Mastorakis, M. Adil, A. Akbar et al., ”LightIoT: Lightweight and secure communication for energy-efficient IoT in health informatics," IEEE Transactions on Green Communications and Networking, vol. 5, no. 3, pp. 1202-1211, 2021.

[42] W. N. Ismail, M. M. Hassan, H. A. Alsalamah and G. Fortino, "CNN-based health model for regular health factors analysis in internet-of-medical things environment," IEEE Access, vol. 8, pp. 52541-52549, 2020.

[43] Prof. Romi Morzelona. (2019). Histogram Based Data Cryptographic Technique with High Level Security. International Journal of New Practices in Management and Engineering, 8(04), 08 - 14. https://doi.org/10.17762/ijnpme.v8i04.80

[44] M. Awais, M. Raza, N. Singh, K. Bashir, U. Manzoor et al., "LSTM-based emotion detection using physiological signals: IoT framework for healthcare and distance learning in COVID-19," IEEE Internet of Things, vol. 8, no. 23, pp. 16863-16871, 2020.

[45] I. de Morais Barroca Filho , G. Aquino, R. S. Malaquias, G. Girão and S. R. M. Melo, "An IoT-based healthcare platform for patients in ICU beds during the COVID-19 outbreak," Ieee Access, vol. 9, pp. 27262-27277, 2021.

[46] K. H. Abdulkareem, M. A. Mohammed, A. Salim, M. Arif, O. Geman et al., "Realizing an effective COVID-19 diagnosis system based on machine learning and IoT in smart hospital environment," IEEE Internet of things journal, vol. 8, no. 21, pp. 15919-15928, 2021.

[47] F. Rodriguez, S Gutierrez, B. A. Reyes, V. Rosas, S. V. M. Rubio et al., "IoMT: Rinku's clinical kit applied to collect information

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7025
***Article Received**: 01 April 2023 **Revised:** 18 May 2023 **Accepted:** 04 June 2023*

related to COVID-19 through medical sensors," IEEE Latin America Transactions, vol. 19, no. 6, pp. 1002-1009, 2021.

[48] V. Bhardwaj, R. Joshi and A. M. Gaur, "IoT-based smart health monitoring system for COVID-19", SN Computer Science, vol. 3, no.2, pp. 137, 2022.

[49] A. Anees, M. Al-Rodhaan, Y. Tian and A. Al-Dhelaan, "A secure privacy-preserving data aggregation scheme based on bilinear ElGamal cryptosystem for remote health monitoring systems", IEEE Access, vol. 5, pp. 12601-12617, 2017.

[50] A. Zhang, L. Wang, X.Ye and X. Lin, "Light-weight and robust security-aware D2D-assist data transmission protocol for mobile-health systems", IEEE Transactions on Information Forensics and Security, vol. 12, no. 3, pp. 662-675, 2016.

[51] S. N. Baldassano, S. W. Roberson, R. Balu, B. Scheid, J. M. Bernabei et.al., "IRIS: A modular platform for continuous monitoring and caretaker notification in the intensive care unit", IEEE journal of biomedical and health informatics, vol. 24, no. 8, pp. 2389-2397, 2020.

[52] N. Nasser, Q. Emad-ul-Haq, M. Imran, A. Ali, I. Razzak et.al, "A smart healthcare framework for detection and monitoring of COVID-19 using IoT and cloud computing" Neural Computing and Applications, pp. 1-15, 2021.

[53] Y. Chen, W. Sun, N. Zhang, Q. Zheng, W. Lou et.al., "Towards efficient fine-grained access control and trustworthy data processing for remote monitoring services in IoT", IEEE Transactions on Information Forensics and Security, vol. 14, no. 7, pp. 1830-1842, 2018.

[54] S. Biswas, K. Sharif, F. Li, Z. Latif, S. S. Kanhere et.al., "Interoperability and Synchronization Management of Blockchain-Based Decentralized e-Health Systems," IEEE Transactions on Engineering Management, vol. 67, no. 4, pp. 1363-1376, 2020.

[55] R. Shahzadi, S. M. Anwar, F. Qamar, M. Ali, J. J. P. C. Rodrigues et.al., "Secure EEG Signal Transmission for Remote Health Monitoring Using Optical Chaos," IEEE Access, vol. 7, pp. 57769-57778, 2019.

[56] R. Atat, L. Liu, J. Ashdown, M. J. Medley, J. D. Matyjas et.al., "A Physical Layer Security Scheme for Mobile Health Cyber-Physical Systems," IEEE Internet of Things Journal, vol. 5, no. 1, pp. 295-309, 2017.

[57] I. Ud Din, A. Almogren, M. Guizani and M. Zuair, "A Decade of Internet of Things: Analysis in the Light of Healthcare Applications," IEEE Access, vol. 7, pp. 89967-89979, 2019.

[58] Garg, P. ., Sharma, N. ., Sonal, & Shukla, B. . (2023). Predicting the Risk of Cardiovascular Diseases using Machine Learning Techniques. International Journal of Intelligent Systems and Applications in Engineering, 11(2s), 165 –. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2520