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A Medical Cyber-Physical System utilizing the Bayes algorithm for post-diagnosis patient supervision

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***Abstract*—Medical treatment is one of the most prominent among several basic human needs. However, since there needs to be more doctors, nurses, and other medical facilities in many places, medical cyber-physical systems (MCPS) are quickly becoming a competitive alternative. MCPS represents a platform through which patient health data are acquired by emergent sensors, preprocessed locally, and managed through machine intelligence algorithms. One important use of these systems is for observation after a diagnosis. Instead of active observation by a caregiver, this can be easily done using various monitoring systems. However, most of the existing systems for this application are inflexible and need to consider the current challenges. On the other hand, these problems can be solved by intelligent and adaptive systems, which is now possible thanks to the growth of relevant technology, especially Healthcare 4.0. Therefore, this article proposes an adaptive system based on the Bayes algorithm for performing medical interventions on patients, reducing the dependence on caregivers, particularly in the post-diagnosis scenario. This system collects sensor information and keeps track of the patient's health. Based on the sensor data, the system can decide what activities are necessary for the patient.**

***Index Terms*—cyber physical system; medical cyber physical system; healthcare 4.0**

I. Introduction

With the development of technology, we are moving toward a smart world. The smart world is a concept derived from ubiquitous computing, which is a scenario of a digital world where the physical world is miraculously and invisibly connected with sensors, actuators, digital displays, and computing devices that are seamlessly integrated into the everyday objects of our lives and connected through a linked network [1], [2]. Smartphones, even the concept of smart cars and smart home systems, take care of our homes. Researchers are conducting research with the goal of developing a smart world where everything is smart. The Internet of Things, Wireless Sensor Networks, Mobile Computing, Pervasive Computing, and Cyber-Physical Systems (CPS) are five of the most critical research areas for achieving this smart world [1], [3]. These areas are so broad and important that they have applications in various fields [4]. The President's Council of Advisors on Science and Technology (PCAST) has ranked CPS as a top priority for federal research investment [5]. Medical Cyber-Physical System (MCPS) is one of the many domains in CPS [6].

For various reasons, people often do not receive appropriate treatment. One of the most common reasons is that fewer doctors are available at any given time. In addition, it is difficult to find capable doctors in rural or remote areas, and hospitals may be staffed by unskilled caregivers [7]. In this case, doctors must be in the hospital almost all the time to ensure that patients get the right care. Also, after the patients are diagnosed, they need to be watched by well-trained, responsible caregivers who do regular checkups. Even so, there is always the possibility of mistreatment. In this study, we consider a scenario where doctors are only sometimes needed to be present in the hospitals, and people also do not need to rely on nurses for regular observational treatment or actuation. The proposed system will adaptively decide treatment based on sensor readings and perform actions. The aim is to design a system that can make decisions about performing predefined treatments on patients based on a defined dataset. The sensors that will be used to track different medical conditions and the actions that will be taken for those conditions need to be found to reach the goal. This work also aims at lessening caregiver dependency in post-diagnosis observation scenarios.

II. Related Works

Cyber-physical systems (CPS) are a new class of technologies that can interact with people through a variety of modalities and integrate computational and physical abilities. The ability to interact with and improve the physical world through computing, communication, and control will be crucial for future technological advancement. A Cyber-Physical System (CPS) is a method with rooted software (as part of devices, constructions, means of conveyance, transport directions, man-

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ufacturing systems, health procedures, coordination processes, and administration processes) [8], which,

- Directly archives physical information using sensors and affects bodily procedures using actuators.
- evaluates and preserves collected data, and engages in proactive or reactive interaction with the digital and physical realms.
- Uses worldwide accessible statistics and facilities.
- Is associated with other CPS and worldwide web platforms via digital communication services (wireless and/or wired, local and/or global).
- Has a sequence of devoted, multi-modal human-machine interfaces.

CPS is a group of diverse computation modules that work together to control the physical entity. They combine computation, communication, and physical dynamics. CPS combines embedded processors and network observers and controls the physical processes with response loops that take into account how the physical processes change. The business and social potential of these systems is much bigger than what has been thought. Technology is based on the study of the systems, computers, and software that are integrated into objects like vehicles, medical equipment, and scientific instruments—things that don't perform computation. CPS combines the dynamic components of physical processes with software and networking to provide ideas and methods for modelling, designing, and disassembling the entire process.

In research [9], they performed a systematic literature review (SLR) to learn about how MCPS has changed the most important aspects of healthcare service delivery over the past decade. The primary goal of this assessment was to compile the most up-to-date data available on MCPS and its effects on vital aspects of healthcare service provision. The research literature was organized and assessed based on its influence on WHO-defined dimensions. Comprehensiveness, availability, coverage, continuity, quality, person-centeredness, coordination, accountability, and efficiency are all areas that may benefit from the use of MCPS, according to the results.

Authors of [10] introduce an enhanced machine learning-based wireless medical cyber-physical system (IWMCPS). Therefore, solutions for these settings' security that rely on deep neural networks to detect and categorize attacks are essential. The proposed IWMCPS is comprised of three main parts: a core for communication and monitoring; a core for computing and safety; and a core for real-time resource planning and management. In this research, we tested our architecture with real patient data against common security threats like data tampering, DoS attacks, and data injection. The IWMCPS approach relies on a patient-centric design that allows the end-user's smartphone to continue acting as the gatekeeper to the data flow. The results of our experiments demonstrated that our approach significantly reduced computational time (13 seconds) and error analysis (8%).

In research [11], authors provide an MCPS architecture that makes use of fog-cloud computing and social network analysis to detect and quickly decide on COVID-19 situations. At the gateway, the fog layer classifies the data after PCA has been used to reduce the data's dimensionality. Events are categorized, and data on the severity of COVID-19 is provided, all while real-time alerts are generated using a classification method based on Ensemble learning. Services based on social network analysis are deployed in the cloud to stop the spread of the disease. The effectiveness and long-term stability of COVID-19 case diagnoses are demonstrated by the results of using the proposed approach. In addition, the suggested system is new since it includes suggestions and an alarm production mechanism.

In the study [12], authors go into the topic of GAN-generated checkerboard artefacts, with a focus on medical images. Checkerboard artefacts can be reduced in GAN-generated images by destroying the rectangle form of the convolution kernel, which is the distinctive trace of transpose-convolution. To avoid these checkerboard effects, we propose using deformable convolution kernels in our image synthesis. Medical diagnosis and care in AI-driven cyber-physical systems can benefit from such an operation since it has the potential to enhance the quality and integrity of GAN-generated images. Consequently, our tests provide evidence that the checkerboard artefacts can be used to forecast GAN-generated images.

In the paper [13], authors propose a reputation-based blockchain system for protecting sensitive patient data without compromising users' right to anonymity. Each potential threat and the steps that can be taken to defend against them are analyzed in depth in a security analysis. As the number of users in the network grows, the suggested framework's results and performance analysis demonstrate low latency in data exchange and high throughput. Calculated results revealed that when the number of users grows, the average latency time decreases by 46-50% and throughput grows by 44-50%.

This paper [14] proposes an IoT–fog–cloud improvised intelligent healthcare cyber-physical architecture for early infection prediction and monitoring. The framework acquires data from numerous sources. A fuzzy-based k-nearest neighbour classifier analyzes data in real time for fog layer decision-making. Thus, when patients are in danger, surrounding caregivers receive signals. The cloud layer uses information fusion to create a rich dataset. Preprocessed data is used to pick the most significant characteristics for ANFIS severity analysis utilizing SVD-based feature selection. The suggested framework is tested against leading prediction methods in a simulated scenario. F-KNN performs well at the fog layer, achieving 85.70% accuracy with a lower classification time.

This study [15] used machine learning to identify such human actions. Security requires robustness. Thus, the research's main goal is to design systems that can detect these behaviours. We optimized CNN, LSTM, and GRU neural networks for this. When used with neural networks, Stochastic Gradient Descent optimizers Adam and RMSProp improve model performance. Thus, models better detect human behaviours. The study used three datasets. The first dataset uses IoMT data from a chest-mounted accelerometer. The other two datasets are smartphone-based. In all three datasets, the optimized model performs better.

In the work[16], authors propose a cyber-physical system (CPS) powered by AI to categorize the severity of Chikungunya outbreaks. Better outcomes are achieved by the CPS system's integration of physical components with computational algorithms. Chikungunya disease severity is categorized via a random forest (RF) classification technique. However, overfitting and slow computing are issues plaguing RF because of its complex architecture and a huge number of link weights.

This research [17] presented an Elapid Crypto (EC) technique for improving Cyber-Physical System (CPS) security. Furthermore, the elapid accelerator includes a memory-mapped interface and instruction set designed to access and control the system and avoid attacks. Finally, the performance characteristics of the created EC mechanism are compared to those of existing approaches. Furthermore, the proposed EC mechanism's performance measurements attained an execution time of 80ms and a latency of 8ms. In addition, power reached 44.37mW, and energy reached 1.245J. The current model's only drawback is measuring security performance against malicious events. As a result, damaging, malicious events will be initiated in the planned CPS system in the future to validate the security stability and confidential score. As a result, feedback on the suggested EC mechanism will be obtained. In some large data-sharing scenarios, packet loss has also happened during communication. As a result, using the optimization technique will reduce the packet loss rate.

Figure 1 depicts the CPS workflow in general. Sensor data collection is represented by Y, physical data aggregation is represented by Z in the network, a valid computed result of the physical system states is represented by U, and valid commands are given to the actuators via V [18].

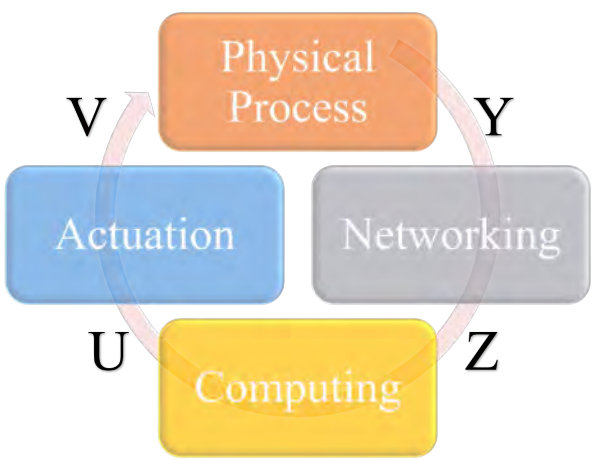

Fig. 1. CPS abstraction

A. Abstraction and Architectures

New ways to abstract and architectures that allow control, communication, and computation to work well together must be created for quick design and CPS placement. For instance, interfaces between several layers have been standardized in communication networks. Upon validation of these interfaces, the modularity permits specialized growth in all layers. The state of science and engineering does not support CPS design and development's drudgery, efficiency, robustness, and modularity. We urgently need standardized abstractions and architectures to fully enable integration, interoperability, and breakthroughs in cyber-physical systems [19]. CPS is usually hard to study, design, and prove because of the two main reasons below:

- CPS emphasises the full system view across both the cyber and physical components, in contrast to the traditional embedded systems viewpoint, which tends to focus more on the cyber modules. To achieve system-level functionality, CPS engineering must consider the behaviours of interconnected and interdependent cyber and physical parts.
- The steady dynamics of physical modules and the fluctuating dynamics of cyber modules are two separate semantic regions that CPS connects. Combining these parts and their abstractions is difficult because of these different semantics.

The two factors listed above make studying CPS quite tricky. For some CPS parts, mostly physical modules, the only existing abstractions are usually simulation models. This makes it impossible to properly analyse and mimic the main way to verify these systems. To address this issue, simulation techniques must simulate the entire sealed-loop system, including physical and cyber elements at the application level.

III. Medical Cyber Physical System

The medical device sector is rapidly transitioning due to integrating embedded software and network connections. Instead of relying on individual devices for treating each patient, distributed systems are now being developed to simultaneously manage multiple physiological aspects of patients. These systems, known as medical Cyber-Physical Systems (MCPS), combine embedded software, networking capabilities, and the complex physical changes exhibited by a patient's body. To ensure the security and effectiveness of MCPS, new design, authentication, and validation approaches are needed. Model-based technology should be central in the development of MCPS, incorporating patients, caregivers, technologies, and their interactions [20], [21].

MCPS provides flexible patient communication with the cyber world to achieve wellness treatment. MCPS changes the computation and nursing of the standalone system. For example, in hospitals, data from many sources, such as bedside monitoring devices, lab results, and specialist observations, are shared to provide information for interventions. Today, many healthcare system modules function in isolation, and there are some partially integrated solutions [22]. They will be combined into networked closed-loop systems that include humans to improve medical workflows and patient safety. New technologies that enable remote patient care will provide doctors with information about how everyday actions affect healthcare and allow them to make more informed decisions about interventions. Bringing together these two currently separate areas of healthcare would make the healthcare system a large, complex, and safety-critical cyber-physical system with many benefits and challenges [23], [24].

Figure 2 provides an overview of MCPS. Based on their fundamental tasks, MCPS devices may be classified into two major categories: monitoring and delivery devices [20]. Monitoring devices in an MCPS may transmit the data they collect to a decision support module or an administrative support module. Each of these components serves a unique function.

Administrative organizations, including Electronic Health Records (EHRs) [25] and medical warehouses, handle and maintain patient health and treatment information gathered over time. With the assistance of this individualized medical data, specific interventions may be made. In this way, they can contribute to continuous patient care. Continuous data collection and serialization are necessary for many of today's chronic health problems, including asthma and diabetes [26].

Decision support systems typically process the collected data and trigger alarms or notifications for many medical emergencies. Alarms are urgently needed so that caregivers can detect changes in the patient's condition. Alternatively, decision support modules can use intelligent controls to examine data received from monitoring devices, assess the patient's health status, and automatically initiate predefined treatment for that specific condition [27].

A. MCPS Challenges

Building these kinds of MCPS necessitates addressing several critical issues [28], [29], [5], including:

High Confidence Software: Software plays a demanding role in medical devices. Some hardware-dependent functionalities can also be executed via software implementation. Therefore, reliable software development is required to assure the security and efficacy of MCPS.

Interoperability: As medical devices connect with numerous communication gateways, ensuring all communicating entities or interfaces' safety, efficacy, and security is essential.

Context-Awareness: Any MCPS must be context-aware as it can provide early detection of patients' health conditions like heart rates and oxygen saturation in the blood.

Autonomy: The various modules of the MCPS should be autonomous based on patients' current health status, and it can be further improved by providing many health conditions and measures against these condition data.

Security and Privacy: Medical data collected and maintained by MCPS is highly personal and critical regarding privacy and security. Loss of data integrity can have serious consequences, as this data is directly related to an individual's health status. Therefore, the security and privacy of the data must be intact in any MCPS environment.

Certifiability: Since MCPS consists of different modules and interfaces, it is very likely that there are different vendors. Therefore, there must be an easier way to integrate all devices or software from different vendors, and certification is one of the ways to achieve this integration of heterogeneous entities.

B. Biomedical and Healthcare Systems

CPS study enlightens various prospects and challenges in medicine and biomedical engineering [30]. These include intelligent operating rooms and hospitals, image-guided surgical treatments, and the growth of physical and neural prostheses. Healthcare increasingly depends on medical devices and systems that are networked. As a result, there is a need for medical devices and systems that are dynamically reconfigured, dispersed, and able to connect with patients and caregivers even in challenging environments. For instance, many operating rooms use devices such as infusion pumps for sedation, ventilators, oxygen delivery systems to support breathing, and various sensors to monitor the patient's condition. Often, these devices must be combined into a new system structure to meet specific patient or practical needs. The challenge is to design and operate these systems demonstrably safely, securely, and consistently.

The research challenges in medical technology and healthcare have been well thought out in a series of workshops summarized by the U.S. National Information Technology Research and Development (NITRD) report [31]. This report identifies research for new systems science and engineering with the following objectives:

- Flexible and interconnected medical systems.
- Real-time communication networks, distributed control, and monitoring for healthcare services.
- Technologies for networked patient monitoring and assistance and system and software certification for medical devices.
- Model-based frameworks that support component-based modelling, design, testing, and certification using patient-specific models.

In the paper [32], the authors proposed an architecture (Figure 3) where sensor data is processed in 3 levels, and they stated that in level 1, decisions would be made using some algorithm. They did not, however, propose any algorithm or method for data processing. We aim to find a way to process data and predict what measures should be taken. Figure 4 shows the system architecture proposed in this study.

IV. Proposed System

Figure 4 depicts the workflow of the proposed system. Let us assume that this system works for a disease X, and sensors S1, S2, S3, S4, and S5 are used to observe the patient's health condition. It is also considered that; this system has memory to store knowledge about actuation for different states and a combination of sensor data.

The system only extracts sensor data if all the system parts are working correctly, which is a safety measure for the patients, as safety is the topmost priority. It is considered that there is a risk for the patients if any part of the system becomes faulty at any point in the treatment. For example, if any sensor goes rogue, it will generate false readings, and the system will keep working with the wrong data. Another case that might occur is that the sensors are generating correct values, but the actuation part is down for some reason. As a result, the system will be incapable of performing any actuation. It is preferred that the system check whether every part of the system is in a perfect working state and only starts extracting values if it is.

After extracting sensor data, the system checks whether the dataset is a new one or not. If the dataset is not new, the system looks for the required treatment and performs it

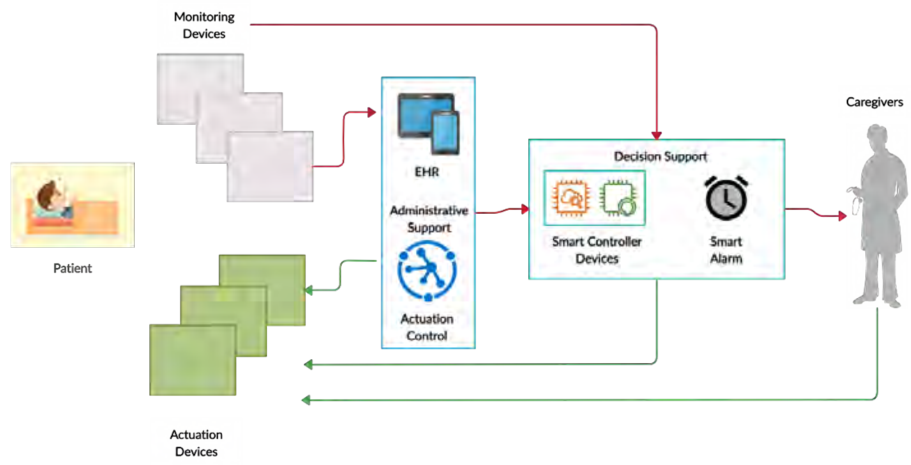

Fig. 2. Conceptual model of Medical Cyber-Physical System (MCPS)

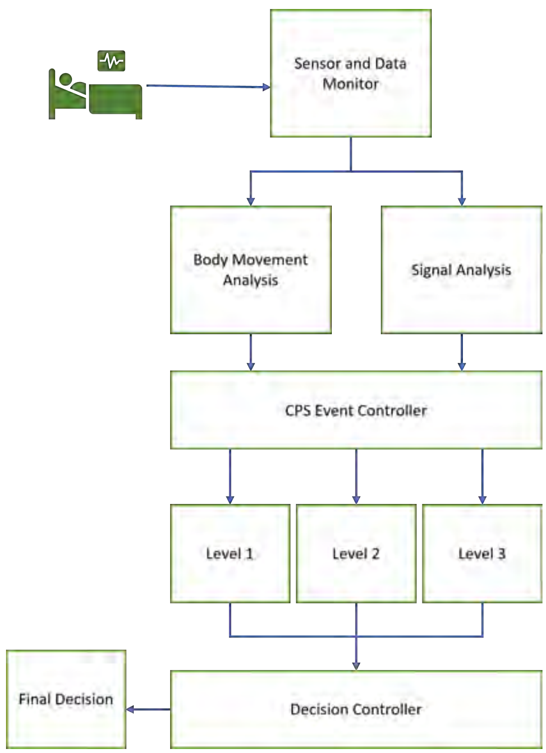

Fig. 3. System Architecture proposed by Jha, Shailesh Kumar [32]

through its actuation system. Let us assume that the system can perform A0, A1, and A2 actions on the patient. However, if the extracted dataset is a new one, the system analyzes the data and stores it in memory. The proposed system uses the Naive Bayes algorithm [33] to decide to choose among the action set. The system stores the new dataset and the result of data analysis in its memory so that it does not need to analyze the same dataset again in future cases. After actuation, the system keeps monitoring the patient's health. If the patient recovers from the disease, the system notifies the caregiver (a nurse, a doctor, or both); otherwise, the system keeps working continuously in this manner.

Let us consider that, Set of sensors to observe patients = {S1, S2, S3, S4, S5}, and, Value Set of Sensor1, $VS1 = \{S10, S11, S12, S13, S14, S15\}$. Value Set of Sensor2, $VS2 = \{S20, S21, S22, S23, S24, S25\}$. Value Set of Sensor3, $VS3 = \{S30, S31, S32, S33, S34, S35\}$. Value Set of Sensor4, $VS4 = \{S40, S41, S42, S43, S44, S45\}$. Value Set of Sensor5, $VS5 = \{S50, S51, S52, S53, S54, S55\}$, and Set of Actions, $A = \{A0, A1, A2\}$.

If we consider a case, $SampleCase1$ with values from different sensors which is denoted as, **SampleCase1** = {Sensor1 = S10, Sensor2 = S20, Sensor3 = S30, Sensor4 = S40, Sensor5 = S50}. The steps of the calculation using the Naive Bayes algorithm for the necessary action for this sample case are shown in the following section. Table I shows the initial state of the sensors with the required action, and Table II shows the new action required for the mentioned sample case achieved by the algorithm.

A. Calculation Steps

$P(ActionRequired = A0)$ = number of A0 / number of total Rows = R0,
$P(ActionRequired = A1)$ = number of A1 / number of total Rows = R1,
$P(ActionRequired = A2)$ = number of A2 / number of total Rows = R2,
$P(Sensor1 = S10|ActionRequired = A0)$ = number of A0 for All S10 / number of A0 = D10
$P(Sensor1 = S10|ActionRequired = A1)$ = number of A1 for All S10 / number of A1 = D11
$P(Sensor1 = S10|ActionRequired = A2)$ = number of A2 for All S10 / number of A2= D12
$P(Sensor2 = S20|ActionRequired = A0)$ = number of A0 for All S20 / number of A0= D20
$P(Sensor2 = S20|ActionRequired = A1)$ = number of A1 for All S20 / number of A1= D21
$P(Sensor2 = S20|ActionRequired = A2)$ = number of A2 for All S20 / number of A2= D22
$P(Sensor3 = S30|ActionRequired = A0)$ = number of A0

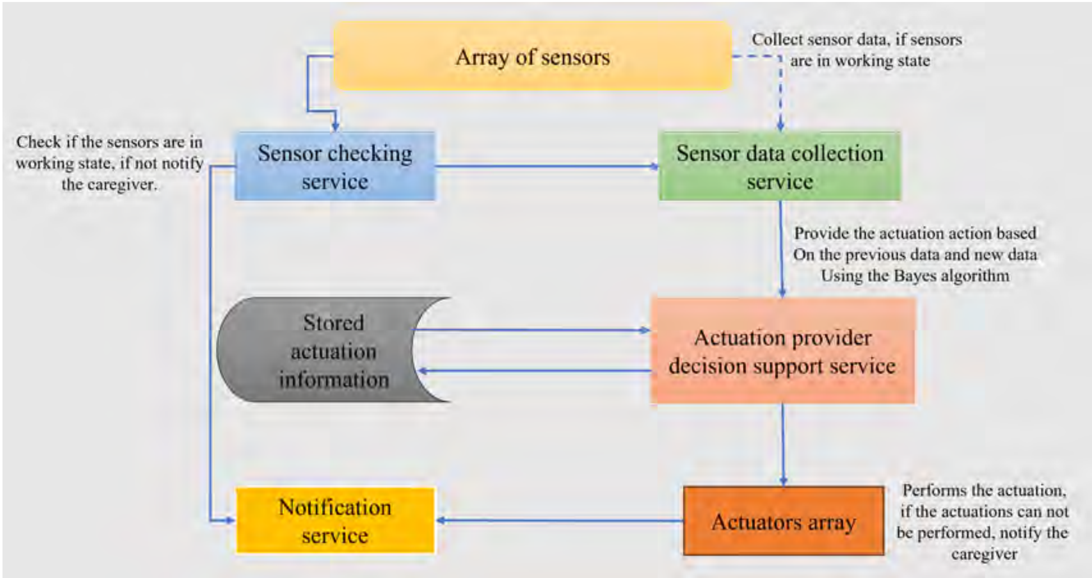

Fig. 4. Proposed System Architecture

for All S30 / number of A0= D30
$P(Sensor3 = S30|ActionRequired = A1)$ = number of A1 for All S30 / number of A1= D31
$P(Sensor3 = S30|ActionRequired = A2)$ = number of A2 for All S30 / number of A2= D32
$P(Sensor4 = S40|ActionRequired = A0)$ = number of A0 for All S40 / number of A0= D40
$P(Sensor4 = S40|ActionRequired = A1)$ = number of A1 for All S40 / number of A1= D41
$P(Sensor4 = S40|ActionRequired = A2)$ = number of A2 for All S40 / number of A2= D42
$P(Sensor5 = S50|ActionRequired = A0)$ = number of A0 for All S50 / number of A0= D50
$P(Sensor5 = S50|ActionRequired = A1)$ = number of A1 for All S50 / number of A1= D51
$P(Sensor5 = S50|ActionRequired = A2)$ = number of A2 for All S50 / number of A2= D52

$P(SampleCase1|ActionRequired = A0) = D10XD20XD30XD40XD50 = D00$ $P(SampleCase1|ActionRequired = A1) = D11XD21XD31XD41XD51 = D11$ $P(SampleCase1|ActionRequired = A2) = D12XD22XD32XD42XD52 = D22$

$P(SampleCase1|ActionRequired = A0)$ $P(ActionRequired = A0) = D00XR0 = R00$ $P(SampleCase1|ActionRequired = A1)$ $P(ActionRequired = A1) = D11XR1 = R11$ $P(SampleCase1|ActionRequired = A2)$ $P(ActionRequired = A2) = D22XR2 = R22$

RequiredAction for SampleCase1 = $max(R00, R11, R22) = RSC1$

TABLE I
INITIAL MEMORY STATE OF THE PROPOSED SYSTEM

RowID	Sensor1	Sensor2	Sensor3	Sensor4	Sensor5	ActionRequired
1	S10	S23	S35	S40	S50	A0
2	S11	S24	S33	S41	S51	A1
3	S12	S21	S31	S45	S52	A2
4	S13	S20	S34	S42	S53	A0
5	S14	S22	S32	S44	S54	A1
6	S15	S25	S30	S43	S55	A2

TABLE II
MEMORY STATE OF THE PROPOSED SYSTEM FOR **SAMPLECASE1**

RowID	Sensor1	Sensor2	Sensor3	Sensor4	Sensor5	ActionRequired
1	S10	S23	S35	S40	S50	A0
2	S11	S24	S33	S41	S51	A1
3	S12	S21	S31	S45	S52	A2
4	S13	S20	S34	S42	S53	A0
5	S14	S22	S32	S44	S54	A1
6	S15	S25	S30	S43	S55	A2
7	S10	S20	S30	S40	S50	RSC1

V. CONCLUSION

This study has proposed a system that extracts sensor data and monitors the patient's health status. This system can decide what actions patients need based on sensor data. Based on the sensor data, this system uses a Naive Bayes algorithm to determine a possible actuation. Since this system is still at a very early stage of development, there is still much room for experimentation with different algorithms for the actuation process and its accuracy. Machine learning and deep neural networks can also be tested.

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