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Chapter 9: Artificial intelligence in patient monitoring: Enhancing care through real-time analytics and remote monitoring

9.1 Introduction

Patient monitoring is a critical aspect of healthcare. Vital signs such as ECG, blood pressure, blood glucose levels, and blood oxygen saturation need to be monitored at frequent intervals to provide timely care and avoid unforeseen adverse events. Currently, these measurements are typically done during an inpatient consultation or periodically during patient visits to a healthcare provider under specific conditions. This in turn generates enormous volumes of data which can be evaluated to identify patterns and anomalies. Real-time monitoring of patients and analyzing these patterns is considered an excellent approach for delivering timely and improved healthcare to patients. This can be achieved by remote monitoring technology which collects patient data in real-time, allows data to be shared with healthcare providers, and employs AI techniques to process and analyze the data continuously and automatically . Digital technologies have made great advancements in monitoring patient health. Modern patient monitoring technologies enable patients to monitor their health parameters continuously and seamlessly using smartphones and wearable health monitoring devices. However, it generates massive health data that need to be monitored and analyzed in real-time to effectively cater to the health needs of the patient.

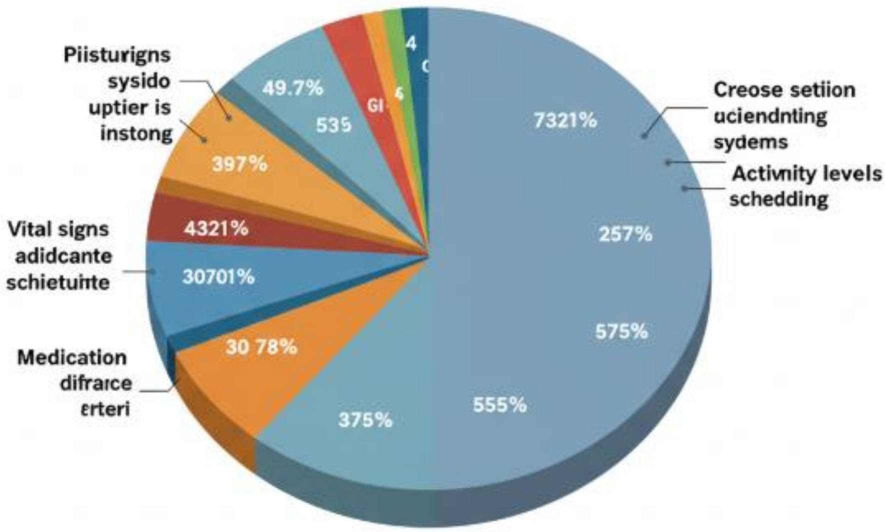

Fig 9.1: Remote Monitoring Patient Systems

There is significant work in developing AI systems to analyze patient data and provide timely insights using real-time monitoring technology. In 2020, a model was developed to prescribe the timing and dosage of medications using wearable sensors in real-time and deep reinforcement learning. The treatment of additional cancer patients experiencing severe bone pain at home consists of taking “as needed” medication, bisphosphonates, without food or drink other than water. In this setup, it is easy for a patient with a busy routine to forget to take the pill on time while the opportunity exists. To increase treatment adherence, an intelligent system was proposed that relies on algorithms of both Reinforcement Learning and Deep Learning to maximize the successful completion of the patient taking the right pill. It can shape patient behavior through reminders and rewards in the form of instant oatmeal breakfast for each successful pill administration. From the user's perspective, a system schedule is a reward of +1, a pill 96 hours of no drinking avail, another 48 hours, and zero rewards otherwise. The system also informs healthcare providers each time the patient goes through the complete schedule. However, these systems do not consider contextual information or actuators and do not optimize the timing of the action. With the rapid development of mobile health, the concept of remote real-time monitoring has attracted more and more attention from the research community, and it has a broader application market. Just-in-Time Adaptive Interventions (JITAIs) are a type of technology that can sense patient states, model the likelihood of a future health-related opportunity, and support patient activities when the opportunity begins. JITAIs provide timely intervention to support patients, and reinforcement learning is an effective method for adapting to a patient's changing environment.

9.1.1. Background and Significance

Mental healthcare is becoming complex and has alarming concerns about depression and stress from patients which leads to self-harm and threats to staff. Thousands of nurses are assaulted each year with some having chronic psychiatric problems. It is found that rural mental healthcare staff, those working in residential settings or facilities such as halfway houses face a serious and escalated risk of being assaulted. The patients with mental health are treated by distressed staff and on the other hand the violent ones have to go through muscle-flexing regulations. A more patient-centered attitude implies that aggressive patients could be given the means to better accommodate their aggression without having their freedom unduly restrained.

The potential ways to alleviate this dilemma may be the setting of a clinic or technical. The latter have seen a surge in the smart nursing research field, where a great amount of calories are spent on the monitoring and passive trend analysis of unsettled behavior. The vast majority of methods reported in the smart nursing literature are based on video-audio sensors, distantly followed by depth sensors, RFID and capacitive sensors. However, the deployment of such devices is invasive, tricky and unethical and in some extreme cases it is specifically forbidden. Today, equipped with cells that bare countless sensors, novel techniques can be designed to record and analyze both voluntarily provided data and unsolicited data. The latter can be employed to trace both the patient's vitals and physical activities with no need to affix any equipment on the patient. This latter type of remote monitoring has been systematically explored in the physical healthcare domain, where a plethora of AI-enabled RPM systems has been recently proposed. Given the limitations of the invasive methods, the goal is to create an AI-enabled RPM system based on non-invasive digital technology, RFID, that is capable of providing contactless, yet precise monitoring of the patient's vital signs and physical activities. To the best of my knowledge, this is the first study that proposed a vision for a patient-centric personalized AI-enabled RPM system for the mental healthcare domain. In this semantic sense, the AI system is built, which uses a technology now pervasive in the healthcare industry, that automatically translates the streams of data into a number of labels that are adequately interpreted by the healthcare professionals. In the material sense, the actual devices that facilitate the deployment of the AI system are devised. It is based on the TIDLO framework, an innovative technology offering a bidirectional data exchange between the tampon-based disposable sensor and the smartphone. By means of TIDLO, the data about the mental patient's vitals and physical activity can be continuously generated without impeding the patient's liberty (Lahari Pandiri et al., 2023; Mahesh Recharla et al., 2023).

9.2. Overview of Patient Monitoring Systems

The healthcare industry continues to embrace emerging technologies to streamline workflows and enhance patient monitoring solutions. Real-Time Analytics is fast becoming an indispensable tool in healthcare, enhancing patient outcomes and safety. This is particularly relevant today due to increasing demands on the healthcare system, especially in the context of aging populations and unprecedented medical burdens. Machine learning and Real-Time Analytics can help to quickly analyze patient health status and provide insights.

Several recent frameworks have successfully helped users build high-performance patient monitoring systems. A smart and core-integrated patient monitoring framework is presented that analyzes patient health statuses down to their basal properties while minimizing the performance-at-a-cost metric.

In order to facilitate early detection of patients' vital signs deterioration, this framework aims to analyze patients' health statuses directly down to their most fundamental properties. To realize this, patient-specific parameter optimization using both statistical techniques and machine learning is introduced, Statistical Missing Data Imputation, Scalable Statistical, Pressure Intelligent Identification of Health Parameters, and Dynamic Bayesian Online Parameter Optimization.

9.2.1. Research design

There has been considerable interest in leveraging various types of wearable, implantable, and portable healthcare devices for patient monitoring that autonomously supervise various signs of patient wellbeing. Prior work has thus advanced patient monitoring systems based on wearable/flexible sensors collecting data, for example, on vital signals, movement, sleep, hydration, and glucose deductions, which allow the evaluation of metrics revealing individual diseases such as chronic obstructive pulmonary disease (COPD), heart breakdown, hypertension, or some mental disorders. In some applications, the collected or retrieved data is examined by a basis to be transferred to the patient, taking preventive measures or not, and a clinician, if necessary. As such, a tool based on the Internet of Things (IoT) is developed for the continuous monitoring of chronic patients outside of healthcare institutions. Incentive spirometry, temperature, pulse oximeter, and Continuous Positive Airway Pressure (CPAP) data is processed and transferred wirelessly to a hospital database where a decision is taken based on expert rules. This decision process can result in direct actions taken by paramedics or personal physicians in real-time.

9.3. The Role of AI in Healthcare

Artificial Intelligence is expanding its horizons in every domain that scholars can think of. Nevertheless, the till-date progress enveloping its use-cases and proficiency in medicine has been incredible, with systems now rivaling their human professionals in aptitude and craftsmanship. Healthcare providers acquire no less significant aspects of patient care other than treatment. This includes numerous monitoring and examination activities to perceive patient changes which primarily require an abundance of time and frequent visits in a hospital. Fortunately, medical IoT devices, for example wearables and implantables have been proliferated by the medical industry of late, and patients now have access to reasonably priced medical devices that they can use in the comfort of their homes. This presents an opening for the development of a REMote patient health strEAMing and anaLytics System, REMEAM. This outlines a deeply accessible, wearable and unobtrusive healthcare awareness recording and observing arrangement which can be exploited for remote patient monitoring and analytics (Nanan & Chitta, 2022; Nampalli & Adusupalli, 2024).

Fig 9.2: Artificial intelligence in healthcare

Apart from monitoring, countless in-time detections (e.g. upcoming arrhythmia, asthma or pain incidents) by the system, which also brings about an event-trigger, tip-off to clinicians can be valuable for the management of patients. Additionally, it is relatively straightforward with cloud-based services to extend the system to the remote monitoring of populations and assigned patient groups using the knowledge base from all datasets.

9.4. Real-Time Analytics in Patient Monitoring

Now more than ever, real-time patient monitoring is at the heart of healthcare performance. In the context of hospitals, long-term care centers and assisted living, ongoing technological progress can bring about real changes in terms of patient care actions, performance and healthcare waste management. For patients, this monitoring ensures closer and immediate care with an increased reactivity and for healthcare decision-makers, this strengthens healthcare decisions management and optimizes resources.

This document details the design and testing of a real-time monitoring application based on the ANAPM platform to analyze patient vitality using smart band data. The objective is to demonstrate the relevance of the platform based on real patient health data as a function of several parameters. These tests involved implementing the real-time care monitoring platform as part of a pilot experiment with real health and activity data. The tested platform is robust to any proposed big data architecture and the data analysis approach in the application is adapted accordingly. It is shown that some specific algorithms alone ensure an acceptable level of accuracy in the patient clustering data analysis for the application. At the same time, it is demonstrated that passing the running time limit, the algorithm does not ensure an accurate data clustering and that the clustering accuracy obtained decreases further with each execution.

However, there is an increasing need for real-time patient monitoring, e.g. for elderly people, acutely ill patients, and patients transferred in emergencies. These monitoring tasks are difficult to be conducted because of the chronic manpower shortage in hospital intensive care units and the need of patients for early and timely intervention. A big data analytics platform can be used to analyze continuous data coming from the large amounts of patient monitors. Various analytical algorithms integrated with hardware devices can study patients' physical condition and alert the healthcare staff when any abnormal symptoms are detected. In this way, the cared patients can easily have a timely intervention. However, the combination of hardware and software is complex. A single hardware device can hardly meet the analyzing needs of all kinds of signals. Thus, developing a platform that incorporates various analytical algorithms and can work with different hardware devices is crucial for successful hospital healthcare.

9.5. Technologies Enabling Remote Monitoring

Technological advancements in data transmission have significantly disrupted the healthcare industry, making continuous patient monitoring possible. The majority of everywhere.

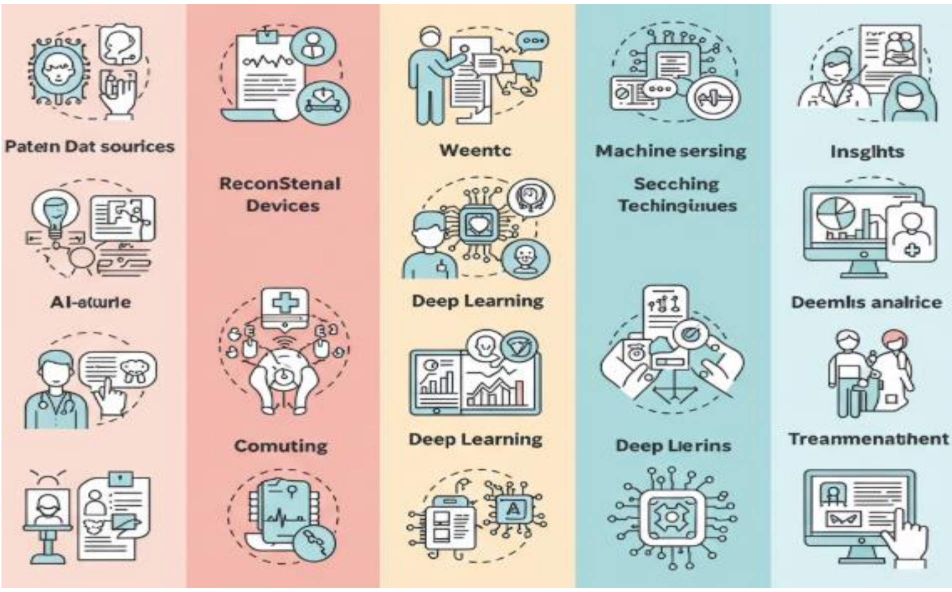

Fig : Remote patient monitoring using artificial intelligence

Monitoring patients continuously is a promising means. Abnormal signs can then be quickly detected during the continuous monitoring. Abnormal signs might include abnormal body temperature and irregular heartbeats. The patient's health status can, therefore, be known continuously. The regular monitoring activities have transformed a traditional pattern of monitoring a patient's health status. Many patient monitoring devices in hospitals are already connected to a center monitoring device which is taken care of by medical staff (Lahari Pandiri et al., 2023; Mahesh Recharla et al., 2023). These devices frequently generate alarms if they detect a problem with the patient. The problem signals a heart attack, for example. However, the monitoring is restricted to hospitals and nursing homes right now. The technological advancement in data transmission has made it possible to monitor these monitoring devices are equipped with noninvasive diagnostic abilities. Medical staff can now have access to the patient's health data without the need for touching their bodies. Continuous health data collection provides an opportunity to monitor patients all of the time. This increases the chance of finding out developing health risks early patients everywhere.

9.6. Data Collection Methods

Despite significant advancements in the care of critically ill patients, mortality rates remain high, with a substantial proportion of deaths occurring within 48 hours of intensive care unit (ICU) admission and the incidence of preventable adverse events. These failures in recognition and response to adverse events are a focus of recent healthcare reform efforts to develop systems of continuous monitoring. Currently, ICU patient monitoring is mostly limited to a degree of manual oversight with the continuous checking and recording of lightweight machine-readable information such as temperature, pulse rate, and blood pressure, available in the electronic medical record. There is, however, a fundamental disconnect between the physiological manifestations of patient deterioration, captured by the complex, multivariable process of multi-organ system physiology, and the univariate vital sign abnormalities that represent reduced resolution summary information available at the bedside. As a result, patient deterioration is often detectable only after it has resulted in life-threatening events. The task of developing more reliable systems for early deterioration detection and prediction of subsequent clinical decompensation is hampered by the inability to effectively capture and analyze the breadth and depth of interconnected physiological signals that are currently available in the ICU without the development and maintenance of complex experimental or research setups. ICUs generate a vast quantity of high-resolution data collected from many disparate multimodal data sources. The potential exists to aggregate, synchronize, and analyze these data to monitor and ultimately model patient condition. However, the physical monitor sampling rates of the various data channels differ and the respective competitive and non-continuous access schemes make achieving acceptable timing uncertainty in the event markers difficult.

9.7. Conclusion

Significant interest and resources have been devoted to monitor and support patients' health, especially for those elderly patients or patients with chronic diseases. There is a long tradition of technological developments within biomedical engineering to monitor vital signs. Plethysmography, Doppler-based technologies, and capacitive sensors have been used in some consumer devices. Combined with advances in wireless data communication, miniaturized wearable sensors are already being used in healthcare applications to monitor patient vital signs. Wearables sensor retail sales in 2023 are projected to exceed 350 million units worldwide as growing numbers of manufacturers introduce these devices for consumer use. AI has recently demonstrated that it can achieve human-level diagnostic performance across a large variety of diseases, from archive image radiology to risk stratification of patients. Using similar developments, the integration of AI processing with the data streaming off wearables sensors suggests that high-quality analytics of real-time biometric data may be performed increasingly at remote settings. There are multiple applications which can be envisaged: continuous monitoring of patients with diseases such as heart disease. It allows timely intervention in response to developing life-threatening events, and patients with diseases needing clinical assessment, such as chest infections. Accuracy in some measurements is significantly improved for semi-automated bimodal processing. All of the patient annotations for cross-validation were performed by expert observers using high-quality sensors connected at the same time while recording with the wearables sensors. In practice the accuracy of measurements remains quite low when recordings produced in daily environments contexts are compared to the expert setting. There are other limitations with the presented work. In all experience described only one single consumer device was used to perform the monitoring. The subjective experience leads to remain cautious about sleep staging outputs, even though visually the segmentation appears in many cases reasonable. Targeting the use of low cost consumer technology, the aim was to describe the broad potential of remote monitoring using these devices. In order to increase the reality of the approach and understanding, the results are from real experiments conducted in a real-life setting, and not in artificial clinical tests. Considerable resources were deployed for a thorough annotation of massive volumes of monitored signal. And thus, developing automatic approaches attempting to recognize automatic medical signs are severely limited in terms of labeled data. In order to circumvent this issue, all proposed sleep monitoring techniques involve learning strategy in the classifying of the indicators, such as processed EEG derived indicators, which should be also translatable in consumer devices. In this respect, deep learning approaches appear to be the most promising and were researched; RF and mDTC were picked to be researched in more detail, as being also appropriate for deployment in resource constraints scenarios as consumer wearables. The motivation is focusing attention on what can be analyzed with the collected data, rather than strictly listing what the collected data are. Additionally, for ethical reasons, the patient’s label data collected will not be shared.

9.7.1. Future Trends

Developed a holistic patient management model that boosts medication adherence and prescription of medications with the best timing and dosage using wearable sensors in real-time analytics, a recommender system, and a reinforcement activity model. A wearable camera monitors pill intakes, a bracelet measures the varying skin temperature when pills are taken (i.e., indicator of them in the stomach), while other sensors continuously monitor the other activities and vital signs. Medication adherence as an individual takes the correct pills at the correct times and the required way. Based on the ingested patterns and tracking of the ring pill sensors, a deep reinforcement learning framework prescribes an alarm by one of the two possible wearable devices when a pill intake is detected late. Moreover, a real-time clinics recommender model prescribes a recommended daily intake time for a list of medications. The latter uses ingestion data, current and personal info, as well as the type of prescribed medications. Finally, it is developed an automatic design model to recommend a personalized alarm device-part for quick-setting.

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