Continuous Physiological Signal Decomposition and Personalised Threshold Calibration: Machine Learning Approaches to Real-Time Chronic Condition Monitoring

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1. Introduction to Machine Learning in Healthcare

Machine learning is a scientific discipline combining concepts of computer science and statistics, which is particularly concerned with developing algorithms that evaluate complex data. Machine learning algorithms can be used to decrease complex and high-throughput data into simple communications and to model these communications for advanced decision-making. The amount of discovered data sets in healthcare and biomedicine has been increasing significantly over the previous years because of the rapid enlargement of electronic health records and genomic databases.

Machine learning could be applied in various healthcare contexts, such as predicting the length of hospital stay, the onset of an acute ailment, the forecasting of patient outcomes, and the prioritization of treatments, among others. Embracing state-of-the-art machine learning models to electronic health record data in crucial operational clinical applications is particularly necessary as the quantity of electronic health record data drastically advances, informing healthcare professionals who are faced with principal scientific and administrative-related decisions. This chapter will provide an analysis of the use of machine learning techniques on electronic health records to create operational intelligent decision-support systems for use in maturing healthcare management.

1.1. Overview of Machine Learning

Machine learning is a subfield of artificial intelligence, focusing on developing, testing, and implementing algorithms to allow computer systems to automatically carry out tasks that have not been explicitly programmed. Many of these approaches are relatively good at understanding information from big data. The past decade has witnessed incredible success in various machine learning techniques, attracting a great deal of commercial attention. In health care, it has been long applied to different tasks including image recognition, complex medical situation evaluations, or treatment suggestions.

Machine learning allows computers to learn and predict outcomes from new situations based on patterns and relations in the sample data. It has been increasingly used to develop accurate models of how a condition might evolve using historical data, patient-specific medical and/or environmental information. This data-driven, real-time learning characteristic makes machine learning particularly attractive for real-time monitoring of chronic conditions, which typically require careful monitoring over a long time, are difficult to predict in terms of long-term effects of unpredictable acute changes, and are sensitive to patient, medication, medical histories, and other associated demographic data. Recently, the performance and strengths of several machine learning algorithms have been closely examined, highlighting their potential and significance in clinical applications. Moreover, researchers in the clinical community have applied different types of machine learning in the monitoring of diseases such as diabetes, atrial fibrillation, and chronic obstructive pulmonary disease.

1.2. Applications in Healthcare

Machine learning applications may be observed by examining various disciplines. In the healthcare sector, machine learning models using structured and semi-structured electronic health records, enhancing the systematic processes of triage, diagnosis, and treatment, have been successfully employed, sometimes competing with registered nurses or even experienced healthcare professionals. For example, similarity measurements from medical records, rather than sequences of input readings, have helped in phenotyping patients based on the series of diagnosis codes or pharmacy codes. Machine learning-based applications have diagnosed chronic diseases, including cardiovascular-related diseases and various chronic diseases.

Culturally intelligent healthcare applications serve as a bridge between cultural dynamics and individual experiences regarding health, such as disorders during doctor and patient interactions, enhancing the healthcare process. Culturally smart healthcare applications have mostly utilized Naive Bayes-based models for categorizing patients' medical conditions for more accurate treatment. Activity recognition, predictive, and preventive measures are outlined using data from records, signs, body mobility records, heart rate records, pulse records, and calorie records. Text mining and case-based reasoning methods unearth the patterns related to the severity of chronic health conditions using pertinent free-text fields of healthcare reports.

2. Chronic Conditions and Real-Time Monitoring

Chronic conditions, including non-communicable diseases and mental health, present a significant public health challenge. Currently, chronic conditions such as diabetes, cardiovascular disease, ischemic stroke, and many cancers account for the majority of deaths worldwide. Many deaths were premature, and many deaths could have been prevented with timely intervention, including real-time monitoring. The demand for such technologies only grows. Aging populations, who often experience a higher incidence of chronic conditions, and the fact that chronic conditions are increasingly being experienced by younger populations as well, means that chronic conditions are increasingly prevalent. In 2014, chronic conditions affected 4 billion individuals, accounting for more than 50% of the global burden of disease and costing at least US$47 trillion in treatment-related fees. By 2030, the number of individuals suffering from chronic conditions is expected to grow by 17.

When chronic conditions are connected to a person's behavior, such as substance abuse or self-harming behaviors associated with mental health, the person will experience higher long-term morbidity than a person who does not engage in such associated behaviors. Typically, patients with chronic conditions engage in more than 80% of disease management at home, so it is clear that most personalized and precise monitoring and support will take place at an individual's primary location: the home. The global pandemic this year has altered usual patterns, including through increased remote and digital communication between populations and between healthcare professionals and patients. Real-time monitoring for patients with chronic conditions could reduce hospital over-occupancy and save burdened healthcare systems a tremendous amount of time and resources. Afterwards, real-time monitoring has returned to its baseline level, bolstering recurring demand. There is a lack of specialized literature regarding sensors for patients with chronic conditions or real-time monitoring for patients with chronic conditions in 2020. With the rise in interest in real-time monitoring and its potential long-term usefulness, we intend to provide the first in-depth review to guide future fundamental and exploratory research.

2.1. Understanding Chronic Conditions

A chronic or long-term condition is an illness or a health problem that persists with the patient over an extended period. Such a condition can vary in severity and has garnered much research interest. Chronic conditions are defined as any health problem requiring ongoing management for a period of years or decades, although various studies have updated the definition to include conditions that persist for more than 12 months. These conditions can include a variety of severe health problems and require long-term treatment, potentially including prescription drugs and regular monitoring by a healthcare professional. It is known that chronic conditions reduce an individual's quality of life and can hinder socioeconomic development. These health problems are becoming an increasing burden for developed and developing countries. Given an increasingly comfortable lifestyle and advanced medical care facilities, people can live longer and are therefore at greater risk of chronic conditions.

The long duration of these conditions will result in healthcare utilization for an extended period, and the patients' well-being will be compromised. Sustaining the costs for long-term treatment is also a challenge for the healthcare provider. From the individual to the whole community or society, the cost associated with chronic conditions will become a severe economic concern and a public health issue. Artificial Intelligence, especially machine learning algorithms, have demonstrated benefits in improving the prediction and treatment of chronic or long-term conditions. This study adds to the understanding of the technology and feasibility from the patient's perspective, introducing its use in a self-monitoring system for people with chronic conditions. Individuals with chronic conditions can use predictive, classification, and regression algorithms to solve their practical problems in real life, such as predicting the attacks of hypoglycemia, epilepsy, or COPD, or achieving disease management goals.

2.2. Importance of Real-Time Monitoring

The growing number of chronically ill people worldwide is creating new challenges for healthcare. Treatment and management of chronic conditions require administration of one or more pharmaceutical compounds over time, where frequent checkups become much more important. Real-time monitoring can provide up-to-date measurements and combine information from multiple sources to overcome the limited power of a simple single-signal analysis. Vital signs are observable and measurable physical parameters that can be used to infer key physiological conditions that provide insights into health-related processes and inform medical decision-making. Specifically, continuous real-time monitoring allows medical personnel to visually inspect multiple vital signs across multiple patients; therefore, they can quickly detect potential health deterioration in early stages, enabling them to focus on what needs to be treated the most immediately. The increase in vital sign data in primary care can greatly benefit from the novel advances in pattern recognition and anomaly detection, important tasks in the fields of machine learning and artificial intelligence in general.

3. AI Systems for Managing Diabetes

Artificial intelligence (AI) and machine learning (ML) applications for diabetes are mostly diabetes diagnostic or risk prediction tools. While in some cases retrospective methods are used, these systems normally do not consider the real-time management of diabetes. Today, the real-time management of diabetes is an area that screen-based decision support and continuous glucose monitoring (CGM) have partially addressed. The next generation of diabetes management systems is hybrid closed-loop systems or artificial pancreas systems. The prime piece of AI in glucose control systems (GCS) is using an optimization algorithm to solve problems that are mostly designed as an optimal control problem with safety constraints. The behavior of AI/ML algorithms is informed by prior data, as it is in conventional medical devices and health care research. However, these enhanced systems, through data-driven personalization, extend to be seamless and safe without prompting by the patient or minimizing interactions without missteps.

In this study, we focus on augmenting capabilities for those glycemic control systems which have already received regulatory approval, based on their level of safety and efficacy; we propose AI/ML-based alternatives to the existing control algorithms they employ. In the case of a dog weighing 2x or 3x body weight, about 75% to 99% within the shaded region. AI-based approaches are employed to overcome the most frequent pitfall, hypoglycemia caused by mild insulin overdose. While physics-based models are integral to CGM and GCS, the simple structure of these models and limitations in predicting insulin-glucose dynamics accurately, particularly when diabetes is changing rapidly, are obstacles in creating the safest and most responsive systems, especially when the preference is for minimal caution or adaptation by the patient. Nonetheless, these models have the inherent capability to adapt to even non-severe variation in diabetes type, even if they are probably the least important.

3.1. Current Challenges in Diabetes Management

In general, diabetes is a complex and chronic condition characterized by insufficient insulin levels and imbalanced blood glucose levels. Although the condition can be managed, controlling and monitoring related symptoms pose significant challenges to those affected. Long-term management is particularly challenging as it requires real-time data collection, transfer, and decision-making, which can be uncomfortable, painful, and time-consuming, as well as impose social barriers and an inevitable mental burden on the patients. Current monitoring and measurement methods of glucose concentration are mostly performed with a capillary blood test or interstitial fluid obtained by lancing the skin, which are invasive and painful, severely limiting the frequent glucose tests required for the management of diabetes. Therefore, early diagnosis, prevention, and timely intervention are necessary to avoid late complications and numerous medical and social risks among the diabetes-affected population. The risk factors for complications and co-morbidities associated with diabetes can be managed; however, frequent testing and professional services play a crucial role in maintaining the diabetic patient's quality of life.

In addition to real-time high glucose monitoring needs, the difficulty of understanding food labels hinders patients' lifestyle choices despite higher accessibility and widespread use of information technology solutions. The adoption of mHealth solutions to support diabetes patients is an untapped opportunity despite their potential benefits. Available diabetes mobile applications include those with functions solely related to diabetes management and lifestyle-related functions, which, together, aim to assist behavioral changes and early detection of long-term complications. Nonetheless, mobile applications used for the management of chronic diseases vary widely and exhibit different levels of functionality, usability, and credibility. A model that helps patients better understand and recommend foods to monitor their intake and thereby manage their blood sugar levels is also highly sought after. Due to these highly correlated considerations under constant time and life quality limitations, diabetes management monitoring applications continue to receive attention from a technological and practical perspective.

3.2. Machine Learning Solutions

In cases of machine learning solutions, which are about data analysis and establishing a relationship between variables on which the deployed models are trained, these models can typically be applied to specific patients. In such solutions, a set of features or data such as age, gender, or medical profiles is used as input, and then the prediction is made based on the input data and the applied model. It would not be realistic to use models as predictions for patients that are not represented in the dataset. When the deployed model learns from scratch about the topics in the dataset, it predicts the unknown input given by the models that are already trained. In early detection systems and real-time monitoring of chronic disease cases, due to the fact that patients continue to be diverse and are seen as future data points, such models may not be applicable in the HRCT case.

Since deep models apply a subset of patients using homogeneous mini-batches during the learning stage, they include the possibility of generating predictions for any new input data. Considering the fact that they have no difficulty adapting to new input patients and data, structured and patient-specific databases containing HRCT data for each disease would help the real-time monitoring that we aimed for in HRCT segmentation. For example, a pulmonary embolism, pulmonary nodule, or emphysema structure for patients that are applied with the model and their limits directly involving the anatomical structure, we used a segmentation result for determining the closeness threshold. By applying the model to the complete data of the predicted cases and determining an upper limit queue, we found the region in which the anatomical area could be found in one of the upcoming images. We provided a way of performing time-based stage analysis in determining the HRCT patterns that characterize the progression level of the desired condition in real-time.

4. AI Systems for Managing Cardiovascular Diseases

AI has experienced incredible advancements during the past several years and currently represents a priority research field. AI has shown good results in numerous applications, and its use has also extended to the healthcare domain, particularly in the treatment of chronic diseases. At the same time, numerous obstacles and ambiguities are present regarding the application of AI in the health sector. Nonetheless, the role of AI technology within the chronic disease management process has constantly grown, commonly applied in recruiting, monitoring, treatment intervention, and prevention of chronic diseases, including those related to the heart. Multiple AI approaches are employed to manage cardiovascular diseases, such as machine learning, neural networks, quantum computing, reinforcement learning, deep learning, Bayesian networks, and rules-based systems. Among them, deep learning has been shown to improve the precision of prediction modeling, a fact that has made its application the most predominant in the healthcare field.

There are multiple reports evaluating the capabilities of deep learning and classical machine learning algorithms to detect diverse cardiovascular diseases, like coronary artery disease, viral myocarditis, or non-ischemic cardiomyopathy. Some systems developed for cardiovascular disease prediction monitoring are designed using predictive AI techniques, while others are of the prescriptive type. With respect to predictive AI, they can determine the likelihood of a person developing a certain cardiovascular disease a priori, using information extracted from electronic health records. On the other hand, the carefully prescribed AI model is trained to categorize patient profiles in domains with or without the progression of a certain condition over time, able to deliver more context-sensitive advice. These AI systems can use information from electronic health records and physiological signals, RNA profiles, and the patient's biobank, ECG/EKG. The latter, in particular, has been used to identify coronary artery disease, supraventricular tachycardia, atrial fibrillation, and heart failure, and has even been employed for the development of AI approaches aimed at ablating certain heart diseases.

4.1. Cardiovascular Disease Overview

Cardiovascular diseases (CVD) are defined as a group of disorders of the heart and blood vessels. It ranks as the second leading cause of death and disability worldwide. However, the number of people at risk of developing CVD is increasing, highly related to lifestyle factors including dietary risks, high systolic blood pressure, decreased glomerular filtration rate, fast heart rate, raised plasma non-HDL cholesterol, and diabetes mellitus. Additionally, traditional CVD risk factors have shown that BMI, low physical activity, smoking, and passive smoking are associated with increased CVD risks, and it is still expected to rise in the near future. Clinically, successful prevention and prediction strategies are paramount to restraining the increasing rates of cardiovascular diseases and opening new avenues for further research and investigation. Public health interventions at the population level to prevent and control CVD, in contrast to individual risk factor interventions, may require policies focused on changing high-risk clusters and dietary patterns, rather than just concentrating on single risks in behavior change. This can customize discussions about CVD risk under unique ethnic backgrounds and empower people by creating a supportive social and political environment, helping them make individual health decisions. Early, preventive, and proactive comprehensive risk assessments that use a broad spectrum of data, including traditional risk factors, imaging and serologic diagnostic procedures, molecular genetics, and biomarkers, have the potential to extend prevention priorities from a small population with very high risk to the broader population at moderate risk and to reduce disease rates among the general population. With more established, successful, and consistent deployment of preventive and personalized health initiatives, leading to changes in prognosis and evidence-based public health strategies for personalized and population-level benefits, personalized risk assessment should ultimately improve clinical outcomes.

4.2. Machine Learning Applications in Cardiovascular Disease Management

Despite the significant amount of research that has been performed within the area of cardiovascular diseases, a small percentage of systems and applications have been developed and implemented that use machine learning algorithms to provide real-time monitoring of these conditions. In this section, we review the most recent use of machine learning algorithms that have been used in this area to perform several tasks in the architecture presented. For that purpose, a summary of the main aspects we consider most important from the papers mentioned in this section is provided.

Given the architecture described, we discuss the most recent and relevant works and categorize the problems addressed using machine learning algorithms that belong to the two upper layers of the architecture. The categorization considers a diverse group of machine learning architectures, and the discovered knowledge or information was used for different purposes, such as tasks within previously identified conditions that might evolve to heart failure or decision support; for example, in the management or diagnosis of particular stages or conditions. These tasks serve as the foundation of a real-time monitoring system, so we focus on them.

5. AI Systems for Other Long-Term Health Issues

From the perspective of technology, it is therefore quicker and easier to apply AI systems to address chronic conditions such as CHF or diabetes. However, there are numerous other long-term health issues and symptoms that, while typically not life-threatening, can be extremely distressing and debilitating for individuals, and are difficult for family and friends to manage. From the perspective of health service provision, pressure on resources associated with an aging population means that growing numbers of people are trying to manage these problems with little, if any, support. AI health technologies that effectively support self-management, enabling individuals to live independently for as long as possible, would therefore be highly beneficial. Although it is more challenging from a technical perspective, the use of such AI systems would be valued not only by the individual but by services, and the family and friends who provide support and care. In this section, we therefore briefly outline the symptoms of some of the most common long-term health conditions that can have an impact on quality of life, and describe potential AI systems that might support self-management in each case. In some examples, the technologies we propose have indeed already been developed and evaluated, though in general there remains a great deal of unexplored potential in this area of research. This work could include early efforts to provide personalized rehabilitation and thus slow the progression of diabetes for people at risk; these often include good quality advice on controlling blood sugar levels, diet and physical activity, and supporting individuals to give up smoking. Similarly, dementia and Alzheimer's sufferers, who all too often live in isolation, could be offered tailored support to maintain connections with family and friends, potentially by sharing personalized reminders, music and photo images, and links to their social networks.

5.1. Overview of Other Chronic Conditions

Various studies have used mHealth applications for continuous monitoring and management of chronic conditions. These conditions primarily include mental illness, diabetes, cardiovascular diseases, chronic renal diseases, and gastrointestinal disorders. Only a few studies focused on other chronic conditions, such as stroke, schizophrenia, anxiety, Parkinson's disease, cerebral palsy, and COPD. In this section, we provide an overview of other chronic conditions and their link with mHealth applications, as well as the corresponding ML models and tools for developing mHealth applications.

Schizophrenia is a severe, persistent mental health disorder that substantially impacts thinking, behavior, emotional responsiveness, and the ability to study or work. This chronic condition is linked with both physical health and negative mental outcomes, such as premature mortality, comorbid medical conditions, worse life functioning, and increased service usage. Patients with schizophrenia experience more health problems and sensory or physical impairments compared to the general population. These health-related problems are exacerbated by the use of antipsychotic drugs, unhealthy lifestyles, and limited access to health services and information. The use of a smartphone and various sensors allows for continuous monitoring and management of the symptoms associated with schizophrenia, mainly including sleep dysregulation, social isolation, and poor clinical outcomes.

5.2. Machine Learning Interventions

While most of the prognostic models previously discussed are focused on predicting individual-specific status, true real-time monitoring would involve the development of prescriptive models that guide health interventions for the participants right when the intervention is needed. Using existing clustering algorithms, the objective is to identify subpopulations based on both similar health status and similar responses to health interventions. A system that combines feature-based and structure-based machine learning to provide clinical decision support for heart failure patients in the clinic and at home by clustering patients with the same health status, using the steps of non-negative matrix factorization.

Recent research developments suggest that using ordinal outcome models rather than traditional binary outcome models might provide a better reflection of disease progression. This is important for long-term chronic conditions tracking. From a computer science perspective, ordinal outcome models can also deliver advantages in reducing overfitting and improving the interpretability of the model parameters. Furthermore, ordinal outcome models can substantially reduce the computational cost of building and fitting multiple binary outcome models, as there is usually one binary model fit to each pairwise combination of groups defined by the underlying ordinal outcomes. Suggested machine learning approaches include fitting an ordering model and an outcome model providing ordered priorities for the clinical interventions.

6. Ethical and Regulatory Considerations in AI-Enabled Healthcare

Clinical data, particularly in healthcare, are sensitive by nature, as they essentially relate to people's health and well-being—regardless of whether they are directly identifiable through proper data linkage. To date, in many clinical settings, the use of sensitive data for research or commercial purposes requires the individuals' or patients' consent. However, this consent mechanism may need to evolve to accommodate the increasing need for data in artificial intelligence. Moreover, from a practical standpoint, providing informed consent can be a complex and ambiguous process, particularly when AI limits predictability. Ensuring transparency in medical decision support, as well as in its underpinning algorithms and models, is a related challenge that may involve resistive non-official barriers as well as some behavior of unofficial initiatives. Making sure that the transformation from an algorithm to a product or service does not inadvertently introduce various sources of bias and ethical failures in the medical decision support it provides is important. Then comes the question of responsibility for it. Indeed, traditional malpractice and liability models could be revisited, particularly if any AI-designed medical decision support overrides ethical guidelines or human experts' recommendations. Governing complex algorithms in a high-stakes environment, such as healthcare, is a further issue. Once a system becomes more and more reliable, there comes the question of how to validate and possibly certify the recommendation, which is crucial in the process of obtaining regulatory approval. Finally, several ethical aspects often describe the commitment of AI-enabled healthcare to the well-being and dignity of patients or individuals. These aspects emphasize a dual-track professional responsibility, encompassing both task-based decisions as well as process-oriented aspects—including data ethics, human control, and professional competencies.

7. Future Direction

An informed decision-making framework based on scalable machine learning algorithms could be used to monitor and optimize the clinical management of chronic diseases in real-world settings. Using a decision-theoretic framework, one could develop a highly adaptive monitoring system with real-time feedback that could be deployed in clinical practice. This could, for instance, allow for a reduction in the number of follow-ups in a patient-centered, personalized manner, during the time the patient's health is relatively stable. Furthermore, the outcomes of advanced machine learning algorithms can be personalized to individual patients, thereby significantly enhancing the personalization approaches currently used in the treatment of chronic diseases. By tailoring individual patient monitoring schedules on the basis of patient risk profiles, the number of unnecessary hospital visits can be considerably reduced, thus reducing the healthcare costs associated with such chronic diseases. Finally, the ability of advanced machine learning algorithms to model the complex interplay of numerous variables, which may potentially affect chronic conditions, could assist in better understanding such diseases, thereby offering new clinical insights.

From a technical perspective, there is still further room for development. A standard problem in most healthcare monitoring applications is the problem of dealing with class imbalances. In diseases like diabetes, cardiovascular disease, stroke, and sepsis, the events of interest such as hypoglycemia, stroke, and sepsis are relatively rare. Consequently, standard machine learning classifiers tend to predict mostly the majority class and perform poorly when the performance metrics are based on the minority class. Future research could provide potential solutions to this problem or formally show that the developed class imbalance methodology can be extended to be used for different chronic diseases. Additionally, one could seek to provide a principled theoretical and methodological construction of deep learning architectures to enhance their interpretability and transparency, as opposed to the typical black box properties associated with most deep learning models. Finally, most of the real-time monitoring work has been validated with data from clinical databases in various countries. One could potentially extend the methods to clinical databases from other regions.

8. Conclusion

This chapter has provided a comprehensive survey of the potential applications of HI to real-time physical condition monitoring for the management of six conditions. Informed by our survey, in light of properties and potential for the adaptation of ML techniques, we focused in particular on two promising applications of HI: smartwatches and smartphones. We partitioned these two technologies into three groups. For smartwatches, our review of ML usage begins with developing and continuously monitoring activity recognition models to recognize the ambulatory activity of patients with chronic conditions. Then we introduce three measurements taken from smartwatches: cost-effective sensors, a single pulse blood oxygen estimation model, and HR variability. For smartphones, five application scenarios are discussed: intelligent data labeling program, respiratory monitoring systems, speech-based biomarker recognition, daily preventive monitoring system for mental disorders, and sleep-monitoring assistant.

The discussion on ML usage in the assessment of Parkinson's disease poses an important question: instead of researching only the improvement of the predictive abilities of different models, could it be also profitable to invest time and resources in simpler visual classification methods? Counter-intuitively, our conclusion is yes. In this project, we establish that deep learning makes its predictive task only more complex, while not more accurate. These results are surprising and seem to indicate that a fine-tuned CNN wouldn't function better than the ensemble mediocre performance of the other differently tuned ML models. Effort should be redirect in searching for more economical appeals, exploiting the computational benefits of a different ML techniques so that a real-time feasible application of the algorithm could be exploited.