Integrating Machine Learning and Big Data Analytics to Transform Patient Outcomes in Chronic Disease Management

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Abstract

Chronic diseases such as diabetes, cancer, and cardiovascular diseases account for nearly 70% of the total healthcare costs that can have a much broader negative impact on the quality of life of patients with decreased life expectancies, productivity loss, and increased healthcare costs. Therefore, a concerted effort is required to alleviate the burden of chronic diseases. Machine learning is becoming more ubiquitous in healthcare because of the exponential growth of electronic health records and the substantial advancement of big data analytics capability. In this study, systematic literature review approaches are employed to identify the machine learning and big data analytics technologies that are already implemented in chronic disease management. Each technology is thoroughly examined in terms of its definition, rationale, and types. In addition, deep coverage of implementation studies of the technologies is provided regarding the motivation, objective, methodology, type of chronic disease, findings, and limitations.

This study focuses on how ML and BDA-enabled chronic disease management systems facilitate the decisions made by doctors, patients, and policymakers in detecting, predicting, managing, and integrating into the patient-centric care paradigm across disease evolution stages. Based on the analytics need and the proposed BDA architecture, this research offers integrated perspectives on how to transform patient outcomes for chronic disease management by synergistically implementing ML and BDA. This research has crucial academic, technical, and managerial implications and opens up other future research avenues. Despite the enormous potential of machine learning and big data analytics to transform chronic disease management, only a handful of innovations have been subjected to larger-scale trials, hindering a swift translation into patient-centric chronic disease care. Many of the innovations hinge on inaccurate or ambiguous clinical concepts and few have considered the social dynamics involved in chronic disease. Concerns surrounding the responsibility of machines or algorithms for unintended negative consequences and the limited accessibility and equity of AI-based technologies further hinder the adoption of these innovations. Hence, innovations should pay special attention to conveyability and accountability that maintain a balance between complexity and interpretability and engage end-users early in the design phase through participatory design principles to foster trust in technology.

Keywords: Machine Learning, Big Data Analytics, Chronic Disease Management, Predictive Modeling, Personalized Medicine, Electronic Health Records (EHRs), Patient Outcomes, Health Informatics, Artificial Intelligence (AI), Remote Patient Monitoring, Data-Driven Healthcare, Clinical Decision Support Systems (CDSS), Population Health Analytics , Wearable Health Technology, Healthcare Data Integration.

1. Introduction

Health systems face increasing pressure due to aging populations, rising chronic disease prevalence, and growing healthcare costs. Health systems handle enormous amounts of data every day, and many hope to find ways to use this information to improve the quality of care they provide. This growing interest in analytics offers the opportunity to dramatically improve patient care by improving clinicians' understanding of patients' likely future trajectories and suggesting and underlining appropriate actions. In this paper, a framework to integrate different forms of analytics into the healthcare workflow, adjusted for chronic disease care, is introduced. The focus is on facilitating the first two components: predictive modeling of future patient outcomes and the proper presentation of the metrics from this modeling to care coordinators and clinicians.

Chronic conditions such as Type 2 Diabetes Mellitus and Chronic Obstructive Pulmonary Disease burden health systems worldwide and are also associated with high costs. Timely forewarning of likely diagnoses enables persons and healthcare practitioners to take preventative measures that may delay or mitigate onset, improving outcomes and reducing costs. Understanding how likely a patient is to progress toward diagnosis is useful both for primary care clinicians in treating this patient themselves and care coordinators in tailoring health interventions for riskier patients. This paper investigates filling this need through a machine learning-based forecasting mechanism that summarizes data surrounding a patient's journeys through the healthcare system through knowledge of expert input and provides background information on model construction, metrics chosen, and biostatistical justifications. A comparison of the proposed model to a standard statistical prediction model and a demonstration of how it can be used to predict the future directly from patients' previous visits is also conducted.

Predicting outcomes for patients is valuable at many points in their healthcare journey. Providing knowledge of likely future trajectories can improve patients' adherence to treatment, motivate them to make necessary lifestyle changes, and catalyze discussions about their care. For care teams, this knowledge helps proper allocation of resources to avoid adverse outcomes. Solutions to this need based on medical data have value, and much current work in this domain focuses on specified discrete, costly future events, such as whether a patient will be diagnosed with a chronic or limited health condition, undergo hospitalization, or whether a clinician will soon leave a practice.

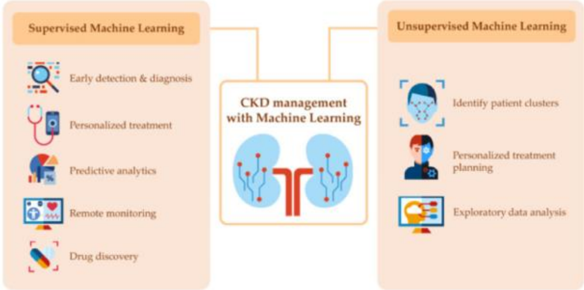

Fig 1: Chronic Kidney Disease Management with Machine Learning.

1.1. Background and Significance

An aging population coupled with increasing chronic disease prevalence and the associated costs of medical care are pressuring health systems. There is a push for health policy-makers to move to a proactive model that intervenes before adverse healthcare events. To identify patients at risk of future adverse events, it is necessary to analyze historical data. Recent advances in Deep Learning (DL) in fields outside of healthcare offer hope for processing large numbers of records and modeling likely future events in healthcare. In general, a patient is represented as a time-ordered list of variable-length inputs each with a number of features describing the care they received. The last input in a patient's list records their time of last observation and a mask indicating whether they are still present in the population. Outputs can predict any number of discrete events taking place within a certain time frame in the future. In addition to prediction, the structure of the DL model allows it to identify significant clinical features of the observations concerned. It is proposed that such a framework could be implemented in more typical healthcare settings and make a significant contribution to population health management. The management of chronic disease is highlighted as an area where DL systems have the potential to identify patients who will benefit from intervention before an adverse medical event occurs, enabling improved outcomes while also reducing avoidable costs.

The chronic disease landscape is one of significant burden and rising costs. In the United States alone, around half of all citizens report suffering from a chronic condition such as heart disease, asthma, or diabetes, and similar trends exist in nearly all developed economies. Such diseases are known to result in significant morbidity, impact quality of life, and severely increase the risk of premature death. These chronic conditions also contribute to a significant and rising cost to society, both through the direct costs of care and through indirect costs incurred as a result of patient mobility. Timely forewarning of likely diagnoses allows for earlier preventative and lifestyle measures to be taken. Similarly, early forewarning of the likely exacerbation and progression of already diagnosed conditions enables preventative therapeutic intervention and lifestyle change.

2. Overview of Chronic Diseases

Chronic diseases refer to a range of conditions that are long-lasting and generally slow in progression in terms of clinical manifestations, treatment, and outcome. A chronic disease may be defined as one lasting three months or longer. Chronic diseases include conditions or diseases, such as: *Heart disease; Chronic respiratory diseases; Cancer; Diabetes; Stroke; Obesity; Multiple Sclerosis; Epilepsy; Chronic kidney disease; Arthritis/rheumatism; and Parkinson's disease*. More than 60% of deaths worldwide are due to chronic diseases, mainly due to the aging population of patients with chronic diseases. Cardiovascular disease is a widely noted chronic disease in the modern world. According to research, more than 1.6 billion people, or 26% of the adult population worldwide, have hypertension. Globally, diabetes alone results in around 5 million deaths annually. Such diseases consume 75% of the country's healthcare expenditure across the world.

Most chronic diseases or conditions are multidimensional problems. Chronic disease problems are hard to measure, assess, and classify as there is no universally accepted outcome measurement scale. There are many risk factors for chronic diseases within individual and demographic variables, which may be ranked higher or lower concerning the importance of causing chronic disease states. In addition, early detection, diagnosis, treatment, recuperation, and rehabilitation of chronic diseases are long-lasting tasks. Comprehensive solutions and integrated chronic disease management systems have not been offered in many developing countries.

Rapid innovations in sensing and wearable technologies have led to the emergence of various wireless wearable devices. With recent advancements in microelectronics, embedded systems, and low-power wireless technology, a new class of wearables has become fashionable and has reshaped the notion of healthcare. The possibility to continuously measure personal physiological indicators in one's daily life opens a new era for advanced intelligent health management systems and computational models. Wearable devices offer a means to unobtrusively collect physiological signals and lifestyle data over days and months. Continuous data streams enable the reconstruction of patients' states, such as disease diagnosis and disease risk prediction. By integrating sensing and processing capabilities, wearable devices measure blood pressure, heart rate, temperature, and ECG signals.

2.1. Prevalence and Impact

Chronic diseases are estimated to be the leading cause of global morbidity and mortality. They tend to be long-standing, continuous illnesses that are generally incurable but treatable. Chronic diseases can last for months or even years and are linked to the aging population, changes in lifestyle and diet, and environmental influences. They refer to a series of physiological ailments that affect human life, most notably, cardiovascular diseases (CVD), chronic renal illness (CKD), chronic obstructive pulmonary disease (COPD), and diabetes mellitus (DM). Each year, an estimated 41 million people, including 1.5 million children and young people, die from chronic diseases, accounting for 74% of all global deaths. One of the direct challenges for healthcare organizations is how to optimize the treatment of patients with chronic diseases. Needing immediate and efficient services, these patients can be seen as a new upstream challenge for healthcare systems. To personalize the treatment of such patients, the management workflow must be deeply understood. Then, the implementation of new information and communication technologies must be assessed for their economic profit to patients and to the healthcare organization.

A solid conceptual model of the operational process is to be implemented. Such a model accounts for stakeholders and their interactions, defined input data, assessment criteria, and output treatment options. Existing models can be extended to incorporate more stakeholders and sub-processes, but such efforts cannot consider the new complexity generated by the overwhelming amount of patients' health data. Expert systems based on the expert knowledge of healthcare professionals can often afford efficient supervision of chronic disease patient treatment. However, the knowledge of healthcare experts can no longer be de facto codified in the presence of high-accuracy, smart decision support systems trained by massive databases. Hence, in a rapidly changing working environment, the feasibility and reliability of human-generated knowledge become ambiguous. The healthcare organization might be hindered by a very complex model with negative issues toward patients and stakeholders.

Equ 1: Predictive Risk Modeling.

$$\text{Patient Risk Score}_i = f(\text{EHR}_i, \text{Vitals}_i, \text{Genomics}_i, \text{Behavioral Data}_i, \text{ML Model})$$

2.2. Current Management Strategies

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Aging is a major risk factor for chronic diseases (CD), which are of paramount concern for public health. The intertwined relationships among various chronic diseases, coupled with the escalating complexity of multi-therapy use, require the adoption of interdisciplinary approaches to better manage chronic diseases. Big data on patients with chronic diseases have been rapidly accumulated owing to the emergence of electronic health records (EHRs). The utilization of such big data analytics (BDA) is anticipated to transform CD management. Machine learning (ML) is a subset of artificial intelligence. An emerging field of deep learning (DL) in ML has received considerable attention due to its powerful feature learning capability. Unlike traditional ML approaches, DL algorithms automatically discover the representation of data from a raw dataset with little or no data preprocessing. The goal of the paper is to integrate ML and BDA to achieve CD management for better patient outcomes.

Comprehensive evaluations of current CD management strategies are summarized in three categories: 1) continuous health monitoring and risk prediction, 2) disease diagnosis and patient stratification, and 3) treatment pattern evaluation and drug repurposing. Comprehensive analyses of the CD management strategies as disease categories: diabetes, cardiovascular disease, cancer, and neurodegenerative disease. With the further increase of big data volume, artificial intelligence and data analysis techniques are anticipated to transform current CD management strategies and improve patient outcomes at the population level. However, many challenges remain to be addressed, including data storage and integration, big data and syntax processing, insider and outsider data mining, and the needs for domain knowledge and collective intelligence to guide the implementation of personalized and precise CD management strategies.

3. Machine Learning in Healthcare

Numerous machine learning methods have been proposed for patient-level predictions. Gradient boosting is one of the most frequently used models in healthcare, including heart failure prediction, diabetes prediction, risk of mortality in kidney transplants, sepsis detection for patients in ICU, and prediction of acute kidney injury. Random forests have been applied widely, including predicting complications after prostate cancer surgery, heart failure detection using electronic health record data, sepsis detection, and diabetes risk prediction. Other applied general-purpose machine learning methods include neural network, support vector machine, and logistic regressions. On the other hand, time-to-event analysis methods, such as Cox regression and survival random forests, have been applied to various medical applications, including heart failure, mortality prediction in ICU, and prediction of return to surgery in pediatric patients after congenital heart surgery. Ensemble methods based on aggregation of models have been used to combine predictions from multiple learned models, including predicting twenty diseases, as well as a prediction of acute kidney injury using ensemble deep learners.

In addition, a deep learning method based on temporal embeddings has been proposed for predicting pneumonia and heart failure within one day of a visit. Machine learning is perhaps the most impactful methodology in recent years, allowing researchers from different backgrounds to leverage a set of generic well-established modeling techniques for a variety of tasks. As an amalgam of statistics, computer science, and behavioral science, machine learning is fundamentally data-driven, attempting to extract useful signals from a big mass of data. Data collection and availability became feasible thanks to advances in centralized data storage. The phenomenal emergence of electronic health record systems in hospitals and clinics widespread the growth of research on machine learning in healthcare.

3.1. Fundamentals of Machine Learning

The concept of "Machine Learning" (ML) has gained increasing attention in healthcare community . Machine Learning is nothing but employing an algorithm to learn from the data in such a way that it is able to make better predictions on applying to new data. The Machine Learning paradigm includes several complex computational approaches that can learn from data and model the underlying processes. These models can then be used for prediction or description, or simply to improve understanding of a process. Traditionally, Machine Learning development was laboriously conducted by hand-coding sophisticated algorithms with deep understanding of the systems studied.

Current state-of-the-art technologies in healthcare revolve around a powerful computational tool called "Big Data Analytics" (BDA). The clamor of big data is reshaping every industry's value chain. Similar to other industries, the advent of large scale heterogeneous data captured via sophisticated platforms offers unprecedented opportunities for transforming health care providers' qualitatively and quantitatively. The convergence of Big Data and Advanced Analytics (BDA) can change the way healthcare providers utilize sophisticated technologies to gain insight from their clinical and non-clinical data repositories to make informed decisions. More importantly, the strategic use of BDA can result in discovering novel findings that has value layers for improving patient outcomes through enhancing productivity, quality of care, and safety. In addition to providers' ecosystem, innovative applications of BDA can enhance health information management and emerge with standards which can solve significant issues in quality and efficiency of care.

Fig 2: Machine learning in healthcare.

3.2. Applications in Chronic Disease Management

Chronic diseases represent an enormous challenge to patients, relatives, and the healthcare system as a whole. These disorders are seen as chronic when they persist for over three months and require continual adjustments in medical care. Some prominent chronic diseases include obesity, hypertension, heart failure, chronic diastolic heart failure, and chronic rapid atrial fibrillation. Chronic diseases are long-lasting conditions with predictable patterns. Patients with chronic diseases frequently receive an over-saturation of health information, which increases the possibility of panic and worry since individuals may think that they have a chronic disease also. Chronic disease management is defined as creating and sustaining the requisite person-centered or patient-centered medical home approaches to improve quality according to transparency results in the health system ecosystem. Chronic disease management instruments contain medical devices that measure real-time data, such as blood pressure bands, ECG recorders, heart rate spectra, 24-hour blood pressure monitoring devices, glucose, and electrolytic multi-tests in adults.

Big data and big data analytics draw on the internet of things, devices, sensors, and cloud-based architecture to collect and analyze data from numerous sources in clinical knowledge. Patient contextual information is converted into big data and information, which help identify the profiles of patients with chronic diseases and predict their states in others. This big data transforms knowledge into graphics and can help clinicians treat patients . Forecast frameworks, including condition forecasting, therapy forecasting, and adverse event forecasting ones, are created using this data. Carrying out historical recording procedures enables a novel portrayal of biomedical attributes across various time intervals and resolutions. Combining the data representation with major data regression and unsupervised learning frameworks is possible. This type of AI technique fosters real precision in chronic disease patient screening.

4. Big Data Analytics in Healthcare

Big Data, Big Data Analytics, and Healthcare Big Data have received considerable attention in recent years from various disciplines, such as physicians, engineers, computer scientists, and even economists. They seek to understand the legal, ethical, and proven use cases for using big data analytics in the healthcare industry as well as its other facets. Big data analytics in healthcare has the potential to help healthcare providers discover insight into their big data repositories and help them make informed and better decisions regarding patient's health care and consequently improve the quality of life of human beings .

Healthcare has relied on data and statistics to a great extent for ages to understand patients' needs, clinical issues, patients' health tracking, forming groups, and providing preventive healthcare advice on a regional basis. The implementation of information technology in healthcare through electronic health records and data warehouses has allowed providers and administrators to access historical data of patients' clinical information on a patient basis as well as data of large groups of patients on a regional basis. However, data that is gathered/influenced by mobile/smart devices such as telephony, gaming, GPS/Geo-tagging, and social networking lack continued reliance from the healthcare sector. However, it is known that healthcare usage over mobile/smart computing is common on a wider population scale across cultures and nationalities and has drastically increased. But, the same data help providers understand social issues affecting patients' health and lifestyle issues affecting health-related decisions, and group patients for personalized/micro healthcare has gone largely unnoticed in healthcare organizations.

In consideration of the amount of big data generated in healthcare, Pfeiffer took a look at hundreds of healthcare data science success stories, in an effort to define success stories in big data analytics in healthcare which is highly successful in advancing medical imaging IT and clinical decision algorithms. However, these explored a few disparate points of success in preventing readmissions of high-risk patients and health mapping approaches. Through a review of the current big data contractual and approach landscape, strategies for providers moving into big data analytics not being abysmally out-spent by Large Tech which can provide better predictions, recommendations, performance measurements, and more. A natality analytics application in birth defect prediction is presented built from free sources of data using low-cost commodity IT and insight into one of many possible low-cost IT, analytics, and data science service strategies for consumer-facing provider organizations.

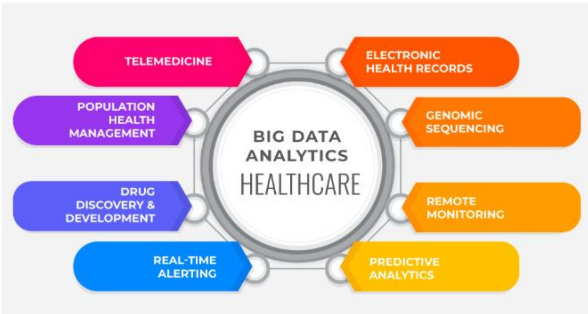

Fig 3: Big Data Analytics in Healthcare.

4.1. Definition and Importance

The management of chronic diseases is crucial for the well-being of the aging population whose big data is fragmented across different systems. It is thus extremely important to integrate machine learning and big data analytics frameworks for interoperable data from different sources and in different formats to build a holistic view of the patient. This enables a transformational change in patient monitoring, treatment optimization, and outcomes. These frameworks remove the burden of advanced analytics from the health practitioners and make the patient management system technology agnostic. The current management models are reactive, tedious, and time and money-consuming. This limits the accessibility to effective treatment for a larger population. The introduction of decision analytics can significantly improve the patient outcome for patients with chronic diseases while allowing health practitioners to treat more patients. This can increase investment in preventive care and enhance healthy aging in turn reducing the pressure from chronic illness on the healthcare system. Multiple stakeholders can also benefit from the provision of technology ecosystem services. These services can be bundled to improve the accuracy of pattern detection and generative services across verticals to build new capabilities in healthcare.

Equ 2: Early Warning System.

$$\text{Alert}_t = \begin{cases} 1, & \text{if } \Delta\text{Health Metrics}_t > \text{Threshold}_{ML} \\ 0, & \text{otherwise} \end{cases}$$

4.2. Data Sources and Types

Data types in DMCH: With the rapid growth of Big Data in HealthCare, health care systems worldwide are struggling with the burden of volume, variety and velocity of the different type of health data being generated every day. The diverse nature of Big Data makes it difficult to capture, store and analyze. Most of the traditional data processing systems fail to maintain the health data collected from very different sources due to structural, semantic and other heterogeneous nature. In DMCH systems, health data is collected from PHR, EHR & EMR, operational data, research data, gene sequencing data, Internet of things data from customized sensors, social networks and other different sensors that measure digital biomarkers etc . Such type of data in health care systems often resulted with critical challenges for storage, processing and effective analysis. So, effective storage systems, architectures and representation models should be introduced to accommodate such difficult challenges with the aim of having the desired velocity. Advanced data processing techniques should be implemented to resolve integration, representation & analysis issues with a goal of transforming them into useful data. Also, advanced visualization techniques should be applied to insight visual data and analysis results. Knowledge representation systems also should be used to acquire knowledge on top of the visual output. Effectively using them together should give a complete view of the health status of a patient at any time, eventually resulting in better planning for treatment or monitoring strategies.

5. Integration of Machine Learning and Big Data

The intersection of machine learning and big data analytics has recently been described as the "new digital dust" that is effortfully being collected and assembled across every sector of the global economy. With the convergence of inexpensive data sensors and storage technologies, algorithms that can crunch data and produce analytics and predictions, as well as computing that can visualize these analytics, most sectors of the economy are attempting to capitalize on this technology. Many CEOs across industries admit that if their organization is not currently collecting the appropriate data in order to make evidence-based decisions, they fear extinction.

Healthcare, however, is lagging behind. Improvement in patient outcomes has intentionally remained the focus area; however, integrating machine learning and big data analytics in healthcare decision-making processes have received little attention. For long-term care patients, unfortunately, the status quo means that the significant clinical, engagement, and economic opportunities afforded by machine learning and analytics are still unreconciled with the status quo of care. As healthcare is pushed toward a value-based paradigm, the delivery system stakeholder that can effectively measure the value of patient outcomes, and engage their patients in their plan of care will define, capture, and dominate the emerging market.

In the landscape of healthcare cost and quality, the patient remains the most underutilized data source. Patients keep record of personal health data, and monitor their input through continuous sensory data collected by devices such as wearables. The significant patient-level health data, which are persistent, regularly-updated digital traces of health trajectories, has not been effectively used for improving patient outcomes and cost-of-care. The convergence of health big data on patients and machine learning algorithms provides new opportunities for chronic disease management populations. Driven by a chronic disease management population, a novel framework integrating machine learning and big data analytics is proposed to transform patient outcomes.

5.1. Synergies and Benefits

The advent of Big Data Analytics (BDA), Machine Learning (ML), and other Artificial Intelligence (AI) approaches, along with the continuous and decreasing costs of data collection, storage, and processing, have enabled researchers to work with various types and large amounts of data. In the healthcare sector, data collection has increased drastically, enabling analysis to support clinical decision-making, practice, and precision medicine. The increasing usage of digital technologies in health and well-being is generating massive amounts of patient data, with great potential for improving health outcomes and quality of care for individuals with chronic diseases. Multiple types of data are available today and applied to healthcare analytics in association with technologies and data manufacturers. Health-related population-level data can include, but are not limited to, claims data, patient reported outcomes, administrative data, diagnostic and drug data, other chronic disease-related data, socio-demographic data, environmental data, health service data, and wearable and biosensor data. Healthcare big data analytics refers to the application of advanced analytic techniques and algorithms to analyze health-related, large-scale, complex, varied, different formats, high-velocity, and rapidly generated data from diverse sources and for different-purpose health-related questions to improve healthcare. BDA can transform healthcare from a reactive to a more proactive and predictive model and can contribute to a big data-informed healthcare ecosystem for improved health outcomes.

Health analytics is grounded on the principles of data, information, and knowledge. Data about past patients can reveal resource consumption, effectiveness of health interventions, and factors and lifestyle habits associated with either treatment response or side effects via data mining algorithms, statistical techniques, and simulation models. Data-driven or informed decisions can help avoid adverse events through preventive actions based on recognized patterns and trends that come by continuous monitoring. By considering more factors (comorbidities, genetic predisposition, environmental factors) and integrating more levels (individual, group, population), precision or personalized medicine is expected to deliver treatments personalized to the patient rather than the disease.

5.2. Challenges and Limitations

The integration of machine learning (ML) and big data analytics (BDA) has significant potential for transforming care processes, disease prevention, and patient outcomes in chronic disease management (CDM). Despite the promise of ML and BDA technologies, their adoption is hindered by a number of challenges. These challenges are briefly discussed below, and are classified as theoretical (data), technical (computational), organizational, and ethical challenges.

One of the major challenges in the ML domain is the missing data problem. Missing data is a common occurrence in electronic health record (EHR) databases. It results from a variety of causes, including equipment adjustment, database updating, patient admission, absence of clinical data, and equipment failure. Missing physiological data often makes it difficult for predictive algorithms to fulfil real-time requirements for clinical practice. Dealing with missing data is one of the most challenging problems in the ML domain. Missing data values may provide useful information instead of noise in data. Most current missing data imputation (MDI) algorithms are either not capable of modelling the underlying missing data mechanism or need the structure of EHR databases to be predefined beforehand. Therefore, MDI in EHR databases is a nondeterministic process.
The integration of diverse data sources from cloud to fog to edge infrastructures for real-time health monitoring and disease prevention in an accelerating manner remains an open challenge in BDA. Current data infrastructure is not able to easily and realistically keep up with the accelerating growth of unstructured and dynamic data as well as the explosive growth of QOC. Further improvements of architectures and platforms for real-time health data integration and QOC adaptation are needed. Existing issues include health data continual arrival, great design diversity of health data visuals, health data quality measurement models, and data quality assurance approaches in edge health monitoring. The integration and coordination of various solutions for addressing these issues is particularly challenging in an emerging, heterogeneous, dynamic, and decentralized environment. Automated and efficient approaches for health data quality measurement and assurance; and effective, adaptive and intuitive system designs for health data integration from diverse sources of health care locations and domains, which are also easily built and extended, are the key to this challenge.

6. Case Studies

A case study of chronic disease management and related artificial intelligence techniques was performed to dramatically advance T2DM care at the University of Utah Heath. It was hypothesized that predictive models for T2DM treatment outcomes can be reasonably and precisely developed with a Midwest-AAP dataset and selected RWD features. It was also hypothesized that an interoperability and standards-based EHR-integrated SMART on FHIR CDSS will be developed and enable clinicians and patients at the University of Utah Heath to receive patient-level treatment outcome predictions and personalized medication recommendations for Type-2 diabetes Mellitus during clinical practice. The chronic diseases lecture notes reviews the background works for developing predictive ML models for T2DM treatment outcomes. Data from a multi-institution partnership and the care improvement workflow at the University of Utah Heath were described. New ML techniques including a hybrid DGN model and a Patient-wise Transfer Learning algorithm were softly introduced and rigorously built. Finally, detailed integration of predictive ML models and automatic medication customization methods into the EHR via a SMART on FHIR CDSS, including candidate medication lists generation, filtering, and patient-to-interval outcome probability calculation were precisely discussed.

6.1. Diabetes Management

The methodological problems that arise in chronic disease management are mostly common across multiple pathologies. The first consideration is the effective collection of health or non-health data. Although risk factors differ greatly among chronic diseases, measurements of weight, height, and physical activity are regularly captured for each disease by GN and MD systems. Furthermore, it is also helpful for HDL cholesterol management of heart diseases and for measuring blood glucose in diabetes management. For instance, smart pedometers can easily collect exercise data in a cross disease fashion. The second consideration is the collection of heterogeneous types of data. Device roughness is likely to differ significantly for each surface. The third consideration is the compulsory filtering and integration of health and non-health data. Input data gathering and filtering differ greatly between chronic diseases. For instance, diabetes education is concentrated mostly on exercise time and weight, while education after heart disease diagnosis focuses primarily on smoking cessation.
Diabetes is the most serious chronic disease in terms of worldwide prevalence. At least 300 million people worldwide are estimated to have the disease directly, and another 300 million are estimated to be at high risk for the disease. Pathology and pathology-related factors controlling blood glucose have been extensively studied. However, continuous glucose monitoring in real life has been a recent innovation in diabetes management. Type 1 diabetes mellitus (T1DM) is an absolute deficiency of insulin that requires an external quantitative glucose equation and perpetual feedback via subcutaneous insulin pump and blood glucose vision. Such continual group pattern or event analysis is also necessary for type 2 diabetes mellitus (T2DM). On the other hand, T2DM is a progressive relative deficiency of insulin; treatment may therefore need to catch the evident risk factors of the disease.

Equ 3: Population Health Insights.

$$\text{Health Trend}_{\text{Population}} = g(\sum_{i=1}^{N} \text{Patient Data}_i, \text{Unsupervised Learning})$$

6.2. Cardiovascular Disease

Cardiovascular disease (CVD) is a term used to describe a range of heart diseases, including coronary artery disease, heart attack, stroke, heart failure, atrial fibrillation, and sudden cardiac death. There are many characteristics of ECG signals which describe heart diseases. But how to use these features for prediction depends upon the expertise of the medical domain knowledge and how to handle this is difficult for one person. Recently, several studies have applied machine learning approaches on ECG signals. A cost-effective medical error-free method for the early diagnosis of various CVDs has been discussed by taking a standard heart-rate dataset. Long short-term memory (LSTM) is applied to extract the features and sorted with the attention technique. By voting of the classifiers the CVDs are detected. Using the Ludwig machine-learning platform improves the performance of the smart health system. The Blinov model has designed a smart health card with a computing cloud dedicated to the early finding of CVD risk factors in patients by migration learning. Aficionado Wayne-Camille developed a mobile health (mHealth) informatic system Dreamer to analyze the ECG signal data in mobile settings. Then it would be used to implement the expansion of population health monitoring around the world due to accelerating smartphones/network connections availability. The heart diseases have been classified in two modes (i) Automatic classification by using detection algorithms and (ii) Manual classification based on the medical features. Automatic classification is very complicated and computing cumbersome but precise. On the other hand, manual classification needs high expertise in the medical domain based on patient cardiovascular signals, which would be less accurate and time-consuming. Hence, an alternate approach that integrates machine learning and big data analytics to transform patient outcomes of heart diseases based on the clinical features of heart disease is framed. Even though the heart disease is well advanced, the existing techniques still need to be improved in order to achieve supreme quality of prediction.

6.3. Chronic Respiratory Diseases

Chronic respiratory diseases (CRDs), also known as chronic respiratory diseases (CRDs), are a group of diseases characterized by chronic and recurrent respiratory symptoms. The health and economic burdens of CRDs, especially asthma and chronic obstructive pulmonary disease (COPD) worldwide, have made them a priority in public health. CRCs can be classified into two broad categories: obstructive chronic respiratory diseases, including asthma, COPD, and bronchiectasis, and restrictive chronic respiratory diseases, including pulmonary fibrosis, sarcoidosis, and neuromuscular diseases. COPD is a common disease that is primarily due to smoking and causes 4 million deaths per year. It accounted for 3% of the global burden of disease in 1990 and 23% of the burden of disease in high-income countries and a similar proportion in middle-income countries. It is also projected to be the fourth leading cause of death by 2030. Asthma is characterized by chronic airway inflammation, hyperresponsiveness, and variable airflow limitation, which are caused by a combination of genetic and environmental factors. Currently, asthma affects about 335 million individuals worldwide and is the most common chronic respiratory disease. New asthma cases occur in about 30% of children in the United States, while asthma induces substantial societal costs, including loss of labor production, school absenteeism, and the economic burden of burden to patients. These rapidly growing CRDs are important for both clinical and public health.

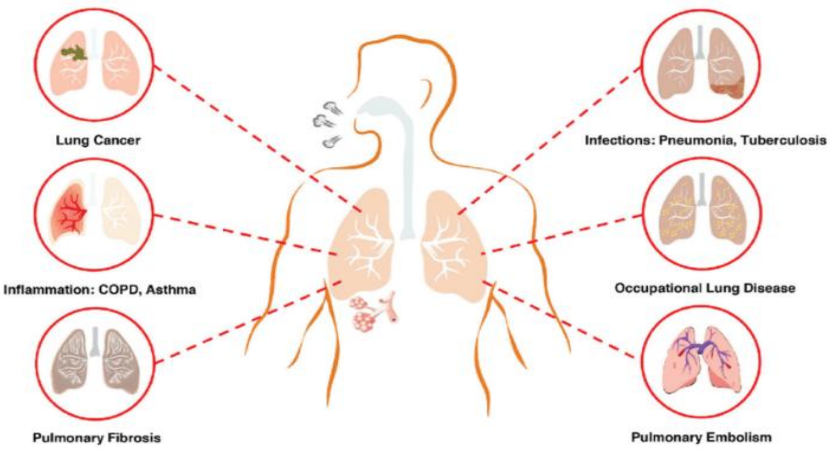

Fig 4: chronic respiratory diseases

7. Ethical Considerations

As healthcare systems strive to better manage populations with chronic disease conditions, technologies and innovations offer growing potential to facilitate the process. A common theme of technological solutions is the introduction of machine learning and big data analytics capabilities within healthcare systems. These contextualized data analytics solutions represent core leveraging mechanisms for optimizing healthcare delivery, unlocking potential value from big data, and ultimately improving patient care. This review provides an overview of core evidence-based functions of contextualized data analytics, examples of their implementation in chronic disease domains, key challenges or barriers that limit their uptake within healthcare, and an initial roadmap for understanding how this technology change can be achieved in the future. Successful implementation of these contextualized data analytics solutions in chronic disease management will require broad healthcare system changes that go beyond the technology and address core issues rooted in policies, practices, processes, culture, funding, human resource and infrastructure.

Innovation, particularly the introduction of new information and communication technologies, has garnered much attention of late as healthcare systems increasingly strive to address the growing issues of managing populations with chronic disease conditions. Different technologies or innovations have emerged, promising to help better manage a variety of non-communicable diseases such as diabetes, cardiovascular disease and cancer. Contextualized data analytics is seen as a viable technological solution for delivery of healthcare, which allows synergistic extraction of value and insight from a variety of contextualized information and knowledge. With contextualized analytics capabilities, healthcare systems are now equipped with the operating potential to achieve systemic transformation. Contextualized data analytics represents an amalgamation of three key technologies: big data, data analytics and contextualization, which collectively facilitate optimization of healthcare system performance as data-driven organizations.

7.1. Patient Privacy and Data Security

The growing demand for healthcare monitoring services paired with the emergence of affordable medical sensor devices has allowed patients to subscribe to monitoring services that utilize their real-time healthcare data to detect potential health anomalies and trigger periods of hospital visits. Monitoring services are usually offered by service providers that collect data from health monitoring and information technologies to detect and report anomalous situations. Following several high-profile breaches of healthcare databases, protecting patients' privacy has become urgent, critical, and challenging due to the highly sensitive nature of healthcare data. Indeed, unauthorized exposure of sensitive health-care data may violate regulations and result in lifelong consequences for patients. This becomes even more crucial when health observations are coupled with mobility patterns, as location and trajectory data can be combined with demographics and social networks to potentially infer inadvertent user information.

Healthcare teams, such as nursing teams, emergency response teams, and social welfare teams, should normally have access to patients' data. Researchers require access to these data for conducting scientific studies on healthcare monitoring services. Conversely, adversaries with unauthorized access to healthcare data may abuse this data to violate patient privacy through identity discovery and health inference. Preserving data privacy from adversaries while still enabling the analytical services without significant degradation of data utility is challenging. It should be noted that data privacy must be maintained throughout the entire lifecycle of the data, including storage, processing, and communication. The determination of which data protection methods to use to counter adversaries throughout the full data lifecycle affects the design of privacy-preserving analytics algorithms. For adversaries with authorized access, most of the encryption schemes on the market today may jeopardize the services that healthcare providers wish to offer. Simpler protection methods, such as data anonymization, are also not sufficient against privacy breaches.

Fig 5: Patient Privacy and Data Security.

7.2. Bias and Fairness in Algorithms

The general concepts of fairness when it comes to machine learning algorithms could be divided into two large themes: (i) fairness issues that arise from the model itself; and (ii) fairness issues that arise from the data used to train the model including sampling biases. One of the considerations in the work presented is the importance of keeping in mind that these definitions of bias are not mutually exclusive, and different machine learning pipelines may have different elements of bias. Some of them might arise from a selection bias of the data, while others might be in the model itself or its resulting predictions. For example, a model can be designed to be perfectly fair based on the training set it was fit on, and yet, when applied to a test set that has new patients with conditions that were not represented in the training data, unfairness can arise entirely out of the data draw and the absence of some true common cause that influences both, the features and the label. Therefore, the actual evaluation of this question of fairness in ML pipelines cannot be deterministic; the methods employed to estimate bias must be sampled through alternative data-driven mechanisms.

There have been a number of works that have already proposed definitions of fairness that are specific to computational medicine. Certainly, there have been studies that highlighted the shortcomings of existing models in clinical prediction. More recently, there has been a surge of interest in the general developments of the notion of fairness itself when broadly applied to the field of machine learning. While these developments are often by-products of theoretical machine learning discussions, several practical notions of fairness have arisen in technical literature directed at specific applications outside of healthcare. These pre-established definitions were also considered to progress research in computational medicine toward the goal of enabling practical applications while broadening the audience of readers.

8. Future Directions

Chronic diseases are a leading cause of mortality, morbidity, and disability in all parts of the world. Efforts for noncommunicable diseases surveillance are still limited in many low and middle income countries. Several studies have analyzed chronic diseases and several risk factors, such as obesity, hypertension, diabetes, smoking, and alcohol drinking, using machine learning algorithms. However, challenges remain for applying these algorithms in surveys. Because most of the diseases are self-reported, traditional machine learning algorithms cannot be used because the algorithms usually require a labeled dataset for training classifiers. The study aimed to apply an unsupervised machine learning method to analyze chronic diseases and risk factors in a middle-income country. Chronic diseases are a leading cause of premature mortality, morbidity, and disability in all parts of the world, with the largest individual burden in diabetes, cardiovascular diseases, cancers, and respiratory diseases. Moreover, chronic diseases not only incur a significant health burden, but also a heavy financial burden due to treatment costs. Efforts for cardiovascular disease surveillance are still limited in many low and middle income countries. Comprehensive assessment of the patterns, trajectories, and risk factors of chronic diseases is crucial for resource allocation. However, surveillance algorithms adopting available methods may not apply to chronic diseases in many low and middle income countries. This study applied an unsupervised machine learning method based on clustering to analyze multiple categories of chronic diseases (hypertension, diabetes, myocardial infarction, stroke, and cancer) along with an array of potentially risk factors in chronic epidemiologic surveys. The study proposed a clustering method by allowing unequal categories by carefully designing the distance metric. The clustering method was applied in both simulated and real surveys. This study focuses on a middle-income country to provide an analysis of a demographic-related surveillance of chronic diseases including the patterns, plasticity, and risk factors using national data.

8.1. Emerging Technologies

Recent advances in artificial intelligence (AI), including machine learning (ML) and deep learning, allow for the automated analysis of rich and complex health-related data for disease detection, progression, and prediction. Recent breakthroughs in blockchain, a decentralized and distributed ledger technology capable of recording the provenance of digital assets, can document digitized health data along with their provenance, providing transparent, robust, and trustworthy summaries of chronic disease management. Mobile communication technologies with big data analytics and considerable off-the-shelf sensor devices provide the opportunity for real-time chronic health monitoring and assessment. It is evident that wearable sensors might become the next frontier for big health data acquisition. Therefore, integrating AI, blockchain, and wearable technologies can provide digitized, trustworthy, and real-time health data, which has great potential for chronic disease management in the era of smart healthcare.

The primary issues include a lack of systematic and theoretical research in smart and trustworthy chronic disease management based on the latest technologies and limited research efforts in chronic disease health monitoring prototypes for commercialized wearable devices. The vision of a new paradigm for chronic disease management powered by the integration of AI, blockchain, and wearable technology, such as smartphones, could greatly enhance the healthcare industry. Implementation strategies include (1) the co-design and co-evolution of AI models and wearable sensors for efficient modeling and low-cost and miniaturized wearable devices; (2) the incorporation of blockchain in a decentralized, privacy-preserving, and trustworthy chronic health data ecosystem; and (3) theoretical studies on AI and deep learning with personalized chronic health data. Fully transformations of the healthcare industry emphasize wellness and health in the earliest stages of the disease.

8.2. Policy Implications

The growing burden of chronic disease is a key challenge facing health systems globally, particularly in light of the COVID-19 pandemic and the challenges it has created for the conduct of routine medical care and management of non-COVID-19 diseases. The pandemic has led to relatively large increases in the burden of chronic disease in population cohorts that were affected the most, and addressing that burden will be important to prevent wide scale adverse patient outcomes. Further, public and health policy makers are seeking to reduce the burden on property funded publicly supported health insurance systems. A key strategy to address these issues is the enhancement of Population Health Management (PHM) systems to support systematic identification of cohorts at risk of future adverse events, and increases in health system resource utilization in the context of chronic disease management across the care continuum of prevention, early intervention, patient education and self-management support, and timely multidimensional patient-centered interventions. There is a double challenge required to achieve this aim. Firstly, much better and broader data is required for routine identification of cohorts at disease risk, quality management of disease cohorts, assessment of the impacts of intervention programs and policy, and short- and long-term health prediction and future forecasting to inform health policy decision making. Secondly, better methods are required to mine the data to develop predictive models and to fully understand the reasons behind the predictions. Eventually, the insights need to be integrated into the health system through targeted user interfaces to support clinical workflows . Responses to both challenges are being actively pursued, often independently. This paper brokers a conversation about rethinking the integration of data and methods into end-to-end systems that improve patient outcomes and transform health care.

9. Conclusion

In summary, leveraging Machine Learning (ML) and Big Data Analytics (BDA) in health care, especially chronic disease management, is needed more than ever. The proposed pipeline, use cases, frameworks, and feasibility studies can raise the stakeholders’ awareness of elevated chronic diseases and guide further focus. This framework can unite researchers and physicians to tackle chronic diseases. It can be continuously updated to keep pace with advances in technologies and deepening insight into chronic diseases. This is a need-of-the-hour and exciting opportunity for interdisciplinary fellows to work together.

A novel computational approach based on a hybrid of ML and BDA was proposed and it was found that this approach can successfully and retrospectively derive insights from electronic health record (EHR) data of patients diagnosed with T2DM to discover predictive variables regarding the prescribed therapeutic regimens and their outcomes even in this big data era. This knowledge can be transformed into supportive smart decision rules on treatment class assignment in a CDSS format and could be smartly integrated with commercial EHR systems to directly support chronic disease care in the real world. These developments would contribute positively to the rise of decision support systems driven by artificial intelligence. Fine-tuning analysis was performed to identify potential points of improvement in terms of the drug usage and clinical outcomes, demonstrating that the proposed framework can be applied beyond just drug treatment support.

It may be now the time for this class of methods and applications to bear fruit for chronic disease care, as once again reaffirmed during the pandemic. Machine learning and big data analytics complement the digitization of health care systems. At the same time, it is also critical to consolidate the necessary infrastructure for data governance to keep personal information protected, while releasing the potential of carefully handled health data. The research may further analyze drug use time series data to determine structural change points, transition rules for prescription changes, or time-series prediction of drug effects on glycated hemoglobin levels. These methods could be adapted to help in health care delivery design, drug repurposing, or the discovery of drug side effects on a more macroscopic scale.

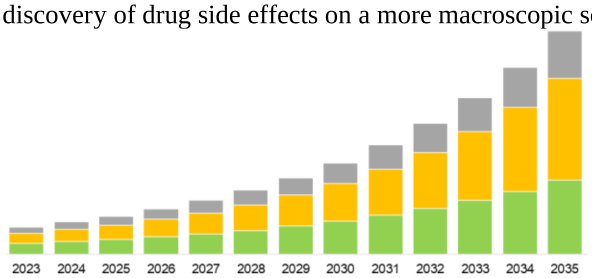

Fig 6: Integrating machine learning and big data in chronic Disease management

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