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Review of Machine Learning Models for Healthcare Business Intelligence and Decision Support

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Abstract: The use of machine learning (ML) has probable to revolutionize healthcare, enabling the extraction of meaningful insights from complex and heterogeneous datasets. The capacity of healthcare systems to facilitate evidence-based decision-making is improved through the integration of many data sources, such as medical imaging, electronic health records, patient-generated, genomic profiles, data, and administrative information. Supervised, unsupervised, and reinforcement learning approaches facilitate accurate diagnosis, risk prediction, patient stratification, and personalized treatment recommendations, while ensemble methods improve predictive robustness and reliability. Machine learning applications extend to operational domains, optimizing patient flow, resource allocation, and appointment scheduling, thereby improving efficiency and reducing costs. Clinical decision support systems benefit from adaptive and real-time analytics, enabling timely interventions and improved patient results. The convergence of ML with business intelligence in healthcare allows stakeholders, including clinicians, administrators, and policymakers, to leverage data-driven strategies for both patient-centered care and institutional management. This review synthesizes current methodologies, applications, and emerging opportunities, delivering a complete resource for researchers and practitioners seeking to employ ML in healthcare business intelligence and decision support.

Keywords: Machine Learning, Healthcare Business Intelligence, Decision Support Systems, Clinical Decision Support, Personalized Medicine, Predictive Analytics.

1. Introduction

Business intelligence for healthcare centers upon combining and analyzing data from many sources counting medical imaging, electronic health records (EHRs), lab outcomes, genomic sequences, and real-time streaming data [1]. These datasets, when integrated with ML models, provide predictive and prescriptive insights that are used in the decision to make evidence-based better patient care decisions. By combining supervised, unsupervised, and reinforcement learning, health systems can make informed decisions in predicting disease, identifying unexplained patterns in data, and providing personalized recommendations for patients. These opportunities in learning either improved clinical decision making or improved operational efficiency of the health system. Machine learning has proven to be a disruptive technology in healthcare, enabling the accurate and rapid analysis of vast volumes of clinical, administrative, and diagnostic data [2]. There are developments in healthcare data, increasing amounts of data, sufficient computational power, and business intelligence (BI) and decision support systems (DSS) that have open new pathways to data intelligence whereby stakeholders including clinicians, administrators, and policymakers can use decisions, actions to impact daily clinical practice; to have insights into new strategies, and utilize data to achieve better patient care outcomes [3]. The function of ML models in healthcare business intelligence (BI) and decision support [4]. It reviews important methods, applications, data sources, and challenges while pointing to prospects for future research and practice.

Incorporating ML into decision support systems has been especially useful in dealing with the unpredictability of current healthcare landscapes [5]. Decision-making has, historically, often been informed by human judgment that relied on rules and processes that were not effective in dealing with data that could be both high-scale, high-dimensional, and heterogeneous. ML-based DSS, on the other hand, can adapt better to new environments, take both structured and unstructured data into account, and provide scalable and more reliable/consistent solutions, as these flaws were often related to human imperfection/limitations. This review discovers ML models role in healthcare BI and DSS by examining key methods, applications, data sources, and implementation challenges while highlighting opportunities for future research and practice [6]. There are still serious and important barriers to the widespread adoption of ML, including data quality, interoperability, scalability, and interpretability [7]. By synthesizing current knowledge and emerging trends, it provides a useful resource for practitioners, researchers, and policymakers seeking to leverage ML to strengthen healthcare delivery and support data-driven decision making.

1.1. Structure of the Paper

This study is organized in the following way: Section II outlines healthcare data sources; Section III reviews ML approaches for BI; Section IV examines applications in decision support, patient flow, and personalized medicine; Section V highlights literature, challenges, and future directions; and Section VI concludes with recommendations for effective ML integration in healthcare BI and DSS.

2. Healthcare Data Sources and Characteristics

Healthcare data originates from diverse sources, each with unique characteristics that influence the application of ML models in business intelligence and decision support. These datasets vary in format, volume, and quality, creating both opportunities and challenges for analysis. Effective integration and preprocessing of such data are essential for obtaining accurate insights and making reliable decisions.

- **Electronic Health Records (EHRs)** – Structured and unstructured patient information, including demographics, diagnoses, lab results, and clinical notes.
- **Medical Imaging Data** – Radiology, pathology, and other imaging modalities offering high-dimensional data for diagnostic support.
- **Genomic and Omics Data** – Genetic sequencing and molecular-level information used for personalized medicine and disease prediction.
- **Patient-Generated Data** – Data from wearables, sensors [8], and mobile health applications providing continuous monitoring.
- **Administrative and Operational Data** – Hospital billing, scheduling, and resource utilization records for BI and optimization.

2.1. Electronic Health Records (EHR)

Electronic health record systems are currently required by law in the US [9]. Healthcare providers and organisations are referred to as "providers" in this article, and the lead agency in this change has been the Centers for Medicaid and Medicare Services. Nevertheless, there are monetary significances for noncompliance if the EHR is not implemented. An outdated system has been serving as an electronic health record (EHR) for many clinicians. Hybrid EHRs are the norm, and some providers' service lines or divisions may not have their own dedicated informatics system. They also lack systems that can communicate with computers in other parts of the company, such as those in the lab or pharmacy. While some providers may have integrated informatics systems in some departments (e.g., billing or lab), the reporting capabilities may not be adequate to meet the objectives of the business or accreditation criteria, necessitating manual report creation. The following healthcare informatics concerns, both administrative and clinical, motivate providers to prioritize the procurement and implementation of certified electronic health records (EHRs)

2.2. Medical Image Processing

With the advent of more reliable 3-D medical imaging, a new era of scientific and medical breakthroughs is within reach [10]. The rapid and continuous development of computerized medical image visualization has propelled it to the forefront of scientific imaging. The two-dimensional picture signal could be anything from a photograph to a piece of text to a graphic (including a synthetic image), a satellite image, a medical image (such as an X-ray, ultrasound, MRI, CT-scan), etc. In the first step, a picture scene is used as input, and a digital image is produced as output. Both the input and the output in the second step of processing are digital images, with the result being an improved version of the input. At this point, the input is still a digital picture, but the output is a content description. An example image processing job is depicted in Figure 1, which is a block diagram.

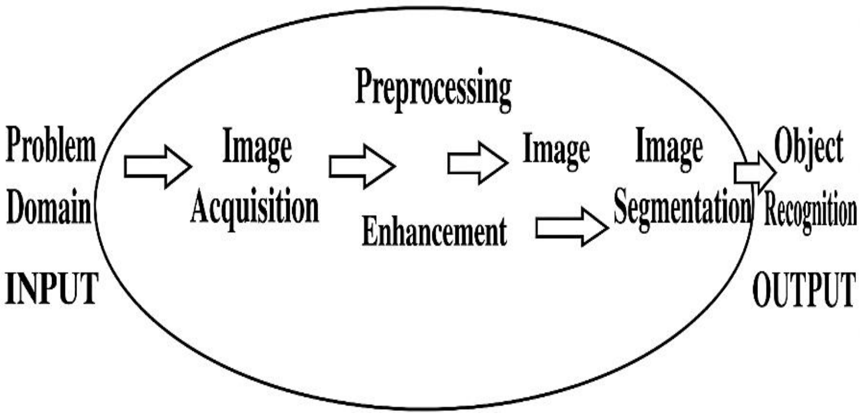

Figure 1: Procedures for preparing images

2.3. Patient-Generated Data

A framework describing the context and usage of PGHD by providers can be developed through the identification of difficulties and possible techniques to working with PGHD [11]. It can observe the three stages of the PGHD process, capture, transfer, and review, in Figure 2.

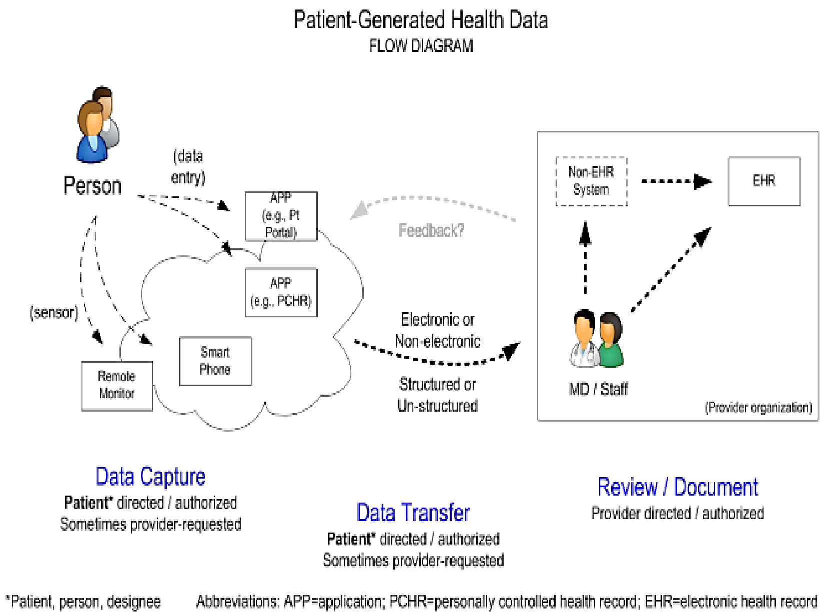

Figure 2: Health Data Flow Generated by Patient

- **Data capture** pertains to the patient's or representative's development and storage of health records, which could comprise:
  - textual information entered using a computer's keyboard or another input device
  - data entered verbally using a microphone, and/or
  - health and/or environmental information captured by a tracking gadget.
- **Data transfer** means that the patient or their representative will share the collected data with an individual working on their healthcare team. Information can be shared using secure email or other Internet-enabled ways, or it can be spoken over the phone, in person, etc.
- **Data review** means making a decision based on the facts or information received by a provider or staff member. The decision to reject, document, or distribute data is based on the data's source, quality, and usefulness for clinical decision-making.

Bioenergy refers to electricity and gas that is generated from organic matter, known as biomass. This can be anything from plant and timber to agriculture and food waste and even sewage. Bioenergy includes the production of fuel from organic matter as well. Energy from biomass can be used for electricity, heating, and transportation, and can be replenished anywhere. Around seventy-five percent of the world's renewable energy is composed of biomass energy due to its potential and wide use [7]. Also, it is carbon-neutral, meaning that it adds no net carbon dioxide to the atmosphere. In addition, it reduces the level of trash in the ground by as much as 90 percent by burning solid waste. Biomass fuels, on the other hand, are not completely clean and can also cause deforestation. They are also less efficient than fossil fuels. But proper management and planning of its disadvantages will improve its potential. Bioenergy refers to electricity and gas that is generated from organic matter, known as biomass. This can be anything from plant and timber to agriculture and food waste and even sewage. Bioenergy includes the production of fuel from organic matter as well. Energy from biomass can be used for electricity, heating, and transportation, and can be replenished anywhere. Around seventy-five percent of the world's renewable energy is composed of biomass energy due to its potential and wide use [7]. Also, it is carbon-neutral, meaning that it adds no net carbon dioxide to the atmosphere. In addition, it reduces the level of trash in the ground by as much as 90 percent by burning solid waste. Biomass fuels, on the other hand, are not completely clean and can also cause deforestation. They are also less efficient than fossil fuels. But proper management and planning of its disadvantages will improve its potential.

3. Machine Learning Approaches in Healthcare BI

ML approaches are key to the business intelligence (BI) and decision support functions of healthcare by maximizing the ability to pull actionable insights from complex, high-dimensional medical datasets in Figure 3. Techniques for include neural networks, supervised learning, decision trees (DT), support vector machines (SVM), and regression [12], are commonly employed for diagnosis, risk assessment, and outcome prediction [13]. Unsupervised learning approaches, such as clustering, dimensionality reduction, and association rule mining, are frequently used for patient stratification, disease or condition subtyping, and identifying hidden or subtle patterns in clinical data. Reinforcement learning methods can provide real-time and adaptable decision-making capabilities and have been utilized for personalized treatment recommendations and the real-time allocation of healthcare resources, taking into account uncertainty in the healthcare environment. Additionally, improve the accuracy and resilience of predictions using ensemble learning methods that combine numerous models, making them particularly useful in clinical decision support systems. The above-mentioned approaches have further enhanced healthcare BI through improved diagnostic accuracy, improved efficiency and effectiveness, and improved delivery of patient-centered care.

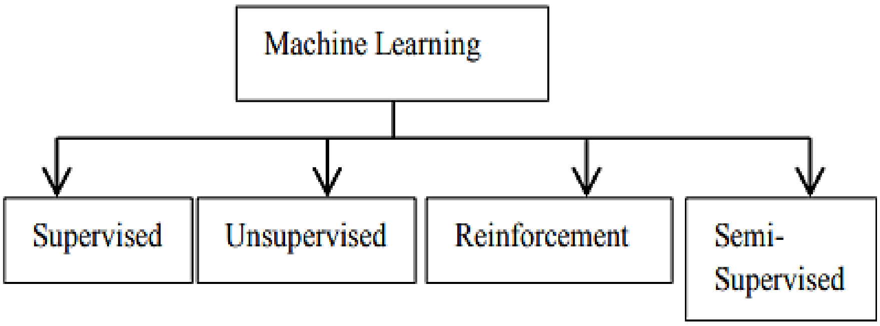

Figure 3: Machine Learning Classification Techniques

3.1. Supervised Learning Models

Supervised learning uses labelled clinical datasets to generate predictions from unlabeled data, it has been popular in healthcare business intelligence (BI) and decision support [14]. Supervised learning provides models that learn from training data that consist of input features and known outcomes. Supervised learning would help healthcare systems provide early diagnosis, predict disease state progression, and assist in personalized decision-making by learning input-output relationships.

- **Regression Models:** Linear and logistic regression models have been among the first methodologies used in healthcare analytics. Long hospital stays and healthcare costs are examples of continuous variables that are best modelled using linear regression [15]. When it comes to healthcare categorization tasks, logistic regression is the approach of choice, such as predicting the presence of a disease or identifying risk factors associated with it.
- **Decision Trees and Random Forests:** Branching tree-based methods provide an order to the decisions made in diagnostic/prognostic help, and the clinician can see the thought process. These have been developed for various procedures, including disease diagnostics, patient triage, and hybrid inventories. RFs - an ensemble of branch trees - have been shown to improve accuracy, decrease overfitting, through generalizability.

3.2. Unsupervised Learning Models

Unsupervised learning models are becoming increasingly relevant in healthcare business intelligence (BI) and healthcare decision support, especially in scenarios where labeled clinical data are either unavailable or too expensive to obtain, as needed in supervised analysis methods [16]. Unsupervised learning models establish and detect relationships, structures, or patterns from large-scale, heterogeneous data in healthcare to support exploratory analysis, knowledge discovery, and patient classification or stratification. Unsupervised methods aim to identify existing groupings and reduce dimensionality but, they do not consider any outcomes. Therefore, they are especially relevant to medical research and clinical understanding.

- **Clustering Methods:** Clustering methods including K-Means, Hierarchical Clustering, and Density-Based Spatial Clustering (DBSCAN) have a strong use in health. They can be employed to identify groups of hospital patients with similar clinical characteristics, subpopulations in epidemiological studies, and cluster patients to develop targeted treatment plans.
- **Dimensionality Reduction Techniques:** Healthcare datasets are frequently high-dimensional, with thousands of attributes derived from electronic health records, genomic sequences, or medical images. Techniques for dimensionality reduction, including Independent Component Analysis (ICA), t-Distributed Stochastic Neighbor Embedding (t-SNE), and Principal Component Analysis (PCA) have been utilized to reduce dimensionality while retaining the relevant data.
- **Association Rule Mining (ARM):** ARM represents another unsupervised method for identifying co-occurrence patterns in healthcare data such as relationships between comorbidities, prescribing drug interactions, and commonly occurring disease symptoms.

3.3. Reinforcement Learning Models

Numerous healthcare fields have thus far seen the successful application of RL techniques [17]. There are three main categories into which these application domains fall: automated medical diagnosis, health management, drug development and discovery, scheduling and distribution of resources, and optimal process control. Furthermore, there are dynamic treatment regimens for chronic diseases and critical care. This survey is structured according to the three primary areas of study in the discipline, as shown in Figure 4, which is a schematic describing the application domains.

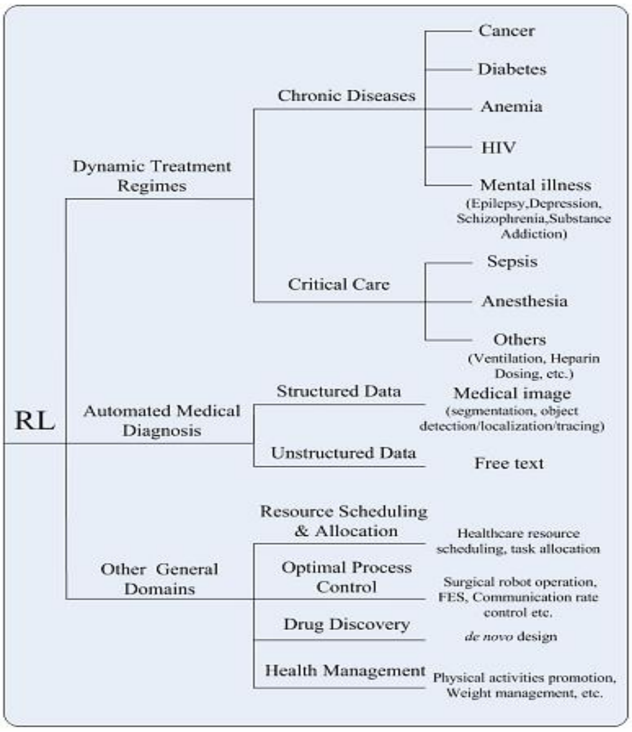

Figure 4: The healthcare application domains of RL are outlined

4. Applications of Ml in Healthcare, Bi, and Dss

Use cases for machine learning in healthcare business intelligence (BI) and decision support systems (DSS) encompass a range of applications related to clinical, operational and patient-centered activities, while enabling more accurate, timely and personalized care [18]. In the clinical setting, machine learning contributes to areas such as disease diagnosis, prognosis, and risk stratification, enabling clinicians to make evidence-based decisions. In an operational area, ML models, for example, facilitate better resource allocation, determine patient scheduling, and streamline hospital workflows, thus ultimately improving efficiency and saving costs. Machine learning-driven applications also aid in personalized medicine by providing treatment recommendations, predicting patient drug responses, and enabling continuous patient monitoring, which enables clinicians to make timely decisions and provide personalized interventions. Applications of machine learning in DSS also expand into population health management, detection of adverse events and planning for preventive care, all of which can improve patient safety and long-term health outcomes [19]. These examples collectively highlight how ML plays a highly strategic role in converting raw healthcare data into actionable information for decision-making at the clinical and organizational levels.

4.1. Clinical Decision Support

The degree to which the user is able to influence the choice to use CDS varies across CDS systems. Both the setup for the CDS to be displayed on demand, giving users complete control over whether or not to access it, and the conditions under which users might accept it after viewing it are considerations that fall under this category [20]. Both parts of control are interdependent and have to do with how well the CDS recommendation lines up with the clinician's goal. CDS can be programmed to do things like remind doctors of their plans, give them information when they're confused, fix their mistakes, or suggest they alter their plans. From this perspective, it's easy to see how users' reactions to CDS could vary depending on their goals. Common desktop computer apps serve as an example of this type of parallel. The calendar alarm is a feature that appears automatically whenever a person uses the calendar capabilities on their computer to remind them of an upcoming task.

4.2. Patient Flow and Scheduling Optimization

Delays can be greatly reduced with well-planned patient flows and appointments, optimizing the utilization of hospital resources, and enhancing the overall quality of care [21]. Machine learning models enable predictive and adaptive approaches that optimize appointments, admissions, and discharges. These systems help balance patient needs, staff workload, and institutional capacity.

- **Predicting Patient Demand –** Regression and time-series models forecast admissions, outpatient visits, and peak demand periods.
- **Appointment Scheduling –** ML algorithms minimize no-shows, optimize time slots, and reduce waiting **times.**
- **Resource Allocation –** Decision trees and reinforcement learning adjust staff availability and bed management dynamically.
- **Patient Grouping –** Clustering techniques categorize patients by service needs, ensuring priority-based scheduling.
- **Operational Efficiency –** Automated scheduling systems reduce bottlenecks, lower costs, and improve patient satisfaction.

4.3. Personalized Medicine

Personalized medicine leverages ML to tailor healthcare treatments, choices, and treatments based on the specifics of each patient [22]. By analyzing clinical histories, genetic profiles, and real-time health data, ML models enable more accurate predictions of treatment outcomes [23]. This approach enhances precision, reduces adverse effects, and supports proactive care strategies.

- **Treatment Recommendation –** ML models suggest individualized therapies based on patient-specific data.
- **Drug Response Prediction –** Predictive analytics assess likely efficacy and side effects for medications.
- **Genomic Analysis –** Algorithms identify genetic markers linked to disease susceptibility and treatment response.
- **Real-Time Patient Monitoring –** Wearable and IoT data integration supports continuous, adaptive care.
- **Risk Stratification –** ML techniques categorize patients into subgroups for targeted preventive measures.

5. Literature Review

This literature Summary highlights progressive advancements in machine learning for healthcare business intelligence and decision support, emphasizing multimodal data integration, predictive modeling, classification techniques, and big data analytics, while addressing key challenges and proposing future directions for enhanced clinical applicability. Carvalho et al. (2019) a comprehensive literature analysis of ML approaches used to PdM, illuminating the methodologies now under investigation and evaluating the efficacy of cutting-edge ML tools. With an emphasis on two scientific databases, this review lays a solid groundwork for future research in the PdM area by outlining the ML methodologies, their primary outcomes, obstacles, and potential. Data collected from manufacturing processes has increased at an exponential rate due to the proliferation of sensing technology. Through processing and analysis, data can be utilized to derive valuable insights and knowledge from production systems, equipment, and processes. Companies can't afford to skimp on machinery maintenance, since it directly impacts the machines' longevity and efficiency [24].

Bote-Curiel et al. (2019) found information in EHRs, MTSs, and MRIs; secondly, a particular area of application is highlighted, with an emphasis on the analysis of electrocardiographic signals, which has seen a flurry of publications over the past two years. The publicly-available MIMIC dataset includes a set of sample toy applications to give beginners a leg up with organized, some basic, and principled content and code. They give a critical analysis of the present and future problems with using both sets of methods in healthcare [25]. Harerimana et al. (2018) provide healthcare big data analytics, including the most pressing issues, relevant data sources, methods, tools, and potential future developments. A comprehensive, simplified, and simply accessible overview of the many technologies utilized in the development of an integrated health analytic application can be provided by means of a do-it-yourself study. Clinical decision support systems, genomic data, medical pictures, cyber-physical systems, electronic medical records, and computerized physician order input, the medical Internet of Things, and a plethora of other sources are contributing to the exponential growth in the volume and complexity of health data [26].

Chen et al. (2017) AI-powered systems for accurate forecasting of chronic illness epidemics in populations prone to such diseases. employing up-to-date prediction algorithms to evaluate data collected from hospitals in central China from 2013 to 2015. To overcome the issue of missing data, one could use a latent factor model to fill in the gaps. conducted the study on a chronic disease of the brain that is localized and affects the brain. They might propose a new multimodal disease risk prediction method based on convolutional neural networks (CNNs) utilizing both structured and unstructured hospital data. As far as they are aware, no prior study in medical big data analytics has combined the two forms of data [27]. Somvanshi et al. (2016) it provides a concise overview of data mining classification using ML methods. DT and SVM are two examples of the machine learning techniques that are crucial to all AI applications. While support vector machines (SVMs) can construct nonlinear borders among classes, decision trees are more effective with discrete data. Each of these methods excels at something specific, making them useful for a wide variety of categorization problems [28].

Belle et al. (2015) address these pressing issues by directing attention to three exciting new directions in medical research: analytics based on images, signals, and genomes. The article discusses recent studies that aim to use massive amounts of medical data by integrating multimodal data from many sources. Additionally, they take a look at some of the possible future directions for study in this area that could have a significant influence on healthcare delivery. Current healthcare systems generate vast amounts of diverse, organized, and unstructured data; they have provided tools to gather, manage, analyze, and integrate this data. Care delivery and illness research have both benefited from the recent application of big data analytics [29]. Table I summarizes key studies on machine learning models for healthcare business intelligence and decision support, outlining research focus, methodologies, findings, challenges, and future directions, offering a comprehensive overview of advancements.

Table 1: Summary of a Study on Machine Learning Models for Healthcare Business Intelligence and Decision Support

Author	Study On	Approach	Key Findings	Challenges	Future Directions
Carvalho et al. (2019)	ML methods applied to Predictive Maintenance (PdM)	Systematic Literature Review across two databases	Identified state-of-the-art ML techniques and their performance in PdM	Limited coverage of diverse databases; integration gaps	Expand database sources, refine PdM applications with ML
Bote-Curiel et al. (2019)	ML in healthcare focusing on ECG analysis	Applied ML on EHR, time signals, and images using MIMIC dataset	Provided practical examples and structured material for beginners	Handling diverse healthcare data types	Advance ML integration in ECG and broader healthcare
Harerimana et al. (2018)	Big Data Analytics in healthcare	Holistic review of data sources, technologies, and techniques	Simplified view of integrated health analytics applications	Complexity and variety of data sources (EHR, IoT, genomic, images)	Develop scalable integrated health analytic systems
Chen et al. (2017)	ML for chronic disease prediction	CNN-based multimodal disease risk prediction using structured + unstructured hospital data	Improved prediction accuracy using latent factor model for missing data	Incomplete/missing data and multimodal integration	Broader application of multimodal ML for big data in healthcare
Somvanshi et al. (2016)	Data mining classification techniques	Survey of Decision Tree and SVM in ML classification	Both models perform well, with different strengths (DT for discrete, SVM for nonlinear boundaries)	Each method has dataset-specific limitations	Combine multiple ML methods for stronger classification
Belle et al. (2015)	Big data analytics in healthcare (image, signal, genomics)	Analysis of multimodal data integration approaches	Highlighted potential of big data for improving healthcare delivery	Managing heterogeneous, large-scale healthcare data	Expand multimodal ML approaches for precision healthcare

6. Conclusion and Future Work

ML has become a pivotal technology in healthcare, enabling the transformation of complex, heterogeneous datasets into actionable insights for decision-making and operational management. Healthcare systems may optimize resource allocation, improve patient flow, and deliver personalized treatment plans by integrating supervised, unsupervised, and reinforcement learning techniques. This improves diagnostic accuracy. Predictive and prescriptive analytics which inform treatments based on evidence are made possible through the integration of data from administrative systems, genomic profiles, patient-generated sources, medical imaging, and electronic health records. Personalized medicine, clinical decision support, and patient scheduling are just a few examples of how ML is changing healthcare industry for the better.

Problems with data quality, interoperability, scalability, and ethical issues like openness and privacy persist despite these improvements. Additionally, limitations including the generalizability of models across populations and dependency on high-quality data may affect performance, requiring careful validation and ongoing refinement to ensure practical and reliable deployment in diverse healthcare environments. Future work should focus on developing interpretable, scalable, and ethically robust frameworks that integrate heterogeneous healthcare data. Emphasis on real-time patient monitoring, explainable AI, and collaborative approaches among clinicians, data scientists, and policymakers can enhance personalized medicine, optimize operational workflows, and ensure equitable, reliable, and clinically relevant decision support systems.

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