Machine Learning for Evidence-Based Telehealth and Smart Care

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Contributor: Stella C. Christopoulou

Clinical studies have utilized machine learning in telehealth and smart care for disease management, self-management, and managing health issues like pulmonary diseases, heart failure, diabetes screening, and intraoperative risks. Machine learning combined with the application of evidence-based practices in healthcare can enhance telehealth and smart care strategies by improving quality of personalized care, early detection of health-related problems, patient quality of life, patient-physician communication, resource efficiency and cost-effectiveness.

Keywords: machine learning ; evidence based ; smart care ; telehealth ; algorithms ; artificial intelligence

1. Introduction

Machine learning (ML) is a subcategory of artificial intelligence (AI) that enables computers to learn and make decisions without explicit programming. It involves developing algorithms and models that analyze and interpret data, identify patterns, and make informed predictions. It has applications in fields like image recognition, natural language processing, recommendation systems, and predictive analytics. AI, a broad term, encompasses various techniques and approaches, including ML and deep learning.

ML algorithms are divided into several types, each with its own approach and purpose. Supervised learning involves training an algorithm on labeled data, unsupervised learning trains an algorithm on unlabeled data, reinforcement learning involves agents learning through trial and error, semi-supervised learning combines supervised and unsupervised learning, and deep learning uses artificial neural networks to represent complex patterns in data.

Healthcare ML is a powerful tool that can improve patient care and outcomes by aiding in disease diagnosis, analyzing medical images, predicting patient outcomes, optimizing workflows, identifying high-risk patients, and providing personalized medicine. The field is constantly evolving, with new applications being explored to improve patient care, enhance diagnostics, and streamline healthcare processes.

1.1. Evidence-Based Telehealth and Smart Care

Telehealth (or telemedicine), as defined in MeSH terminology [1], refers to the provision of health services through remote telecommunications. This includes interactive consulting and diagnostic services. Telehealth can include various methods such as video consultations, remote monitoring of vital signs, and the use of mobile apps or messaging platforms for communication between patients and healthcare providers.

Alongside telehealth, smart care (SC) is a health services system that uses technology like wearable devices, IoT, and mobile internet to dynamically access information, and connect people, materials, and institutions that are related to healthcare [2]. It eliminates delays in identifying patient records, improves information exchange among parties, and encourages patient active participation in treatment. SC aims to manage clinical data effectively, ensuring efficient and effective healthcare services.

Moreover, evidence-based healthcare (or evidence-based practice) is a method of healthcare that integrates scientific knowledge with clinical expertise [3]. It involves assessing research data, clinical guidelines, and other resources to identify clinical problems, apply high-quality interventions, and re-evaluate outcomes for improvement. This approach aims to use the best available evidence from scientific research to inform decision-making and improve patient outcomes.

Subsequently, EBHI (evidence-based health informatics) is a field that supports health information technology platforms and e-health interventions [4]. It involves the synthesis of optimal evidence from clinical trials for decision-making on HIT introduction and operation [5]. EBHI is crucial for physicians' support in clinical decision-making, relying on accurate data from rigorous studies [6].

EBHI has significantly impacted telehealth and smart care, with a significant increase in physicians recognizing the benefits of digital health tools. An American Medical Association (AMA) study found that the percentage of physicians who believe digital health tools are advantageous for patient care grew from 85% in 2016 to 93% in 2022 [7]. The largest growth in adoption occurred in remote care tools, with tele-visits/virtual visits and remote monitoring devices increasing from 12% in 2016 to 30% in 2021.

1.2. Machine Learning

There are several types of ML algorithms, each with its characteristics and applications. Here are some common types:

- *Supervised Learning (SL) Models*: These models learn from labeled data to make predictions or classifications. SL is a machine learning paradigm where input objects and desired output values are used to train a model [8]. The model maps new data on expected output values, ensuring the algorithm can correctly determine output values for unseen instances. The statistical quality of an algorithm is measured through the generalization error. SL models learn from labeled training data, aiming to find patterns in the data to predict target variables for new, unseen data. Common supervised learning algorithms include linear regression, decision trees, SVMs, neural networks, random forests, logistic regression, and naive bayes.

- *Unsupervised Learning (UL) Models*: Unsupervised learning is the process of grouping data into clusters using automated algorithms to learn underlying relationships or features [9]. Common UL models analyze unlabeled data to discover hidden patterns or structures. Common algorithms include clustering, dimensionality reduction techniques, and association rule learning. Unlike supervised learning, UL learns patterns exclusively from unlabeled data, aiming to build a concise representation of the world through mimicry, generating imaginative content from unlabeled data.

- *Reinforcement Learning (RL) Models*: RL is a model that involves discrete environment states, agent actions, and scalar reinforcement signals. It differs from supervised learning by not presenting input/output pairs and requiring agents to gather experience [10]. It focuses on finding a balance between exploration and exploitation, aiming to maximize long-term rewards, and is closely related to artificial intelligence search and planning issues.

- *Deep Learning (DL) Models*: DL is a rapidly growing machine learning technique that has significantly impacted human life through applications like virtual personal assistants and automated number-plate recognition, but it also faces challenges and controversies [11]. Deep learning (DL) algorithms are neural networks used to learn hierarchical data representations. They can be supervised, semi-supervised, unsupervised, or reinforcement based. Common DL algorithms include CNN for image analysis, RNN for sequential data analysis, and LSTM for time series data, particularly effective in image and speech recognition.

2. Machine Learning for Evidence-Based Telehealth and Smart Care

Classification of Machine Learning Models Based on Their Specific Applications

In the healthcare domain, ML models can be classified into various types based on their specific applications. The following are the most common types of them:

Diagnostic models are tools used to diagnose diseases or conditions by analyzing patient data [12].

Prognostic models predict future outcomes or progression of diseases by estimating the likelihood of certain events [13].

Treatment recommendation models help healthcare professionals make treatment decisions and provide available treatment options [14].

Patient Risk stratification models assess the risk of developing certain diseases or conditions by identifying individuals at higher risk, allowing for targeted interventions and preventive measures [15].

Patient monitoring models continuously monitor patient data to detect deviations from normal patterns and alert healthcare providers to potential issues [16].

Healthcare resource allocation models optimize resource allocation by analyzing patient flow, resource utilization, and demand patterns. These models consider factors like patient characteristics, medical history, and treatment options, enabling informed decisions. They also incorporate guidelines and evidence-based practices to provide personalized treatment plans. By leveraging technology and data-driven approaches, healthcare professionals can optimize resource allocation and improve patient outcomes [17].

Machine Learning Sectors in Evidence-Based Telehealth and Smart Care

Category I, as classified by HCs classification system, which includes:

- *Disease diagnosis/management healthcare sector*: Approaches identified in this sector mainly belong to two studies on the supervised machine learning approach [13][15], one study on the deep learning approach [12], one study [18] on all approaches, and one more study [19] that uses statistical analysis, the backbone of ML, but does not describe an ML approach clearly.

  Basically, this sector uses algorithms that can be trained on labeled medical data to classify and diagnose diseases based on symptoms, medical images, or patient data. These algorithms are being used in various fields, including cancer diagnosis, cardiovascular disease diagnosis, diabetes diagnosis, respiratory disease diagnosis, and neurological disease diagnosis.

  The study in ref. [12] uses logistic regression analysis to compare the performance of deep learning black boxes with classical statistical approaches. It uses univariate and multivariate analyses, including logistic regression, to understand the relationship between input features and classification results. This helps in comparing the performance of these models with classical statistical approaches.

- *Disease clustering and subtyping healthcare sector*: Approaches identified in this sector belong two studies on the supervised machine learning approach [13][20]; one study (as described in two articles) on the unsupervised approach [21][22]; one jointly examining supervised, semi-supervised, and unsupervised machine learning approaches [23]; and one more with an unclear approach [19].

  Disease clustering and subtyping is a method of identifying patterns or groups within a disease population based on specific characteristics, such as clinical features or genetic markers. This helps researchers understand the disease's heterogeneity and potentially identify different disease mechanisms or treatment approaches for each subtype, thereby improving their understanding of the disease [23].

  Disease clustering involves using unsupervised and etiology-independent clustering analysis to identify patient groups with similar characteristics or disease patterns. This method uses machine learning techniques to classify patients into distinct phenogroups based on clinical characteristics and treatment responses [13]. More specific ML has been applied to disease subtyping in various types of diseases. Some examples include multiple sclerosis (MS) [23], and chronic obstructive pulmonary disease (COPD) [20].

- *Anomaly detection healthcare sector*: One study [23] is identified in this health sector that mainly belongs to the supervised machine learning approach.

- The development of anomaly detection algorithms in health and medicine is crucial for identifying deviations from normal patterns, aiding in the early diagnosis of health conditions. More specifically, it helps in identifying outliers in physiological signals, abnormal heart rate variability, and unusual patterns in patient data, such as changes in speech or language [24].

Category II, as classified by DHIs classification system, which includes:

- *Electronic health records (EHR) healthcare sector*: Approaches [17][25] identified in this health sector mainly belong to the supervised machine learning approach.

  The supervised learning approach in the EHR sector uses algorithms that can analyze large volumes of patient data from electronic health records including medical history, lab results, medications, and demographics.

  The results can help identify high-risk patients, predict patients' results, support clinical decisions, monitor diseases, and more generally support in the health management of the population and the improvement of the supply of health care.

- *Telemedicine healthcare sector*: Approaches identified in this sector belong to the supervised machine learning approach [15][25][26], to the reinforcement machine learning approach [27], to the supervised and deep machine learning and neural networks approaches [28], and to an unclear approach [19].

  More specifically, supervised learning algorithms can be employed in telemedicine applications to analyze patient data collected remotely and provide diagnostic recommendations or monitor disease progression [15][25][26].

  Moreover, the deep learning approach can analyze data from wearable devices, detect anomalies, and provide personalized health recommendations. This approach enables remote monitoring and the early detection of health issues [28].

- *Image analysis healthcare sector*: One study [28] is identified in this sector that belongs to the supervised, deep machine learning and neural networks approaches. This study aims to implement machine learning and artificial intelligence in optimizing healthcare for patients with cardiac implantable electronic devices. This study is an open product, available for additional testing and improvement with supplementary functionalities: quality of life assessment, teleconsultation, video-streaming, and automated image recognition.

- *Patient risk stratification healthcare sector:* In this sector, two studies [14][15] are identified, the first dealing with all types of machine learning and the second with the supervised machine learning approach.

  In these studies, algorithms are used to analyze personal data, identify patterns, and group patients based on their profiles. This approach enables the use of personalized medicine, helps healthcare providers prioritize interventions, and allocates resources effectively. More specifically, in the second study [15] various machine learning algorithms were applied for risk stratification, with the SVM model showing the best prediction performance at 84.7%.

- *Natural language processing (NLP) healthcare sector*: The studies identified in this healthcare sector mainly belong to all types of machine learning methods [18] with an emphasis on the supervised learning approach [16].

  NLP can be used for various tasks such as text classification, sentiment analysis, named entity recognition, machine translation, text generation, and question answering. These techniques classify text, analyze sentiment, extract named entities, and develop translation models. They can also generate human-like text and answer questions based on a given text or knowledge base [18].

  Also, a random forest machine learning algorithm, as a supervised ML approach, that combines multiple decision trees to make predictions was used in three experiments in the study by ref. [16] to show the accuracy of pain scores in chronic cancer patients.

- *Clinical decision support healthcare sector*: One study [19] is identified in this sector, but it is unclear what machine learning approach it supports. Clinical decision support can provide decision support to healthcare professionals by analyzing patient data and recommending appropriate treatment options.

- *Healthcare resource allocation healthcare sector*: One study [15] is clearly identified as managing issues related to the management of limited resources, alongside managing medical issues. Resource allocation is the process of allocating available resources to various uses, particularly in health care. However, at-risk individuals often find it difficult to comply due to the cost of diagnostic tests and scarce medical resources. Resource constraints can affect health care by reducing access to care, compromising quality of care, and limiting treatment options, thus leading to worse health outcomes, and exacerbating existing health disparities. Resource allocation is critical to optimizing productivity, managing costs, and ensuring the strategic use of resources. Thus, beyond the medical issues they cover, many applications in the health field aim to solve the issue of limited resources. For example, BGEM™ is a cloud-based solution that uses advanced machine learning functions to monitor multiple digital biomarkers and provide targeted information to high-risk individuals who would otherwise not have access to the prevention and early treatment of their health problems.

- *Predictive analytics healthcare sector*: Approaches identified in this health sector mainly belong to the supervised machine learning approach [13][17][20][23][29].

  Supervised ML approaches are widely utilized for predictive analytics in healthcare, including predictive analytics for classification, regression, clustering, time series analysis, and recommendation systems [14].

Ref. [17] studies predictive management in healthcare. ML analysis and modeling based on available data have shown promise in predicting outcomes (such as admission and length of stay) for severe COPD exacerbation. These models utilize EHR at triage assessment to make predictions.

Also, the authors of ref. [23] studied supervised, semi-supervised, and unsupervised ML techniques in a multimodal machine-learning-based system for anomaly and fall detection, combining heuristics and hard rules based on acceleration magnitude features.

Category III, as classified by ICHI classification system, which includes:

- *Drug discovery healthcare sector*: In this sector, one study [14] is identified which deals with all machine learning approaches.

  The development of this sector can help identify patterns and relationships in large datasets of chemical compounds, aiding in the discovery of new drugs and understanding their mechanisms of action.

  Supervised learning, reinforcement learning, and deep learning are algorithms used in drug discovery to predict the effectiveness and safety of new compounds. Supervised learning predicts drug efficacy based on molecular structures and biological data, reinforcement learning optimizes candidate selection and design, and deep learning analyzes large datasets to identify potential candidates.

- *Personalized medicine healthcare sector*: Approaches identified in this health sector mainly belong to the supervised machine learning approach [29][30]. Moreover, one study belongs to supervised, deep machine learning, and neural networks [28], and one more study [14] studies all approaches.

  Personalized medicine is used to develop personalized care plans based on individual patient characteristics, optimizing treatment effectiveness, and minimizing side effects.

  Decision trees are often used for specific cases including personalized medicine and treatment recommendations are made based on historical data to guide treatment decisions, benefit–risk judgment, and quality analysis. These tools help weigh different treatments and predict the optimal medication for individual patients, ultimately improving overall patient outcomes [14].

- *Genomics and precision medicine healthcare sector*: In this sector, one study is identified that belongs to the supervised machine learning approach [15].

Machine Learning Algorithms in Evidence-Based Telehealth and Smart Care

- Supervised machine learning algorithms:

  - *A linear classifier*: This is a type of machine learning algorithm that separates data points into different classes using a linear decision boundary. Linear classifiers are used in various cases [15][23] in EBTM and SC. These studies demonstrate the use of linear SVM classifiers in different contexts, such as fall detection and blood glucose level detection.

    A linear classifier classifies data based on a linear combination of input features. In terms of classification, linear classifiers can be classified into two main types: binary linear classifiers and multi-class linear classifiers.

    Binary linear classifiers are used for binary classification tasks, where the goal is to separate data points into two classes. A binary linear classifier is a machine learning model used for binary classification tasks, dividing instances into two classes based on features. It assigns a class label to each instance based on its position on the linear boundary and makes predictions by calculating a weighted sum of feature values [23].

    Examples of binary linear classifiers include logistic regression and SVM with linear kernels [15].

    Multi-class linear classifiers are used for multi-class classification tasks, where the goal is to separate data points into more than two classes. An example of a multi-class linear classifier is the SVM with a linear kernel.

    Mosquera-Lopez et al. [23] discuss the use of support vector machine (SVM) models (the linear SVM classifier and SVM model with a radial basis function kernel) for fall detection.

Specifically, the linear SVM classifier separates classes by finding a hyperplane that maximally separates the data points of different classes in the feature space. It assigns new instances to classes based on which side of the hyperplane they fall on. This type of classifier is commonly used in tasks such as image classification, text categorization, and sentiment analysis [23].

Indeed, according to [15], the SVM can be used as both a binary linear classifier and a multi-class linear classifier.

Overall, linear classifiers are effective for linearly separable data and can provide good performance in many classification tasks.

- *KNN*: KNN is an ML algorithm commonly used for classification and regression tasks in EBTC and SC [12][13][27].

- Reinforcement machine learning algorithms.

  - *Contextual bandit algorithm*: This algorithm is used in an in-home monitoring system to make recommendations based on the caregiver's interaction history, current behaviors, and other observations. It helps increase the utility of the system's recommendations and the acceptance of those recommendations by the end users [29].

- Support of many types of machine learning algorithms.

  - *Machine learning fall detection algorithms*: These algorithms use ML techniques to detect falls. The accuracy of the detector is improved by training the algorithm using real-world fall data from the target population [23].

    This algorithm combines an auto-encoder, which is an unsupervised learning algorithm, and a hyper-ensemble of balanced random forests to detect fall candidates based on acceleration data. The auto-encoder re-constructs the input acceleration signal, identifying fall candidates with a root-mean-square error (RMSE) higher than a certain threshold. The hyper-ensemble of balanced random forests assigns final labels to fall candidates, reducing false positives. This two-stage classification method aims to improve fall detection accuracy in real-world scenarios by combining acceleration and movement features. By combining both acceleration and movement features, this algorithm aims to improve the accuracy of fall detection in real-world scenarios [23].

  - *APPRAISE-RS*: This algorithm is used to develop recommender systems that provide automated, updated, participatory, and personalized treatments. It uses rule-based systems that belong to the symbolic or knowledge-based learning approach and the GRADE heuristic to form recommendations [14]. Specifically, rule-based systems, categorized as supervised, unsupervised, or reinforcement learning, use rules to make decisions or solve problems. They can also be integrated with deep learning models for enhanced performance.

  - *Real-time self-learning algorithm*: This is an algorithm that can continuously learn from and adapt to new data in real time. Real-time self-learning algorithms can be implemented using various methods, such as neural networks, deep reinforcement learning for autonomous driving simulations, and unsupervised learning for real-time learning from unlabeled data.

    The study by ref. [28] is designed to update its knowledge and improve its performance as it receives new information. This type of algorithm is often used in applications where the data are dynamic and constantly changing, such as in online recommendation systems, fraud detection, or autonomous vehicles. The algorithm uses techniques such as online learning or incremental learning to update its model and make predictions or decisions. This algorithm is used in the health care optimization of patients with cardiac implantable electronic devices (CIED).

Machine Learning Tasks used in Evidence-Based Telehealth and Smart Care

In EBTH and SC-related problems, several ML tasks can be used to classify, analyze, and interpret data. These tasks include:

Predictive modeling: This is a powerful tool in machine learning that allows for the development of models that can make predictions based on historical data [15]. ML algorithms are used to predict various outcomes in telehealth, such as predicting exacerbations in patients with COPD based on physiological parameters [17][20].

Classification: ML algorithms can classify patients into different risk categories based on their health data [13]. For example, patients can be classified into high-risk or low-risk groups for developing certain conditions or experiencing exacerbations.

Feature selection: ML algorithms are used to identify suitable features or variables for the prediction of exacerbations [15]. This helps in identifying the key factors that should be monitored and considered in telehealth interventions.

Clustering: ML algorithms are used to group patients with similar characteristics or patterns of symptoms [13]. This can help in personalizing telehealth interventions and tailoring them to the specific needs of different patient clusters.

Anomaly detection: This is a technique used to identify patterns or instances that deviate significantly from the normal behavior of a dataset [23]. ML algorithms may detect anomalies or deviations from expected patterns in patient's physiological parameters.

Regression: Used to predict numerical values or continuous variables, such as predicting the progression of a disease or estimating patient outcomes [30]. For example, predicting the length of hospital stay or the risk of readmission for a patient.

Natural language processing (NLP): This is a field of artificial intelligence that analyzes and extracts information from unstructured text data, such as medical records, clinical notes, or patient feedback [16][18]. It focuses on the interaction between computers and human language. It involves the development of algorithms and models that enable computers to understand patient symptoms, disease progression, treatment plans, treatment effectiveness, and outcomes or adverse events. These algorithms and models can also interpret and generate human language in a way that is meaningful and useful.

Time series analysis: This method involves analyzing data collected to find trends and anomalies. This can be useful in monitoring patient vital signs, disease progression, or treatment effectiveness [15][17][25].

Recommendation systems: This method involves providing personalized recommendations for treatment plans, interventions, or healthcare services based on patient data and historical records. This can help in improving patient outcomes and adherence to treatment plans [14][29].

These ML tasks can be combined and customized to address specific challenges in EBTH and SC, enabling healthcare providers to make data-driven decisions, to improve the effectiveness of telehealth interventions by providing timely alerts, personalized care, and better management strategies.

Functional and Technical Features of ML Systems Technology Applied to Evidence-Based Telehealth and Smart Care

ML system can be used in healthcare to address various health-related problems by leveraging ML algorithms to provide solutions. The following are some commonly used functional and technical features of ML systems technology that are applied to telehealth and evidence-based smart care:

Understanding and analyzing medical data: The ML system can process and analyze large volumes of medical data, including text, audio, and video, to extract valuable insights and patterns [12].

Patient engagement: The ML system can engage with patients, providing them with personalized information, answering their queries, and offering guidance on healthcare topics [17][27].

Fact-checking and information verification: An ML system can ensure access to reliable and up-to-date information through the development of ML algorithms for real-time decision-support instruments. These algorithms are designed to dynamically assess risk, diagnose negative patient trajectories, implement evidence-based practices, and improve outcomes for patients. By leveraging these technologies, the ML system aims to provide evidence-based care and improve the quality-of-care metrics [25].

Integration with databases and patient care directives: The ML system can integrate with databases and patient care directives, allowing healthcare teams to access the most up-to-date information and guidelines [14][19].

Global (multilingual or different accents and dialects) interaction: The ML system can interact with users in multiple languages, enabling clear communication and addressing the needs of a global user base [18].

Customization for specific healthcare challenges: The ML system can be tailored to address the nuanced challenges and questions specific to the healthcare industry, providing customized solutions [27].

These features of the ML system help healthcare organizations improve patient care, enhance operational efficiency, and ensure accurate and reliable information dissemination.

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