INTEGRATING MACHINE LEARNING IN CLINICAL DECISION SUPPORT SYSTEMS

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ABSTRACT

This review article examines the role of machine learning (ML) in enhancing Clinical Decision Support Systems (CDSSs) within the modern healthcare landscape. Focusing on the integration of various ML algorithms, such as regression, random forest, and neural networks, the review aims to showcase their potential in advancing patient care. A rapid review methodology was utilized, involving a survey of recent articles from PubMed and Google Scholar on ML applications in healthcare. Key findings include the demonstration of ML's predictive power in patient outcomes, its ability to augment clinician knowledge, and the effectiveness of ensemble algorithmic approaches. The review highlights specific applications of diverse ML models, including moment kernel machines in predicting surgical outcomes, k-means clustering in simplifying disease phenotypes, and extreme gradient boosting in estimating injury risk. Emphasizing the potential of ML to tackle current healthcare challenges, the article highlights the critical role of ML in evolving CDSSs for improved clinical decision-making and patient care. This comprehensive review also addresses the challenges and limitations of integrating ML into healthcare systems, advocating for a collaborative approach to refine these systems for safety, efficacy, and equity.

KEYWORDS

Clinical Decision Support Systems, Machine Learning, Predictive Analytics, Ensemble Algorithms

1. INTRODUCTION

In the rapidly evolving landscape of modern healthcare, technological advancements play a pivotal role in delivering efficient patient-centered care. However, the healthcare industry continues to struggle with significant challenges - notably medical errors and clinician burnout - which underscore the dire need for innovative solutions. In this context, clinical decision support systems (CDSSs) emerge as a revolutionary technological intervention that can enhance healthcare. These computer systems assist clinicians in making informed decisions by combining medical knowledge, patient data, and algorithms to provide timely context-specific information.

While the advantages of CDSSs are numerous, it is essential to also consider the potential drawbacks to them. One case study, which echoes concerns about CDSSs outlined in other case studies and research articles, is particularly relevant. This case involves a 63-year-old male patient who was hospitalized due to an acute myocardial infarction (AMI). An alpha/beta blocker called carvedilol was prescribed and continued through hospital discharge. At discharge, a clinician acted on a CDSS alert to start a beta blocker known as atenolol in this patient. A few days later, this patient presented to the emergency department with hypotension and bradycardia.
A clinician had determined that the combination of carvedilol and atenolol had led to this emergency. After interviewing the builder of the CDSS alert, the staff realized that the CDSS's logic didn't take into account that alpha/beta blockers also have beta-blocker activity. The builder had programmed the alert based on the assumption that the hospital's third-party pharmacy database vendor had categorized alpha/beta blockers into both the alpha blocker and beta blocker

DOI : 10.5121/hiij.2024.13101

categories. Conversely, the vendor had placed alpha/beta blockers in a separate category that did not overlap with the alpha blocker or beta blocker categories [1].

The above case study was chosen to reflect growing concerns about CDSSs, demonstrating how software errors and assumptions can compromise patient outcomes. The advantages of this case include highlighting the potential for errors in CDSSs due to programming oversights by the developer, emphasizing the importance of accurate software in revolutionizing patient care with technology. However, it is important to clarify that this case focuses on one cautionary incident, which doesn't represent the broader transformative potential of CDSSs.

Amidst the growing importance of CDSSs, a fundamental research question arises: What machine learning algorithms, when integrated into clinical decision support systems, most significantly improve patient care? This review aims to delve into this inquiry, exploring diverse machine learning (ML) algorithms and their specific applications to CDSSs, to ultimately advance patient outcomes.

2. METHODOLOGY

To find articles related to my review, I identified a breadth of articles pertaining to ML applications in CDSSs. The scope of my sources was case studies and research articles in PubMed and Google Scholar. My search strategy began with broadly searching for "machine learning in clinical decision support systems." Starting with a broad search helped me get acquainted with the general context of this topic and learn about the overarching trends pertaining to this subject. I skimmed through about 50 articles and determined the most common ML algorithms that these articles could be divided into (ex: regression, random forest, neural networks). I also noted the standardized Medical Subject Heading (MeSH) terms for each of these algorithms that were recognized by various databases.

In the last stage of my rapid review, I searched for sources containing each of the aforementioned ML categories' applications to healthcare. My final search queries employed boolean logic by combining specific MeSH terms such as ("Machine Learning" OR "Neural Networks" OR "Random Forest") AND ("Decision Support Systems, Clinical" OR "Medicine" OR "Healthcare"). My inclusion criteria was any article discussing the implementation of a specific ML algorithm in medicine. I made sure to include research studies that integrated these tools into CDSSs, as well as articles that used these algorithms outside of a decision support context. My exclusion criteria was articles that were published prior to 2013 in order to reference findings that were up to date, as algorithms have drastically changed in the past decade.

3. RESULTS AND DISCUSSION

It is clear that different ML algorithms have diverse applications. The versatility that these algorithms demonstrate can be leveraged in distinct scenarios such as drug discovery, triage, and early detection of diseases. Several themes also emerged from this review. Notably, machine learning excels in predicting patient outcomes, enhancing the clinician's knowledge base, and demonstrating increased effectiveness through ensemble algorithmic approaches.

3.1. Predicting Patient Outcomes

Machine learning (ML) algorithms have demonstrated a wide range of use cases, with a notable emphasis on predicting patient outcomes in various healthcare scenarios. One approach, highlighted in Yu's study, introduces the moment kernel machine (MKM), a novel approach to representing patient data as a probability distribution. By using moment representations, the MKM transforms high-dimensional clinical data into low-dimensional representations, successfully predicting surgical outcomes with increased computational efficiency. This tool's ability to focus on essential details reduces the risk of overfitting and enhances the performance of clinical decision support systems (CDSSs) in predicting surgical intervention outcomes [2]. With more accurate estimates of patient outcomes following surgery, patients can act on higher quality information to help them decide whether to pursue surgical intervention.

Building on the foundation laid by Yu's research, Fernandes' work delves into the application of various ML techniques for improving triage in emergency departments. Her team compared different machine learning techniques, including logistic regression, support vector machines, Naïve Bayes, and decision trees, focusing on their ability to predict patient outcomes in emergency settings. For instance, logistic regression was used to assess the likelihood of specific outcomes based on initial patient data, while decision trees helped in categorizing patients into various risk groups. Their study demonstrated that these techniques could predict outcomes with a high degree of accuracy and streamline the triage process, ensuring that patients receive timely and appropriate care [3].

Lupei is another proponent of the belief that CDSSs employing ML can effectively predict patient outcomes. Their research group evaluated how well a logistic regression algorithm could predict severe COVID-19 patients, individuals who required ICU admission or invasive procedures, or those who died. The model, which utilized patient data such as age, comorbidities, and initial symptoms, was highly successful, with an area under the receiver operating characteristic curve (AUROC) of 0.87 and a validation score of 0.82, indicating its high reliability and accuracy [4]. Consequently, this research suggests that logistic regression can be effectively used in CDSSs to predict patients who might develop severe conditions, enabling healthcare providers to take a preventative approach to care.

The k-nearest neighbor (KNN) algorithm, as described by Mitnitski, offers another perspective on the predictive capabilities of ML. KNN, known for its simplicity and effectiveness in classification tasks, has been found to outperform the current Clinical Assessment Protocol (CAP) in predicting an individual's rehabilitation potential. KNN works by comparing a new patient's data with existing cases, identifying the “k” number of most similar patients based on factors like symptoms and medical history, and then predicts the new patient’s outcome based on the outcomes of these similar cases. Mitnitski’s research demonstrated how KNN could analyze patient data, such as their functional status and medical history, to provide more accurate predictions about their rehabilitation needs [5]. By advising clinicians on the most beneficial post-hospital care options, CDSSs that utilize KNN can significantly improve patient recovery trajectories, leading to better long-term patient outcomes.

Jiang’s team took a further step by implementing the Naive Bayes algorithm to enrich the traditional two-layer knowledge base model used in most CDSSs. Typically, the first layer characterizes diseases and the second layer describes symptoms. However, Jiang added a third layer to list the properties of symptoms, such as duration, intensity, and associated factors [6]. This enhancement allowed for a more nuanced analysis of patient data, improving the accuracy in predicting patient diseases. The Naive Bayes algorithm, which works by calculating the probability of a disease given certain symptoms and their properties, could effectively process complex information, making it a valuable tool for CDSSs in various forecasting and diagnostic applications.

Artificial neural networks (ANNs) have also been successfully integrated into CDSSs to improve emergency surgeries, as evidenced by Litvin's team. Their research found that an ANN could accurately predict, diagnose, and treat abdominal emergency conditions. Neural networks function by mimicking the human brain's structure, using interconnected nodes or neurons that process information in layers, allowing the network to learn from data by adjusting the connections based on the patterns it detects. By analyzing large datasets of patient symptoms, histories, and outcomes, the ANN they developed could identify patterns and correlations that human clinicians often missed [7]. This capability of deep learning can be particularly useful in CDSSs to improve surgical procedures and reduce complications.

The research conducted by Uddin compared different supervised machine learning algorithms for disease prediction. Their study found that while support vector machine (SVM) and Naïve Bayes algorithms are most commonly used, the random forest (RF) algorithm stands out for its performance, particularly in handling large and complex datasets [8]. RF works by creating multiple decision trees, each analyzing a different subset of the data, and then combining their predictions to arrive at a more accurate unbiased conclusion. CDSSs can benefit from employing a RF to enhance the forecasting of patient conditions with various treatment plans.

The application of ML algorithms in CDSSs offers a transformative approach to predicting patient outcomes. From MKM's efficient data representation to the predictive prowess of logistic regression, KNN, Naïve Bayes, and ANNs, these algorithms provide an array of tools that can be tailored to specific clinical scenarios. Their integration into CDSSs holds the potential to significantly improve patient care by enabling more accurate predictions and informed decision-making.

3.2. Enhancing Clinical Knowledge

Advancing the clinician's knowledge base through machine learning is a pivotal second theme in this review. Loftus's research demonstrates how the k-means clustering algorithm, a method that groups data into “k” number of clusters based on feature similarity, can categorize phenotypes, thereby aiding clinicians in understanding disease pathophysiology. This algorithm excels in dimension reduction, simplifying complex medical concepts by identifying clusters of symptoms that can be incorporated into traditional regression methods [9]. This simplification is critical to equipping clinicians with only the most relevant data points so that they are not overwhelmed by the patient’s vast medical history, a contemporary issue driving physician burnout.

Turning to the realm of text analysis, Berge and his team's work underscores the utility of natural language processing (NLP) in CDSSs. Their system, adept at parsing and interpreting the complex language of electronic health records (EHRs), significantly improved the identification of patient allergies [10]. NLP works by extracting pertinent information from the unstructured text of EHRs, like specific mentions of allergies or past adverse reactions, to enable a computer system to derive meaning from human language. This algorithm can advance the clinician’s knowledge by highlighting important text from EHRs, thereby reducing medical errors associated with incorrect medication administration.

Building on the approach of Berge, Liu and his team tested large-language models (LLMs) like ChatGPT in clinical settings, opening up novel avenues for decision support. These models, known for generating unique, understandable, and relevant suggestions with minimal bias, can be invaluable in guiding clinicians towards improved patient care [11]. LLMs work by analyzing text from massive datasets to understand and respond to queries. The extensive database and sophisticated language capabilities of LLMs make them an excellent tool for pointing clinicians in the right direction of patient care.

In the field of medical imaging, Shaikh's innovative research in radiomics introduces a new frontier. By enabling CDSSs to analyze complex imaging data from MRI or CT scans, radiomics supports radiologists in confirming their diagnoses or considering alternative interpretations [12]. This technology, which extracts many quantitative features from medical images to identify patterns, can enhance the clinician's understanding and management of various conditions. Specifically, radiologists can harness radiomics to catch details they might miss or reinforce their beliefs.

Further advancing clinical knowledge, Yang's research on medical imaging using a kernel support vector machine (SVM) algorithm stands out. This advanced algorithm, designed for categorizing parotid tissue from non-parotid tissue, has shown substantial benefits in refining cancer radiation therapy [13]. The SVM operates by finding the optimal boundary between classes of data, making it ideal for binary categorization tasks in medical imaging, thereby reducing errors and improving treatment accuracy. Clinicians can leverage SVM to accurately distinguish between different types of tissues or diagnoses based on imaging data.

From simplifying complex EHR data with k-means clustering to classifying tumors with SVMs, machine learning algorithms offer significant benefits to clinicians. As technology continues to evolve, ML's role in augmenting clinicians' knowledge base becomes increasingly vital, promising more accurate, efficient, and personalized patient care.

3.3. Increased Effectiveness of Ensemble Approaches

The integration of multiple ML algorithms, or ensemble approaches, is another pivotal theme in this review. These ensemble models drastically enhance the performance of CDSSs, as evidenced by their superior accuracy, sensitivity, and specificity compared to single-algorithm systems. Ensemble approaches amalgamate the strengths of various algorithms, reducing the likelihood of errors that might arise from relying on a singular method.

For example, Casey elucidates that dynamic decision networks (DDNs), a type of Bayesian network, can effectively model the clinical decision-making process. DDNs incorporate Markov decision processes (MDPs) to model clinical decisions, leveraging probabilistic inference to predict treatment outcomes over time, instead of compounding uncertainty over a series of treatments. Such a conjunctive framework proved to outperform current models of healthcare [14]. Integrating MDPs and DDNs into CDSSs could offer more robust simulations of healthcare policies and patient environments, enhancing decision-making processes.

Temidayo's team further exemplifies the power of ensemble methods in healthcare with their TPE-optimized Borderline-SMOTE LightGBM model. This ensemble, combining Tree-Structured Parzen Estimator (TPE), Borderline-Synthetic Minority Oversampling Technique (SMOTE), and Light Gradient-Boosting Machine (LightGBM), achieved remarkable diagnostic accuracy for breast cancer – averaging 99.12% accuracy, 100% specificity, and 100% precision [15]. TPE optimizes ML models by extracting the most promising parameters; Borderline-SMOTE enhances the training process by generating synthetic samples, particularly focusing on the borderline cases between different classes; and LightGBM is a highly efficient gradient boosting framework known for its speed and accuracy, especially suitable for large datasets. This blend of algorithms not only provides high accuracy but also paves the way for more sophisticated and reliable diagnostic tools in CDSSs.

The research by Karthikeyan provides insight into the use of diverse ML models, such as neural networks, logistic regression, XGBoost, random forests, and SVM, in predicting COVID-19 mortality risk. The study found that combining XGBoost feature importance with neural network classification resulted in a 90% accuracy rate, up to 16 days before the outcome [16]. Feature importance involves identifying the most relevant data points to make predictions, while neural network classification refers to a computer model that mimics the human brain's processing to categorize data it receives. Such predictive capabilities can significantly impact CDSSs, enabling early detection and treatment strategies.

Kaushik’s team found similar success with their ensemble model combining autoregressive integrated moving average (ARIMA), multilayer perceptron (MLP), and long short-term memory (LSTM) models, proving to be highly effective in time-series forecasting [17]. ARIMA is a statistical model which analyzes and forecasts time-series data based on historic patterns; MLP, a type of artificial neural network, classifies data based on learned experiences; and LSTM, another neural network variant, identifies predictions over extended periods. CDSSs could use the ensemble model to forecast various time-series models such as monitoring patient health over time.

The synergy of various algorithms, including support vector machines, neural networks, and gradient boosting machines, has repeatedly proven to yield more accurate predictions than traditional methods, sometimes even outperforming clinicians. The application of ML in CDSSs promises not only enhanced early detection and proactive management of health conditions but also a substantial improvement in patient outcomes.

4. CONCLUSIONS

Revisiting the case study which sparked this review, the 63-year-old patient who experienced adverse effects due to programming errors in a CDSS underscores the necessity for meticulous development and maintenance of clinical decision support systems. Furthermore, this incident highlights the importance of incorporating robust, well-tested ML algorithms that can adapt and learn from mistakes and ongoing clinical data, ensuring that CDSSs remain reliable and effective in real-world healthcare settings.

The integration of diverse machine learning algorithms into CDSSs, as explored in this review, demonstrates the potential to significantly enhance patient care. From predicting patient outcomes to augmenting clinicians' knowledge and utilizing powerful ensemble methods, ML has shown its capacity to transform healthcare delivery. These technologies can provide clinicians with more accurate diagnostic tools, predictive analytics, and personalized treatment plans, ultimately leading to better patient outcomes.

However, it's imperative to acknowledge and address the limitations and challenges inherent in integrating ML into healthcare systems. These include ensuring data privacy and security, managing the complexity of healthcare data, and providing adequate training for healthcare professionals to effectively utilize these tools. Additionally, the ethical considerations surrounding automated decision-making in healthcare must be carefully considered to maintain patient trust and autonomy.

The future of healthcare is promising with the integration of machine learning in clinical decision support systems. The potential for these technologies to reduce medical errors, alleviate clinician burnout, and improve patient outcomes is immense. As we move forward, it will be crucial for healthcare providers, policymakers, and technologists to collaborate in refining these systems, ensuring they are safe, effective, and equitable. This review not only highlights the advancements in the field but also calls for a concerted effort to navigate the challenges ahead, aiming for a healthcare system that is more informed, efficient, and patient-centered.

ACKNOWLEDGEMENTS

Thank you to Professor Neil Sarkar, who played an instrumental role in guiding this research. His expertise in biomedical informatics has been invaluable, providing critical insights and direction throughout the course of this study.

REFERENCES

[1] Stone EG. Unintended adverse consequences of a clinical decision support system: two cases. J Am Med Inform Assoc. 2018 May 1;25(5):564-567. doi: 10.1093/jamia/ocx096. PMID: 29036296; PMCID: PMC7646869.

[2] Yu, YC., Zhang, W., O'Gara, D. et al. A moment kernel machine for clinical data mining to inform medical decision making. Sci Rep 13, 10459 (2023). https://doi.org/10.1038/s41598-023-36752-7

[3] Fernandes M, Vieira SM, Leite F, Palos C, Finkelstein S, Sousa JMC. Clinical Decision Support Systems for Triage in the Emergency Department using Intelligent Systems: a Review. Artif Intell Med. 2020 Jan;102:101762. doi: 10.1016/j.artmed.2019.101762. Epub 2019 Nov 17. PMID: 31980099.

[4] Lupei MI, Li D, Ingraham NE, Baum KD, Benson B, Puskarich M, Milbrandt D, Melton GB, Scheppmann D, Usher MG, Tignanelli CJ. A 12-hospital prospective evaluation of a clinical decision support prognostic algorithm based on logistic regression as a form of machine learning to facilitate decision making for patients with suspected COVID-19. PLoS One. 2022 Jan 5;17(1):e0262193. doi: 10.1371/journal.pone.0262193. PMID: 34986168; PMCID: PMC8730444.

[5] Mitnitski, A.B., et al. "The K-Nearest Neighbor Algorithm Predicted Rehabilitation Potential Better than Current Clinical Assessment Protocol." Journal of Clinical Epidemiology, Pergamon, 3 Aug. 2007, www.sciencedirect.com/science/article/pii/S0895435607001941.

[6] Jiang Y, Qiu B, Xu C, Li C. The Research of Clinical Decision Support System Based on Three-Layer Knowledge Base Model. J Healthc Eng. 2017;2017:6535286. doi: 10.1155/2017/6535286. Epub 2017 Jul 27. PMID: 29065633; PMCID: PMC5551511.

[7] Litvin A, Korenev S, Rumovskaya S, Sartelli M, Baiocchi G, Biffl WL, Coccolini F, Di Saverio S, Kelly MD, Kluger Y, Leppäniemi A, Sugrue M, Catena F. WSES project on decision support systems based on artificial neural networks in emergency surgery. World J Emerg Surg. 2021 Sep 26;16(1):50. doi: 10.1186/s13017-021-00394-9. PMID: 34565420; PMCID: PMC8474926.

[8] Uddin S, Khan A, Hossain ME, Moni MA. Comparing different supervised machine learning algorithms for disease prediction. BMC Med Inform Decis Mak. 2019 Dec 21;19(1):281. doi: 10.1186/s12911-019-1004-8. PMID: 31864346; PMCID: PMC6925840.

[9] Loftus TJ, Shickel B, Balch JA, Tighe PJ, Abbott KL, Fazzone B, Anderson EM, Rozowsky J, Ozrazgat-Baslanti T, Ren Y, Berceli SA, Hogan WR, Efron PA, Moorman JR, Rashidi P, Upchurch GR Jr, Bihorac A. Phenotype clustering in health care: A narrative review for clinicians. Front Artif Intell. 2022 Aug 12;5:842306. doi: 10.3389/frai.2022.842306. PMID: 36034597; PMCID: PMC9411746.

[10] Berge GT, Granmo OC, Tveit TO, Munkvold BE, Ruthjersen AL, Sharma J. Machine learning-driven clinical decision support system for concept-based searching: a field trial in a Norwegian hospital. BMC Med Inform Decis Mak. 2023 Jan 10;23(1):5. doi: 10.1186/s12911-023-02101-x. PMID: 36627624; PMCID: PMC9832658.

[11] Liu S, Wright AP, Patterson BL, Wanderer JP, Turer RW, Nelson SD, McCoy AB, Sittig DF, Wright A. Using AI-generated suggestions from ChatGPT to optimize clinical decision support. J Am Med Inform Assoc. 2023 Jun 20;30(7):1237-1245. doi: 10.1093/jamia/ocad072. PMID: 37087108; PMCID: PMC10280357.

[12] Shaikh F, Dehmeshki J, Bisdas S, Roettger-Dupont D, Kubassova O, Aziz M, Awan O. Artificial Intelligence-Based Clinical Decision Support Systems Using Advanced Medical Imaging and Radiomics. Curr Probl Diagn Radiol. 2021 Mar-Apr;50(2):262-267. doi: 10.1067/j.cpradiol.2020.05.006. Epub 2020 Jun 6. PMID: 32591104.

[13] Yang X, Wu N, Cheng G, Zhou Z, Yu DS, Beitler JJ, Curran WJ, Liu T. Automated segmentation of the parotid gland based on atlas registration and machine learning: a longitudinal MRI study in head-

and-neck radiation therapy. Int J Radiat Oncol Biol Phys. 2014 Dec 1;90(5):1225-33. doi: 10.1016/j.ijrobp.2014.08.350. Epub 2014 Oct 13. PMID: 25442347; PMCID: PMC4362545.

[14] Casey C. Bennett, Kris Hauser, Artificial intelligence framework for simulating clinical decision-making: A Markov decision process approach, Artificial Intelligence in Medicine, Volume 57, Issue 1, 2013, Pages 9-19, ISSN 0933-3657, https://doi.org/10.1016/j.artmed.2012.12.003.

[15] Temidayo Oluwatosin Omotehinwa, David Opeoluwa Oyewola, Emmanuel Gbenga Dada, A Light Gradient-Boosting Machine algorithm with Tree-Structured Parzen Estimator for breast cancer diagnosis, Healthcare Analytics, Volume 4, 2023, 100218, ISSN 2772-4425, https://doi.org/10.1016/j.health.2023.100218.

[16] Karthikeyan A, Garg A, Vinod PK, Priyakumar UD. Machine Learning Based Clinical Decision Support System for Early COVID-19 Mortality Prediction. Front Public Health. 2021 May 12;9:626697. doi: 10.3389/fpubh.2021.626697. PMID: 34055710; PMCID: PMC8149622.

[17] Kaushik S, Choudhury A, Sheron PK, Dasgupta N, Natarajan S, Pickett LA, Dutt V. AI in Healthcare: Time-Series Forecasting Using Statistical, Neural, and Ensemble Architectures. Front Big Data. 2020 Mar 19;3:4. doi: 10.3389/fdata.2020.00004. PMID: 33693379; PMCID: PMC7931939.

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