**Utilizing Machine Learning in Healthcare: A Brief Overview and Recommendations**

Machine learning (ML) is the subfield of artificial intelligence that uses algorithms trained on data sets to create models and imitate intelligent human behavior– essentially, computers can learn how to model their behavior as if they were a human doing data projects. Digitizing health data has created a need and potential to explore machine learning to create better outcomes for patients and the healthcare systems that support them. The United States is estimated to generate 150 exabytes or 1018 bytes of data annually, growing by 48% annually (Esteva et al., 2019). With that output of data and the use of ML in healthcare, ML has opened up the doors for exciting new opportunities in healthcare. AI has the potential to help with case triage and diagnosing, enhance imaging, support decision-making, and predict the risk of disease (Habehh & Gohel, 2021). It can also help eliminate costs and help with regimen adherence.

Case Triage and Diagnosing

ML can help providers and healthcare systems in triaging and diagnosing. Through ML, providers, hospitals, and emergency care systems can prioritize the most urgent cases based on symptoms, medical histories, and vital signs. ML is utilized to analyze large amounts of data and find disease patterns. For example, ML has been used to predict the risk of hospitalization and readmittance, septic shock, COVID-19, and many other use cases. In a study completed by Richens et al. (2020), their models demonstrated that compared to a cohort of 44 doctors, they found that the model outperformed the doctors and achieved expert clinical accuracy.

Imaging

ML provides ample opportunities for developing new techniques in medical imaging. ML can do image reconstruction, complete image segmentation, complete detection (e.g., finding faces, tumors, or lesions), classify images (e.g., stage, progression, or prognoses), and complete image generation.

Eliminate Costs

A thorough study by Langenberger et al. (2023) shows that five percent of the population accounts for about half of the healthcare costs in the US, Germany, Canada, Denmark, Japan, Netherlands, and Australia. These are all due to high-cost patients. They are likely to be lower income, have multiple chronic conditions, be on multiple drugs, be inactive, lower weight, and smoke. Age is also a factor in being a high-cost patient. Rakshit et al. (2021) emphasized the need to identify these patients at risk of becoming high-risk and costly patients. They suggested creating models to predict the cost of any new patient. These models would help patient outcomes and prevent crises in the healthcare system and organization.

Challenges with Machine Learning

Although there are many uses of ML, there are implications that more work is needed to understand the complexity of ML. An ML model will only work well with the information in the data. Due to this, there are several issues present in ML: insufficient quantity of training data, nonrepresentation of training data, sampling, and other biases, poor data quality, irrelevant features picked, and overfitting or underfitting the data. In a review of ML models used in the emergency care department by Miles et al. (2020), out of 92 models, only three would be considered at low risk of biases.

In a review of bias in ML, Gervasi et al. (2022) suggested that biases exist due to the initial selection of the prediction problem, lack of data in those not utilizing healthcare, and racial and socioeconomic disparities.

Recommended Actions

Due to all the biases in ML, several recommendations exist to improve their use. Miles et al. (2020) suggested the usage of PROBAST. PROBAST is a prediction model risk of Bias Assessment tool developed by Moon et al. (2019). This tool provides 20 signaling questions that can help eliminate biases in participant selection, pick predictors, and determine an outcome appropriate for all study participants and biases.

Gervasi suggests that to eliminate biases, stakeholders should consider representational fairness in models and improving care programs. If the models represent only some population, misclassification and fair classification may occur. It is also essential to consider counterfactual reasoning. If a person was from a different subpopulation, it is vital to see if they would have received the exact prediction and probability of an outcome. Models need to ensure that predictions work equally well with all subpopulations. Models should utilize chi-square tests and other statistical methods to balance these.

When completing project plans, stakeholders and data scientists should strategize the different model approaches that could reduce biases, including potentially redefining the target outcome, experimenting with sample methods, doing data augmentation, and picking a model. These techniques may lead to models that are a poorer fit, but they may be fairer in representing the whole.

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