HexagonML

Predictive model risks in HealthCare

Seven pillars of healthcare predictive model risks

Predictive modeling is a process that uses data and statistics to create, process, and validate models for future outcomes. The healthcare system consists of massive biological data that can be unstructured or semi-structured which can be analyzed and processed using a predictive model for early disease detection. While there are multiple positive impacts of Predictive modeling, it does possess a dark side as well. In this white paper, we will systematically analyze the different areas of risks involved with predictive modeling in Health Care.

Our framework for analyzing the health care model risks consists of looking into governance or the following areas:

Liability

With the increase in the number of software predicting the outcomes and suggesting the course of treatment to the physicians the questions on liability remains to be answered. Predictive model decisions are not error-proof and the patient can file a medical negligence lawsuit if patients feel a physician overrode software's recommendation or if a physician followed a predictive analytics model recommendation and it was incorrect. [1] In a traditional scenario, the Physician or Institution's insurance will cover damages. In case of software error who should be considered liable.

Standardization

Predictive models churn out results based on the existing data which could be location, regional, or ethnicity-specific. When such models are applied in a different setting, the model fails to give optimal results. Evercare, a US model of care management, when used in the UK revealed that the approach to case-finding may not predict sufficiently accurately in older people who are at risk of unplanned admission in the future. [3]

The predictive model also suffers from the overfitting or underfitting of the models based on the intake data or parameters used, hence a model working in a hospital setting may not give desired results in another due to variations in the region or ethnicity.

Transparency

Predictive models making individualized diagnostic or prognostic risk predictions which impact life, hence it should adhere to independent external validation. Models need to validate performance heterogeneity across settings and over time, and algorithm refinement or updating. Hiding an algorithm for commercial gain is unethical. Algorithms need to be publicly available so that it can be verified it is working as advertised or to monitor when and how algorithms were updated. [4][5]

Government legislation and regulations do not specifically cover algorithm development or use. Furthermore, Predictive models and the algorithm behind them are not shared and audited to know it's efficiency. In the absence of governance, each predictive algorithm has its margin of error. The margin of error impact in some cases could mean the difference between life or death [1].

Fig 1: Hexagon-ml's Seven Pillars for Healthcare Predictive Model Risks Areas

Algorithm bias

Algorithms have an unknown bias which results from the data that was used to create the model. Algorithms that were trained with data that do not represent the whole population often perform worse for underrepresented groups. This model when used in practice performs poorly on the population on which it has less or no information [9][10]

Privacy

Predictive models are created by using data that has been anonymized and sanitized of personally identifiable information (PII or PHI), still, fMRI scans that are used in the models pose a threat to the human face [8]. Privacy remains an important concern that needs to be solved.

Human- Machine Conflict

Chad Mather III, MD, MBA, assistant professor at Duke University School of Medicine in North Carolina, believes predictive analytics is vital but should not replace human thinking.

“*A physician should always be able to override the recommendations of a system,”* he says[6].

A predictive model could have been created by subject matter experts with the latest information at hand, but with discoveries the model needs to be updated and made robust. Even when the analytics gives optimal results, the physician should check for any errors or items not considered in the model which can skew the results. When the person starts relying too much on the model, this leads to a dependency on the model and a decrease in intellectual capacity.

Prof Stephen Hawking, one of Britain's pre-eminent scientists, has said that efforts to create thinking machines pose a threat to our very existence. [7]

Interpreting information

Predictive algorithms (or models) gives results based on the input data, the results are as good as the data. It could be extremely helpful or useless. Craig A.

Umscheid, MD, MS, associate professor of medicine and epidemiology at the University of Pennsylvania Health System found that predictive analytics can produce benefits, problems, and unintended consequences like not knowing how to correctly interpret it. When predictive analytics was introduced for the diagnosis of sepsis, he discovered that the software was successful in identifying the condition, but this didn't solve the problem.

"*Teams didn't know what to do because the software wasn't necessarily detecting active clinical deterioration. It was simply predicting that sepsis could occur in the future*" he explains [6]

For questions and comments on this white paper please reach out to support@hexagon-ml.com.

About Hexagon-ml

Hexagon-ml is a New Jersey based startup leading in data science platforms. Our model insights platform provides state of the model inspection and analysis capabilities.

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