The Multi-Dimensional Process of Developing a Clinical Decision Support System using Machine Learning

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ABSTRACT

Machine Learning based Clinical Decision Support Systems (CDSS) can play an important role in enhancing the quality of healthcare provided to patients. In this work, we elaborate on the issues around building such a system and on ways to address them.

CCS CONCEPTS

• **Applied computing → Health care information systems**; **Health informatics**.

KEYWORDS

clinical decision support system, machine learning, ethics, transparency, interpretability

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1 INTRODUCTION

Clinical Decision Support Systems (CDSS) are pieces of software that can be used by healthcare professionals or patients as an assisting tool for clinical decision-making. The radical growth and interest in the field of Machine Learning (ML) and predictive analytics can lead to the development of more powerful CDSS. However, the creation of such systems using these techniques is a multi-dimensional process. We aim for a system that will advise towards the right decision (accurate), will provide an explanation on how that decision was made (transparent), will present it in a clear manner (interpretable) and will preserve the privacy of the information it used. In this work, we elaborate on these issues and on the means and challenges of addressing them.

2 TRANSPARENCY

Many times, an accurate model may be complex and difficult to interpret. For this reason, deep learning and ensemble techniques were deemed inappropriate for clinical decision support [4]. These drawbacks of "black-box" models raised an interest in explainable artificial intelligence (XAI). One option is to use techniques that are transparent by design (e.g. linear regression, decision tree), however, one may fail to capture more complicated patterns in the data; another is post-hoc explanation on black-box models, but this requires caution to avoid inaccurate explanations[3].

3 INTERPRETABILITY

Interpretability of a CDSS allows the user to understand the result it provides. The creators of a CDSS need to identify the end-user of the system, as interpretations may differ between different user types. In order to ensure risk understanding, the result should be put in a clinical context by presenting the factors that lead to this result and using appropriate wording to explain it. This study will focus on understanding appropriate ways of risk communication (such as framing, risk reduction presentation personalised risk information[1]), as this will affect the usage of a CDSS.

4 ETHICAL CONCERNS

Ethics regulations surround any study that requires the use of personal data. The European General Data Protection Regulation (GDPR) was developed to protect EU citizens from data breaches and misuse. This study will expand on the appropriate, yet non-trivial, arrangements that need to be in place for Health Research, as the process of developing a CDSS involves the analysis of sensitive personal data. An Irish case-study will be used as an example.

5 CONCLUSION

There is great potential for the creation of accurate CDSS [2]. Respecting the data subjects' rights to privacy and talking into account the user's needs we believe will make a fair and usable system that will fulfil its purpose in the healthcare environment.

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