An Explainable Intervention Prediction for Trauma Patients

Zoe Vasileiou[1,2,*], Georgios Meditskos[2], Stefanos Vrochidis[1] and Nick Bassiliades[2]

[1] School of Informatics, Aristotle University of Thessaloniki, Greece

[2]Centre for Research & Technology Hellas, Information Technologies Institute, Thessaloniki, Greece

Abstract

Trauma patients are commonly severely injured people that require systematic evaluation and rapid response. This paper presents work in progress for an explainable, late fusion and Deep Learning-based prediction system for interventions in Intensive Care Units (ICU) by employing neurosumbolic Explainable Artificial Intelligence (XAI) techniques.

Keywords

Trauma, Ventilation, Neurosymbolic, Explainability, Logic Tensor Networks,

1. A Neural-Symbolic XAI Intervention Prediction System

There are many causes of trauma-related deaths that need immediate intervention within the first hour of arrival to a trauma center. There are limited Clinical Decision Support Systems (CDSS) for predicting ICU interventions for patients such as an interpretable deep learning system [1]. Interpretability discovers the cause and effect behind the decisions, while the XAI provides a human-understandable way. Current CDSS mainly focus on the interpretability, while our work targets explainability by involving user engagement in an interactive way.

Our methodology focuses on the early prediction of interventions in ICUs by fusing the multimodal input with regards to the patient. A late fusion architecture is adopted based on a Deep Learning architecture that is illustrated in Figure 1. LSTMs are selected as classifiers for predicting different interventions, namely need for mechanical ventilation, vasopressor administration and transfusion (red blood cell, fresh frozen plasma, and platelet). However, Explainability is prerequisite for the development of Artificial Intelligence (AI)-based CDSS.

Inspired from an interactive learning approach [2], complex conceptual explanations and interactive learning are incorporated in our system. A Long Tensor Network (LTN) [3] implementation is adopted where the individual classifiers of Figure 1 are mapped to LTN predicates. In LTN, there is a First-Order Logic Knowledge Base (K) containing a set of axioms, namely

SWAT4HCLS 2023: The 14th International Conference on Semantic Web Applications and Tools for Health Care and Life Sciences

*Corresponding author.

zvasileiou@csd.auth.gr (Z. Vasileiou); gmeditsk@csd.auth.gr (G. Meditskos); stefanos@iti.gr (S. Vrochidis); nbassili@csd.auth.gr (N. Bassiliades)

0000-0003-0634-6793 (Z. Vasileiou); 0000-0003-4242-5245 (G. Meditskos); 0000-0002-2505-9178 (S. Vrochidis); 0000-0001-6035-1038 (N. Bassiliades)

CEUR Workshop Proceedings (CEUR-WS.org)

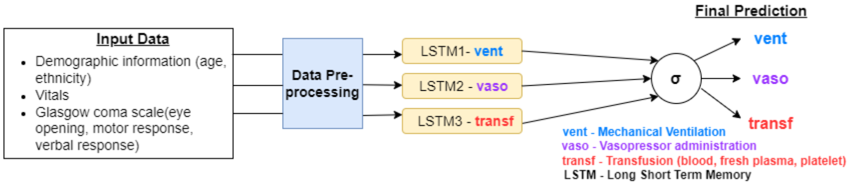

Figure 1: Late fusion classification

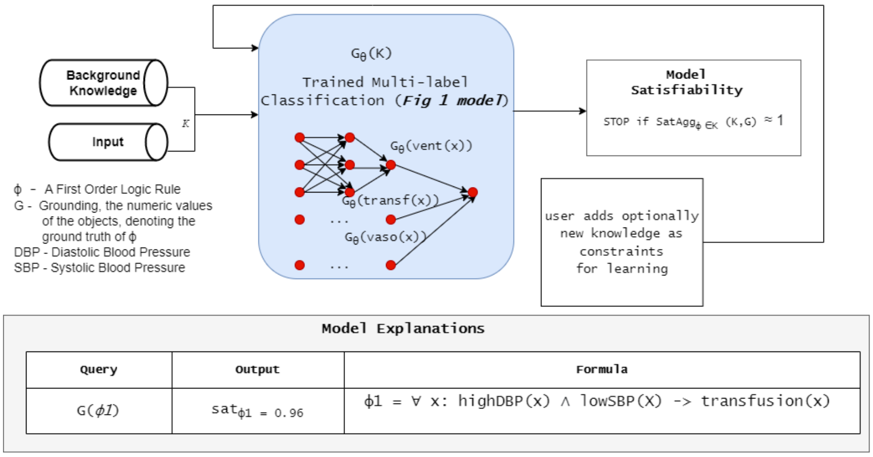

Figure 2: Interactive XAI architecture

logical rules. The logical domain concepts are mapped to tensors (Real Logic) that are saved in K. The main objective is a logical-based loss function that satisfy the K axioms (`SatAgg`) to the greatest degree. The users can participate in the learning process by defining the constraints as axioms to be saved in K and adding new logical rules until satisfaction is reached.

Acknowledgments

This work has received funding from the European Union's H2020 RIA projects INGENIOUS (833435) and NIGHTINGALE (101021957). Content reflects only the authors' view and the Research Executive Agency (REA) and the European Commission are not responsible for any use that may be made of the information it contains.

References

[1] H. Suresh, et al., Clinical intervention prediction and understanding using deep networks (2017).
[2] B. Wagner, A. Garcez, Neural-symbolic integration for interactive learning and conceptual grounding, NeurIPS (2021).
[3] S. Badreddine, et al., Logic tensor networks, Artificial Intelligence 303 (2022).