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Temporal Context Matters: An Explainable Model for Medical Resource Utilization in Chronic Kidney Disease

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Abstract. The prediction of medical resource utilization is beneficial for effective healthcare resource planning and allocation. Previous work in resource utilization prediction can be categorized into two main classes, count-based and trajectory-based. Both of these classes have some challenges, in this work we propose a hybrid approach to overcome these challenges. Our initial results promote the value of temporal context in resource utilization prediction and highlight the importance of model explainability in understanding the main important variables.

Keywords. Resources Utilization, XAI, Electronic Health Records, Deep Learning

1. Introduction

The availability of medical resources is essential to provide a quality care service. These resources are expensive and can be in short supply. Forecasting resource utilization can help healthcare providers and governments estimate future utilization for each patient, especially in cases of chronic diseases. Previous methods for forecasting resource utilization can be grouped into count-based and trajectory-based [1,2], both using medical and administrative variables from electronic health records (EHRs). However, count-based methods ignore the temporal context and health status progression, while trajectory-based methods face challenges with irregular time spans and lengthy sequences [2]. To address these issues, this paper proposes a new hybrid approach that considers temporal context while avoiding lengthy sequences and irregular time spans.

2. Methods

This study is based on retrospective data from EHR in Region Halland, Sweden. The cohort consisted of 27,519 patients diagnosed with chronic kidney disease (CKD) according to ICD-10-SE, estimated glomerular filtration rate (eGFR) and urine albumin-creatinine ratio (uACR) lab values [1], between January 1, 2015, and December 31, 2019. The outcome is to predict only the count of next year visits to specialists based on data from the previous year. We adopted a deep learning approach using Long Short Term Memory (LSTM) architecture. Additionally, to unveil the reasoning behind the model decision, we used SHapley Additive exPlanations (SHAP) as Explainable AI (XAI) technique. The input variables consisted of medical codes (diagnoses, procedures, medications, and abnormal lab codes), CKD-related variables (CKD stage, eGFR and

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uACR lab values), and non-medical variables (such as patient age, gender, and previous year care consumption). In order to overcome very long sequences and huge variance in the length of encounters-sequence, all variables were aggregated over a fixed time window. In our experiments we investigated one, two, four, and six months aggregation periods. The same data is used in all experiments, yet the representation differs with respect to aggregation period.

3. Results

The proposed method was compared to trajectory-based approach (considering all patient encounters) and count-based approach by aggregating historical data and feeding it into a Multilayer Perceptron (MLP) neural network. All models were trained using 5-fold cross-validation. The evaluation metrics used were area under the curve of receiver operating characteristic (ROC-AUC) and the harmonic mean of precision and recall (F1-score). Table 1 shows that the proposed method outperformed the other approaches, with the best performance obtained when using a one-month aggregation period, highlighting the importance of considering more temporal context. Using a six-month aggregation period resulted in the worst performance.

Table 1. Performance metrics of different approaches.

Aggregation period	AUC	F1
Trajectory-based (sequence of visits)	71.8 ± 0.34	70.3 ± 0.59
Count-based (MLP)	73.8 ± 0.20	73.0 ± 0.43
Our method (6 months)	74.5 ± 0.11	73.1 ± 0.58
Our method (4 months)	74.6 ± 0.11	73.5 ± 0.52
Our method (2 months)	74.7 ± 0.42	74.2 ± 0.57
Our method (1 month)	**74.9 ± 0.35**	**74.3 ± 0.57**

4. Discussion and Conclusions

The same data is used in all experiments, yet the representation differs with respect to aggregation period. The initial results show that temporal context embedded in the patient's trajectory can help resource utilization prediction models to perform better by being aware of the changes of patient health state across time. Our work also highlights the importance of model's explainability in resource utilization hence using SHAP method helped to learn about the most important variables that influence model predictions. Next steps are to investigate considering a longer period of patient history and to compare the performance of different state-of-the-art deep learning architectures such as transformers.

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