

CS598 DL4H Project Proposal Spring 2023

Sagar Dalwadi and Murtaza Lodgher

{sagardd2, lodgher2}@illinois.edu

Group ID: 83

Paper ID: 12

1) Cite the original paper.

Choi, E., Schuetz, A., Stewart, W. F., & Sun, J. (2017). Using recurrent neural network models for early detection of heart failure onset. *Journal of the American Medical Informatics Association*, 24(2), 361–370.
<https://doi.org/10.1093/jamia/ocw112/>

2) State the general problem the paper aims to solve. Do not use the same language as the paper.

- The paper aims to explore whether using deep learning models to capture temporal relations among events in electronic health records (EHRs) would improve the performance of predictive models for early detection of heart failure (HF) compared to traditional machine learning approaches that ignore temporality.
- The study explores the use of recurrent neural network (RNN) models to capture temporal patterns present in longitudinal electronic health record (EHR) data and detect temporal event sequences that reliably distinguish heart failure cases from controls. The paper compares the performance of RNN models with traditional machine learning approaches and investigates the applicability of deep learning methods in health data.
- Additionally, the general problem the paper aims to solve is improving early detection of HF, which is a major cause of morbidity and mortality among elderly individuals and results in significant healthcare expenditures.

3) Describe the new and specific approach taken by the paper. Discuss why it is interesting or innovative.

- The paper explores the use of deep learning techniques, specifically recurrent neural network (RNN) models, to improve the detection of incident heart failure (HF) by leveraging the temporal relations among events in electronic health records (EHRs). The authors adapt RNN models using gated recurrent units (GRUs) to detect relations among time-stamped

events such as disease diagnoses, medication orders, and procedure orders, with a 12- to 18-month observation window of cases and controls.

- What makes this approach innovative and interesting is that it captures the temporal relations among the events in the EHR data, which are often missed by traditional modeling techniques that rely on aggregate features. This allows the RNN models to detect patterns and sequences of events that are indicative of the early stages of heart failure, leading to improved performance in predictive modeling.
- In addition, the authors of the paper used the one-hot vector format to represent clinical events in EHR data as computable event sequences. In this format, each of the unique clinical events was represented as an N-dimensional vector, where one dimension is set to 1 and the rest are 0. Using these one-hot vectors, a sequence of clinical events can be converted to a sequence of one-hot vectors, which were used to train the GRU model for heart failure (HF) prediction. The GRU model accepts an input vector at each timestep, while storing information in a single hidden layer whose state changes over time. The logistic regression model applied to the final state of the hidden layer is formulated to calculate the risk score of the patient for future diagnosis of HF.

4) Identify the specific hypotheses you plan to verify in your reproduction study.

The paper investigates the use of recurrent neural network (RNN) models to detect temporal relations among events in electronic health records (EHRs) for the early detection of heart failure (HF) and compares their performance with conventional methods. We plan to verify one of the following hypotheses in the reproduction study:

- 1) RNN models can improve the detection of incident heart failure compared to conventional methods that ignore temporality.
- 2) RNN models can capture temporal patterns present in longitudinal data for the early detection of heart failure.

5) Outline any additional ablations you plan to do and explain why they are interesting.

Some of the ablations we can implement into our reproduction include:

1. Changing the observation and prediction time windows that the symptoms of heart failure were detected in the patient. The change in the

prediction time could be interesting to observe and see just how it could affect the overall results from the model.

2. One other ablation we can use to affect the results would be to use a different activation function. The paper specifies using a sigmoid function as the activation function used in the mathematical operations, but we can try to see if implementing different activation functions produce different results.

6) Explain how you have access to the necessary data.

While there are synthetic data files located in the code repository of the paper, the authors claim that these files are only to be used to illustrate how the code operates on such structured data at runtime. While the authors state that they retrieved their data from Sutter-PAMF, they don't provide an access link or instructions to access this data (understandably so, as to maintain patient privacy). For our reproduction, we will gather data from physio.net and structure it to how the input vector data was structured in the method implementation shown in the paper.

7) Discuss the computational feasibility of your proposed work.

This reproduction seems feasible to run on a regular computer. There doesn't seem to be any additional computational power required for this reproduction that can't be handled on a standard computer currently available in the market.

8) Specify if you will be re-using existing code and provide a link to it, or if you will implement the code yourself.

While the paper did provide a link to the authors' code repository, we only plan to use that for referential purposes and plan to write all original code that can interpret the similar structured data used in the paper.

Authors have made their codes and synthetic data available on a public repository: https://github.com/mp2893/rnn_predict