Comparative Study of Light-GBM and a Combination of Survival Analysis with Deep Learning for Early Detection of Sepsis

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Abstract— Sepsis is a severe medical condition caused by body's extreme response to an infection causing tissue damage, organ failure and even death. The emergence of advanced technologies like Artificial Intelligence and machine learning, allowed faster exploration of advanced way to recognize sepsis cases. In this paper, we will present two main approaches that has been tested using medical data. First is the combination of survival analysis and neural networks, and the second is based on booting trees.

Index Terms—Sepsis, early detection, predictive model.

I. INTRODUCTION

Sepsis is a severe medical condition caused by body's extreme response to an infection causing tissue damage, organ failure and even death. Every 3-4 seconds, at least one person dies because of sepsis worldwide. Sepsis affect about 1.6 million American yearly [8]. As a leading cause of death in the US hospitals, sepsis costs the US about 24 billion USD, 6.2% of the total hospital costs in 2013. [1].

The early detection of sepsis has proven to be a key factor in increasing the efficiency of antibiotic treatment for septic patients. Related studies [2] demonstrated that early detection will prevent 80% of death cases caused by sepsis. On the other hand, it was reported that the sepsis mortality significantly increases with the length of stay of the septic patient in the hospital. In order words, delayed recognition of sepsis exacerbates the risk of death of a septic patient by 7.6% every hour [3].

Furthermore, with the emergence of more advanced technologies, there is a significant amount of electronic health records that became available. The HERs are a systematic collection of data used as health indicators of a patient. The growing availability of the HERs brought so much interests and opportunities to think of more advanced predictive models to early recognize septic patients.

The electronic health records can be dynamic changing over time (time series) like heart rate or blood pressure. Also, they can be static like demographic information such as Age and gender.

The clinical definition [4] of systemic inflammatory response (SIRS) to infection, specifies four conditions which only two of them are sufficient to trigger an alert of sepsis:

1. Temperature of >38 °C or <36 °C
2. White blood cell count of >12,000 per ml or <4,000 per ml, or >10% immature (band) forms
3. Heart rate of >90 beats per minute
4. Respiratory rate of >20 breaths per minute or partial pressure of CO2 of <32 mmHg

II. PHYSIONET CHALLENGE: PROBLEM DEFINITION

Saving septic patients' lives comes with a combination of efforts from different perspective of sepsis. While more advanced instruments allow closer and more accurate follow-up of the septic patient situation. They only can tell about the current situation of a patient in a potential risk of sepsis.

However, in most of the time when we a patient arrive to the confirmed sepsis shock stage, it most probably too late for us to save their lives. Launching the antibiotic culture take time and is less effective when a patient is in serious stage of sepsis that become pretty evident.

The instrument tells what have already happened to the patient but alone they cannot tell a lot about the future development of the patient situation. This later information is more relevant for saving infectious patient from death of sepsis.

An effective treatment of sepsis is performed through different aspect and numerous sides. From one side, there is the instrumentational part, and on the other hand, there is the computational part.

It's worth noting that early detection and recognition of sepsis and antibiotic treatment are critical key factor of improving sepsis outcomes [7].

Each time we detect sepsis patient one hour earlier, we get more 4-8% chance to save the patient's life. With the classical tools of data analysis in the last decade, scientist still face a lot of limitations to detect sepsis early enough.

With the emergence of machine learning techniques, a lot research has been made to improve the current detection tools. [8,9,10]

III. DATA OF THE CHALLENGE

There are more than 40 health variables used to track the health situation of the patients in this challenge. In the next paragraphs, I explain some of them since we can't elaborate a lot of details in this paper. The 40 columns are classified into three classes: vital signs, lab test, and static variables. I'll pick examples of each class and explain how it's related to the early detection of sepsis.

1) Vitals signs

Most of these features concern the main screening signal that would reflect continuous situation of the patient health. There are 8 vital signs provided in the data and we can cluster them into three main categories:

- ECG signals: HR, SBP and DBP
- Pulse signals: Respiration rate, O2Sat, and EtCO2 (End tidal carbon dioxide)
- Temperature

a) ECG signals

The main signals here are the heart rate. From this signal we extract the systolic blood pressure and diastolic blood pressure. The severity of sepsis is very correlated to the number of beats per minute. Many studies have shown that the more sepsis get worse, the more we observe ECG abnormalities. This can be explained by loss of excitability in cardiac tissue during the sepsis.

From the ECG and Blood pressure, we extract the systolic and diastolic blood pressure and the heart rate which are used in this challenge.

b) EtCO2

The EtCO2 is a continuous variable by basal metabolic rate, cardiac output and ventilation. The abnormal levels of EtCO2 may reflect derangement in perfusion, metabolism or gas exchange. This variable is very effective to detect septic shock when used to screen a conscious patient.

Severe sepsis is characterized by poor perfusion, leading to buildup pf serum lactate and metabolic acidosis. EtCO2 levels decline in both cases of poor perfusion and metabolic acidosis. Also, the EtCO2 levels are inversely proportional to lactate. For sepsis patients, the levels of lactate rise as their situation get worse, and thus the EtCO2 levels drop.

It was shown in several works, that a drop of EtCO2 is correlated to rise of lactate levels. This fact helps a lot for the prediction/detection of mortality in patients in the three stages of sepsis: suspicion, severe sepsis, and septic shock. [ref2, ref3].

c) Temperature

Symptoms of sepsis include: a fever above 101ºF (38ºC) or a temperature below 96.8ºF (36ºC) heart rate higher than 90 beats per minute. So, tracking the temperature is very important for the early detection task. In fact, the predictive model uses a certain number of the previous data points from the current time and try to detect any significant shift on temperature (drop or rise).

2) Lab tests

The role of laboratory test is very significant for early detection of sepsis. Since the main definition of sepsis is the body's systemic inflammatory response to a bacterial infection [11]. The spread of bacteria in the blood (bacteremia) make it a big indicator of sepsis infection. About 25 lab tests have been provided in the data for sepsis detection. These features include: White blood cells count, Blood urea nitrogen, Lactic acid, partial thromboplastin time, Leukocyte count, Platelets.

3) Static/Demographical features

There were some studies that have shown that sepsis mortality has a little thing to do with demographics. Especially age and length of stay. In our current model, we still find this is not the case. More results will be shown on the next paragraphs. [12]. The main demographic features in the data are: Gender, Age, and length of stay.

IV. METHODS AND APPROACHES

a) Related studies

The early detection of sepsis has proven to be a key factor in increasing the efficiency of antibiotic treatment for septic patients. Related studies [5] demonstrated that early detection will prevent 80% of death cases caused by sepsis. On the other hand, it was reported that the sepsis mortality significantly increases with the length of stay of the septic patient in the hospital.

The complexity of sepsis is still high and depends on so many factors. There were so many studies and attempts to propose a predictive model for this purpose, but they are facing some challenges.

Chen Lin, in his work [6,7], used dynamic EHRs and proposed a generic framework of deep learning to detect septic patients 5 hours earlier. The framework consisted of two experimental setups: one with Convolutional Neural Network (CNN) added before Long Short-Term Memory (LSTM) to extract patterns from time series features (e.g. EHRs). This component will be connected later with a fully connected network. This later component makes use of the static features and extract local characteristics and dependencies in this type of EHRs.

LSTM is very effective in extracting patterns from long sequences. It's always considered as strong candidate to handle date with temporal structures like time series signals, videos, or text data…etc.

In fact, LSTM [8] is neural network with a memory component that save the previous inputs and use them along with the current inputs. This is a very efficient strategy to capture the dynamic dependencies of the EHRs for sepsis patients. It will help to detect the physiological deterioration in the data earlier than a classical structure of neural network with no memory.

In addition, the CNN [9] is more known for image data rather than temporal data. This structure has achieved great results on many hard topics such as object detection. There was a work made by Krizhevsky where the temporal data was converted into image format and fed to a CNN. This achieve interesting results and shown promising potential of applied CNN on time series.

b) Methods

While some research works [6,11] showed a great ability to predict sepsis in infectious patients. It was still limited since many of these simulations could not predict earlier than 6 hours. As this time frame increases, the accuracy decreases a lot.

In this section, I am going to outline two approaches that we continue improving in order to use the features pre-mentioned

earlier, to predict sepsis patient no earlier than 12 hours and no later than 6 hours.

2) Weibull Time-To-Event- RNN model (WTTE_RNN)

Early detection is the typical application of Survival Analysis (SA); it has been used in medicine and early detection of catastrophic events.

However, SA despite being able to fit perfectly and handle the censored nature of data used to estimate Time-To-Event (TTE) problems, it still remains a statistical modelling approach and not able to keep up with the advanced approaches of deep learning.

Likewise, the fundamental idea of deep learning architectures still does not take into consideration the censorship aspect of the data as is needed TTE problems. As a result, deep learning itself would not be able to provide high performance on such problems. In this paper, a combination of survival analysis and deep learning is proposed for early detection of patients with potential sepsis using the data provided for PhysioNet Challenge 2019.

In WTTE-RNN [13] model we assume that TTE variable follow Weibull distribution governed by two parameters: alpha and beta. The idea is to estimate the TTE distribution instead of directly estimating the TTE variable.

This approach was not very successful, it's still vague how the algorithm is learning in the data. I needed more clarity in the model and that's why I thought about boosting trees. Light-GBM was the best candidate.

3) Light-GBM

This approach is a gradient boosting learning framework that uses tree-based learning algorithm. The difference between light-GBM and other tree-based algorithms is that it grows tree leaf-wise while other algorithms grows level-wise.

It will choose the leaf with max delta loss to grow. When growing the same leaf, Leaf-wise algorithm can reduce more loss than a level-wise algorithm. Below is the diagram that show LIGHT-GBM mechanism:

Fig. 1. Light-GBM is growing leaf-wise while the other boosting trees are growing level wise.

B. Results

WTTE-RNN: This model is more promising from the mathematical standpoint. It pays closer attention to the special nature of the data we have in hand and the problem we trying to solve.

While this model could have good AUC score (80%). The result on the utility function are not still very competitive. Our model is subject to be improved and changed to gain more consistent results. These are the preliminary results and further areas of improvement have been identified.

It worth noting that the advantage of this approach is not only its ability of handling the censorship of the data, but also it

requires almost no features preprocessing which make it computationally affordable and less expensive.

Light-GBM: The results of this approach are more interesting. We not only got a great classifier, but we also learned those variables that contribute the most in the prediction of sepsis. After running this iteration with light-GBM, I figured out that a combination of both would give better results. With almost equal AUC score (83%), we have learned some importance features that contribute to the prediction.

The primary results report that some demographics like Age and Hours between hospital admit and ICU admit are very significant in predicting sepsis patient.

Furthermore, the lab test that concern the cell count are very significant. For instance, white blood cells and Platelets are very helpful features. The Fig.2 gives more details about features importance.
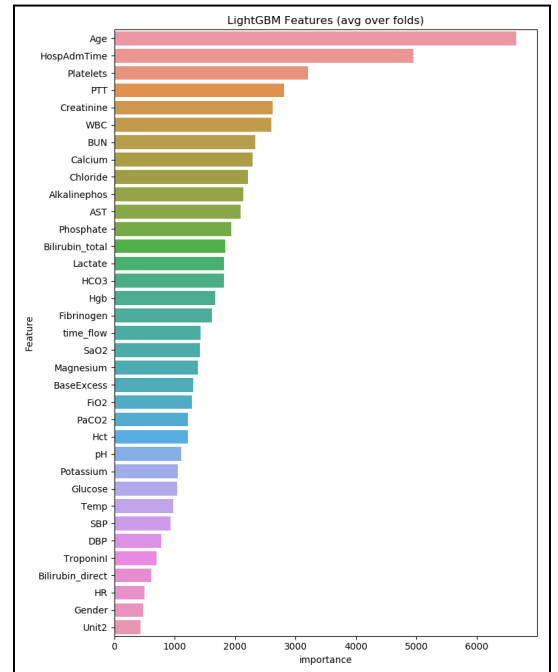

Fig. 2. Feature Importance provide better model clarity

V. CONCLUSION

In this work, we have tried two main approaches for the early detection of sepsis. While the neural network is very promising tool, but more they require more exploration to see how they can handle both static and time-based features. On the other hand, the boosting trees seems to be very insightful. We could see the features that would contribute the most for recognition of the sepsis cases.

In the future, I believe that a combination of both algorithms will help to give better results. The LSTM will be efficient in handling the time series features, and while light-GBM will handle the static variables.

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