Detecting Sepsis in the Intensive Care Unit

CIS400/401 Senior Design Final Report

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ABSTRACT

Severe sepsis and septic shock are major healthcare concerns that impact patients in hospital settings. The onset of sepsis occurs rapidly, giving nurses and physicians little time to react and this results in high mortality rates. Sepsis is especially a concern in Intensive Care Units (ICUs), as these patients are in critical conditions and undergo operations where the risk of contracting sepsis is high. While there are guidelines for the management of sepsis, these only address how to handle patients after they have become septic. Our project will attempt to aid in the early detection of sepsis in hopes of giving nurses and physicians more time to treat patients. Given past sepsis patient data, we expect to build a predictive model that will be able to detect sepsis before the typical symptoms arise, decreasing the mortality rate from sepsis and septic shock.

1. INTRODUCTION

Intro...

2. RELATED WORK

Related work...

3. DATA COLLECTION

Sepsis data was intended to be collected from three different data sources: the Surgical and Medical ICUs at the Hospital of the University of Pennsylvania and Penn Presbyterian Medical Center. Data from the SICU was not obtained, but the details of the intended data are discussed below. Data from the MICU was statistically analyzed for trends in lab values but not incorporated into the smart alarm framework that was developed due to several reasons discussed below. The data from Penn Presbyterian was ultimately used in the smart alarm framework.

3.1 Surgical ICU

The original intent was to use prospective data from the SICU because it was easier to monitor the patients. With a manageable number of patients at any given time, it would be possible to keep track of which patients got septic and which ones did not. After sepsis diagnosis, data from each classification of patients could be pulled and aggregated. Data from the SICU comes from two sources: streaming vital sign data from the patient bedside monitors and daily lab tests from blood cultures. The streaming vital sign data comes at a frequency of 58 seconds, whereas the lab tests are taken a few times a day. Institutional Review Board (IRB) approval was submitted for this data, but due to HIPAA constraints, consent from each patient was required to access their data. This level of consent was unfeasible to obtain, as the data would need to be continually collected from new patients. The list of available data items from the SICU is listed in the Appendix.

3.2 Medical ICU

Data from the MICU was collected from Dr. Barry Fuchs, the medical director of the MICU, who had been looking at septic patients. The data set included 934 unique patients from July 2, 2008 - September 18, 2009. The logic rule for this set of patients is as follows: the patient was on the general care ward, had a blood culture taken, and was transferred to the MICU in the following 2-24 hours. The data set contains two consecutive labs for each patient that are within twelve hours of when the blood culture was drawn. There is also information for the lab data from the last blood culture that was drawn. The date range for the previous blood culture varies widely, ranging from within the same day to over a year. Due to the large gap in time between some of the blood cultures, many of the patients were unusable in determining sepsis trends. The values that were collected in this data set are listed below.

Patient information:

- Date / time of blood culture
- Location at order time
- Time of transfer to ICU

- Discharge time
- Deceased status
- Discharge description

Lab values:

- Bicarbonate
- Bilirubin
- Creatinine
- Glucose
- International Normalized Ratio (INR)
- Lactic acid
- Platelets
- PO2 Arterial
- White blood cell count

Due to the limited nature of this data set, only a statistical analysis was performed. In order to do this, a few assumptions were made. None of the classifications of the patients were included with the data set, so which patients ultimately became septic is unknown. However, a patient being transferred from the general ward to the MICU suggests that the patient was suspected to be septic. For the analysis, the transfer time to the MICU was considered as the reference point to compare all patients. Ideally, the reference point would have been when each patient was diagnosed with sepsis, but this information was unavailable. Also, since each patient only has two data points for each lab value (one from the blood culture taken at transfer and the other being the most recent blood culture before that), the patients were grouped into buckets according to the time difference between blood cultures. The patients were grouped into five different buckets, representing time differences ranging from one to five days. Median values for each lab result were evaluated for trends. Trends in the data for lab values from five days before transfer to one day before transfer were evident in INR and bilirubin.

For both INR and bilirubin, median values steadily increased from five days prior to transfer to one day prior. INR values reached 1.5, which is the threshold value for sepsis according to the Surviving Sepsis Campaign guidelines. Bilirubin values reached 2 mg/dL, which is the stated threshold value for severe sepsis. The trends for INR and bilirubin are shown in Figure 1 and Figure 2 respectively.

3.3 Penn Presbyterian Medical Center

Data from Presby was collected by a sepsis study group from patients in the month of October 2011. The data set includes 1254 unique patients, each of which has been de-identified of personal information and newly identified by a unique ID number. For each patient, there is basic information and information for six vital signs for each patient. The number of vital signs depends on the length of stay for each patient, which varies. The patient information and six vital signs collected are listed below.

Patient information:

- Hospital
- Emergency room time (if applicable)
- Arrival time
- Admission time
- First ICU time (if applicable)

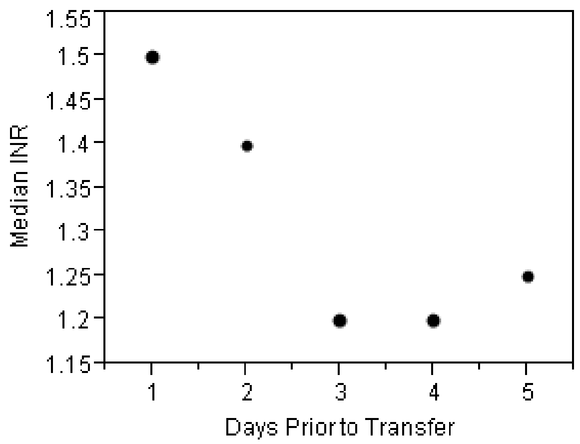

Figure 1: Median INR values before MICU transfer

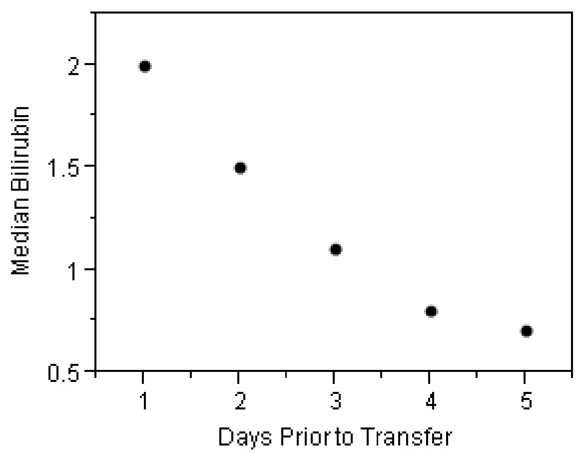

Figure 2: Median Bilirubin values before MICU transfer

- Final location
- Discharge time
- Hours to the ICU (if applicable)
- Deceased status
- Rapid Response Team (RRT) Call time (if applicable)
- Age

Vital signs / lab values:

- Heart rate
- Lactate
- Respiratory rate
- Systolic blood pressure
- Temperature
- White blood cell count

Similar to the MICU data, classifications for whether the patient ultimately got septic are unknown for this data set. However, the frequency of this data set was greater than the MICU data, and was ultimately used to build the sepsis smart alarm framework.

3.4 Ethics

Ethics...

4. SMART ALARM FRAMEWORK

Since patient classifications were unknown, a smart alarm framework that could alert for suspect patients as well as serve as a research tool was built. The main functionality is to provide a set of adjustable thresholds for each vital sign collected. Depending on the values of the thresholds and the number of thresholds that needed to be triggered, the smart alarm displays a different set of patients. This was motivated by interviews and surveys that were conducted with nurses and physicians in the University of Pennsylvania Health System. There was a general consensus that the vital signs provided in the Presby data set were helpful in determining whether or not a patient gets septic, but the threshold values each nurse or physician assigned varied. Even though there are guideline values set by the Surviving Sepsis Campaign, each nurse and physician may deviate from these values. There was also a discrepancy in the number of thresholds the nurses and physicians would look at to raise attention to that patient. Most respondents said that three was their threshold limit. Our framework takes into account these differences and allows the user to changes these values.

Due to the relatively small Presby data set, several assumptions were made when building the framework. Ideally, such a smart alarm system would be used with streaming vital sign and lab data so that the information is collected in real time. As the data is only from one month, a reference date was required to signify the current point in time. The framework has an adjustable reference date that can be set to any time during the month of October 2011 to model how the smart alarm would look at that date. Each patient has multiple values for each vital sign over the course of their stay at the hospital, but the date and time of each reading rarely matches up with other vital signs. For example, respiratory rate, heart rate, systolic blood pressure, and

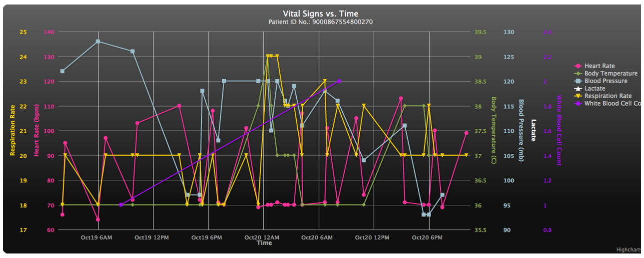

Figure 4: Snapshot of a patient's vital sign history graph

temperature are often taken together on the same reading. However, since white blood cell count and lactate require a blood sampling, these tests are taken less often and at different times than the other four vitals. When trying to identify which patients trigger more than the specified level of thresholds, a time window had to be specified for those threshold trips to take place. From the reference date, a time window of one day was used to pull the patients who met the threshold criteria.

4.1 User Interface

In Figure 3, the home screen of the smart alarm is displayed. The current threshold values, number of thresholds, and reference date are displayed on top, along with a legend with each of the vital signs. "Active Patients" are those who triggered more than the specified number of thresholds within one day of the reference date. "Past Patients" are those who triggered the set number of thresholds the day before the active patients. Beside each of the patients, the symbols with the thresholds that were triggered are listed. This gives the user a quick intuition into why that patient was alerted. Clicking on a patient ID will bring the user to the patient profile page.

The user profile page contains basic information about the patient, such as their age and time admitted. The page also provides a more detailed view of each of the vital signs so that a nurse or physician get get a better snapshot of that patient's history. While the main page notifies which thresholds were triggered, the patient profile can show how that vital sign has been trending. A consolidated graph with each vital sign is shown in Figure 4.

5. SCORING ALGORITHMS

Another feature of the smart alarm framework is the ability to test different sepsis scoring algorithms. The main scoring algorithm employed was a basic count of the number of thresholds that were triggered at the current threshold levels. If the number of thresholds exceeded the specified limit, the patient would be alerted on the screen. The baseline values for the thresholds were taken from the Surviving Sepsis Campaign guidelines, and the threshold values are listed in Table 1. Additionally, scoring algorithms from the University of Kentucky Medical Center, Robert Wood Johnson (RWJ) University Hospital, and the Methodist Hospital Sys-

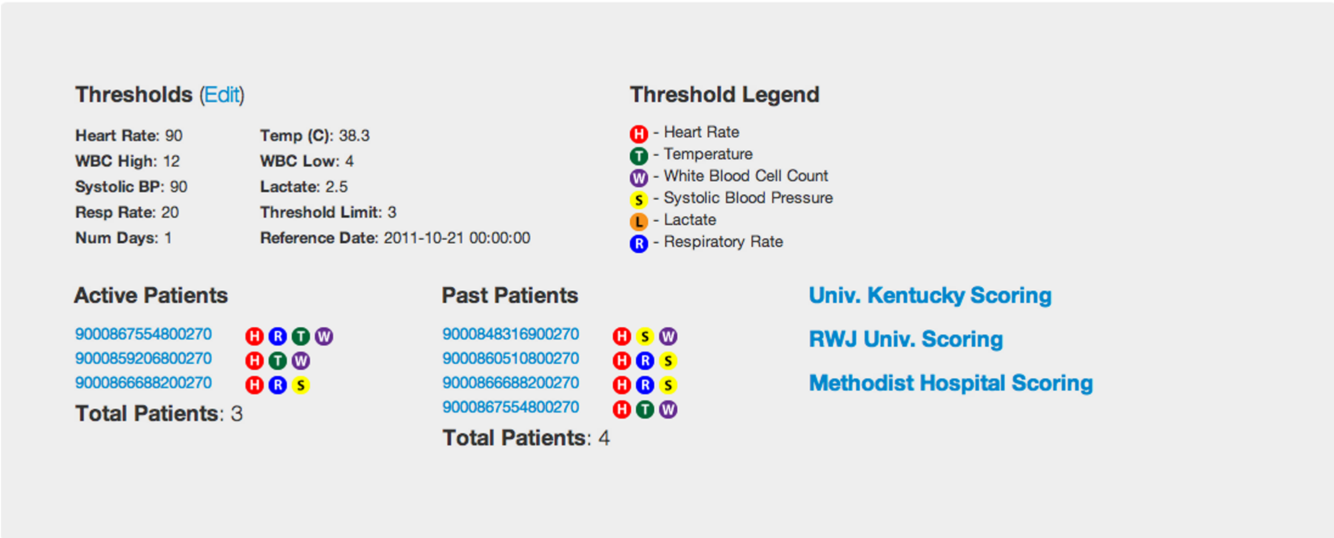

Figure 3: Snapshot of home screen

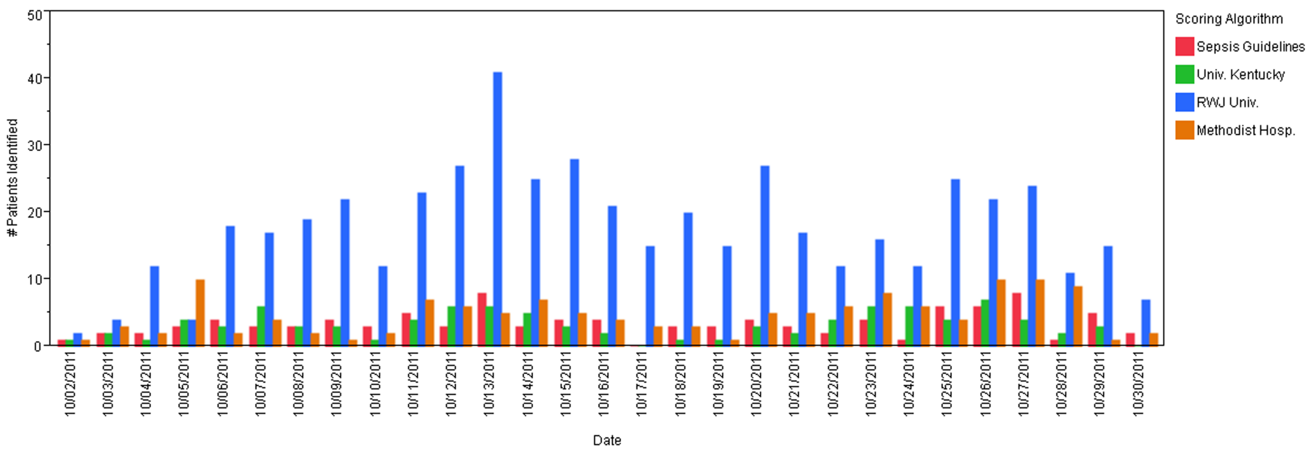

Figure 5: Number of patients alerted by each scoring algorithm

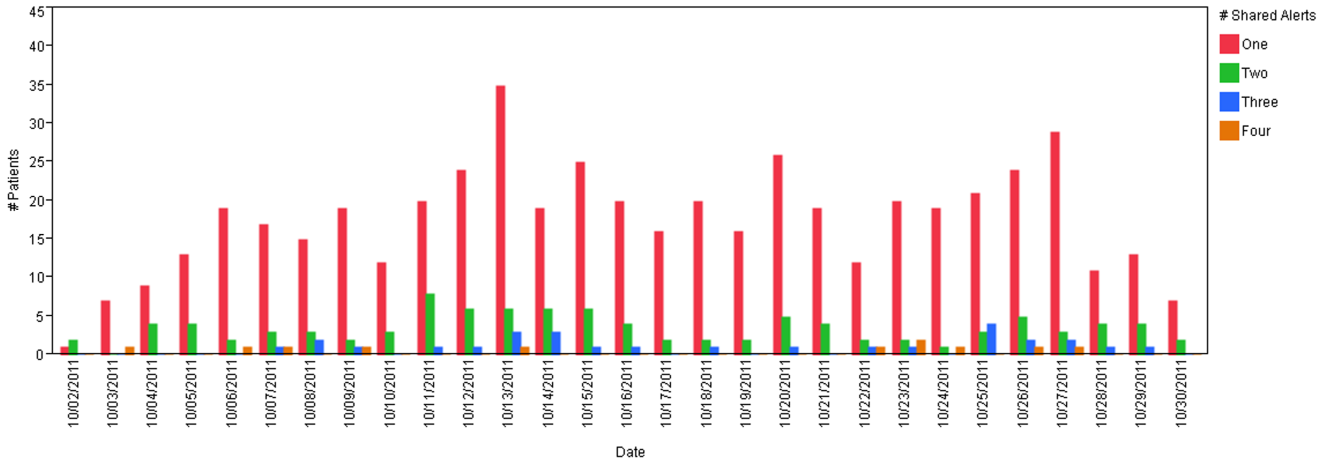

Figure 6: Consistency of alert algorithms

Value	Threshold
Heart Rate	$>$ 90 bpm
Temperature	$>$ 38.3 °C
White Blood Cell Count	$>12000/\mu$L or $<4000/\mu$L
Systolic Blood Pressure	$<$ 90 mm Hg
Lactate	$>$ 2.5 mmol/L
Respiratory Rate	$>$ 20 bpm
Rule: any three thresholds will set off the alert	

Table 1: Baseline threshold values from the Surviving Sepsis Campaign guidelines

tem were tested. The University of Kentucky used a more gradual scoring criteria, assigning a score to a range of values for each vital sign. This sliding scale took into account the severity of the vital sign and assigned a higher score for vital signs that were further from the normal range. Their system would alert a patient if the score was greater than six. The RWJ University Hospital algorithm was similar to the baseline algorithm from the Surviving Sepsis Campaign Guidelines, but used a two step triggering process. First, vital signs were tested with defined threshold values. If any one of these four signs were triggered, lab values were tested with defined threshold values. If any two indicators were triggered (one vital plus one lab value, or two vitals), that patient would be alerted. The Methodist Hospital scoring algorithm is similar to that of the University of Kentucky, using a sliding scale of ranges for each value and assigning a score to each range. A patient was alerted if the score totalled four or greater. The algorithm constraints for the University of Kentucky, RWJ University Hospital, and Methodist Hospital are shown in Table 2, Table 3, and Table 4 respectively. Each of these scoring algorithms was coded into the smart alarm framework and compared to the output of the other scoring algorithms.

Value	Threshold
Heart Rate	$>$ 100 bpm
Temperature	$<$ 36 or $>$ 38.3 °C
Systolic Blood Pressure	$<$ 90 mm Hg
Respiratory Rate	$>$ 24 bpm
White Blood Cell Count	$>12000/\mu$L or $<4000/\mu$L
Lactate	$>$ 2.0 mmol/L
Bands	$>$ 10%
Rule: two thresholds, either two vitals or a vital and a lab value, will set off the alert	

Table 3: Threshold values from RWJ University Hospital sepsis detection algorithm

While the accuracy of each scoring algorithm could not be accessed, a comparison was made to see how consistent each scoring scheme was. The reference date was changed to each day during the month of October 2011, and the outputted patients were compared for each scoring algorithm. Each algorithm varied in sensitivity. The RWJ University algorithm was by far the most sensitive, alerting the greatest number of patients each day. The other three algorithms were more consistent in terms of the number of patients alerted. On average, the four algorithms did a poor job of agreeing on septic patients. This shows that scoring algorithms between hospitals do not agree consistently on septic patients and further research needs to be done to refine these alerts. A summary of the number of patients alerted by each algorithm is shown in Figure 5 and a summary of the consistency between scoring algorithms is shown in Figure 6.

6. FURTHER WORK

The most immediate future work would be to obtain clas-

Score	**3**	**2**	**1**	**0**	**1**	**2**	**3**
Heart Rate (bpm)		< 40	41-50	51-100	101-110	110-129	>= 130
Temperature (°C)		< 35		35-38.4		>= 38.5	
Systolic Blood Pressure (mm Hg)	< 70	71-80	81-100	101-199		>= 200	
Respiratory Rate (bpm)		< 9		9-14	15-20	21-29	>= 30
Age (years)					65-74	75-84	>= 85
BMI (kg/m^2)			< 18.5		25.1-34.9	> 35	
Rule: a score of 6 or greater will set off the alert							

Table 2: University of Kentucky internal sepsis scoring algorithm thresholds

Score	**0**	**1**	**2**	**3**	**4**
Heart Rate (bpm)	70-109		59-69 or 110-139	40-54 or 140-179	<=39 or >=180
Temperature (°C)	36-38.4	34-35.9 or 38.5-38.9	32-33.9	30-31.9 or 39-40.9	<=29.9 or >=41
Respiratory Rate (bpm)	12-24	10-11 or 25-34	6-9	35-49	<=5 or >=50
Systolic Blood Pressure (mm Hg)	3-14.9	15-19.9	1-2.9 or 20-39.9		<1 or >=40
Rule: a score of 4 or greater will set off the alert					

Table 4: The Methodist Hospital sepsis scoring algorithm

sification labels for the patients of the Penn Presbyterian data set. While an adjustable smart alarm framework is in place, the results and parameters cannot be evaluated without knowing which patients got septic. Additionally, with patient labels, researchers would be able to individually alter thresholds to try to find which individual thresholds have the greatest impact on determining sepsis.

The smart alarm framework that was created serves two purposes moving forward. First, it acts as a research platform where the researcher can continue to alter threshold values and evaluate how accurate the detection of sepsis is. Additionally, researchers can continue to apply scoring algorithms from other health systems to compare the relative effectiveness. Second, as more effective scoring algorithms are developed, the framework can serve as the basis for a patient monitor alert system. With streaming, real-time data, the home screen will constantly update as the scoring for each patient changes. This will be useful for nurses and physicians to monitor their patients. They can both get a broad overview of the state of their patients and have the option to click on individual patients to view specific vital signs.

7. CONCLUSION

Sepsis is a serious concern in the ICU as it has a high mortality rate and extends the length of a patient's stay. Many hospitals currently have protocols for how to manage sepsis and different alert algorithms for detecting patients with sepsis. While some hospitals have been able to improve sepsis detection, there is currently no effective set of thresholds that accurately predicts if a patient will become septic. The sepsis smart alarm framework that was developed brings researchers and medical professionals one step closer to finding such a set of thresholds by supplying a data-driven method of analyzing sepsis scoring algorithms. Using a patient data set and set of scoring algorithms, researchers can evaluate the accuracy of each algorithm and tweak threshold levels. Ultimately, a reliable sepsis detection system will decrease the mortality rate for septic patients in the ICU and shorten the average length of a patient's stay, helping to reduce the high costs of care that a hospital faces.

8. REFERENCES

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APPENDIX

A. SICU DATA LIST

SICU vital sign data:

- Heart rate
- Blood pressure
- Urine output
- Respiratory rate
- Pulsoximetry
- Supplemental oxygen level
- Temperature
- Cardiac rhythm

SICU lab work data:

- WBC count
- ANC
- Bands
- Hemoglobin
- Hematocrit
- Platelet count
- Sodium
- Potassium
- Chloride
- Bicarbonate
- Bun
- Creatinine
- Glucose
- Bilirubin
- AST
- ALT
- Ammonia
- Albumin
- Amylase
- Lipase
- Lactate
- Pt (INR)
- PTT
- Fibrinogen
- Sedimentation rate
- C-Reactive protein
- SVO2
- Venous blood gas sample
- Arterial blood gas sample
- Blood cultures
- Sputum cultures
- Urine cultures
- CSF cultures
- Sterile body fluid cultures