Predicting Surgical Site Infections in Real-Time

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ABSTRACT
Surgical site infections (SSIs) are a major cause of morbidity, mortality, and hospital readmissions in general surgery patients. Real-time prediction of risk is needed prior to and during the time of an operation so that preventative strategies can be applied. In this study, we develop classifiers that can be used in real-time from combining operative data entered through a web interface and patient variables extracted from the EHR, to predict patients at risk for SSIs within 30 days of their operation, even before the patient leaves the operating room. We show that naïve Bayes (NB) and support vector machines (SVMs) can predict patients at risk for any SSI, or superficial SSIs, with high discriminatory power. We also show that applying the ChiMerge discretization method improves classifier performance to a greater extent in NB models than in SVMs. In addition, we identify the most important predictors by evaluating their normalized mutual information and chi squared statistic. Finally, we compare the SSI rates of discretized continuous variables and categorical variables, concluding that higher SSI rates are associated with lower preoperative hemoglobin, lower intraoperative temperature, larger estimated blood loss (EBL), longer procedure duration, larger transfusion volume, specific zip codes, dirtier wound class, specific surgeons, lower surgical apgar score (SAS), presence of an ostomy, higher American Society of Anesthesiology (ASA) score, higher total number of procedures during hospitalization, and open (vs laparoscopic) procedures.

Categories and Subject Descriptors
J.3 [**Life and Medical Sciences**]: Medical Information Systems

General Terms
Experimentation

Keywords
Surgical Site Infections, Data Mining, Clinical Decision Support Systems, Computer Support for Surgical Intervention, Data Analytics for Clinical Care

1. INTRODUCTION
Surgical site infections (SSIs) are a major cause of morbidity and hospital readmission, affecting 3-11% of general surgery patients in the United States [1,2]. They are associated with worse postoperative outcomes, including prolonged length of stay and higher mortality [3,4]. The additional healthcare costs attributed to SSIs are estimated to be over $20,000 per infection [5,6]. The increased morbidity and costs from SSIs, combined with their preventability, has led to numerous quality improvement initiatives focused on reducing their occurrence [7].

SSIs are categorized into 3 distinct types by the Centers for Disease Control [8]. The 3 types are superficial (most common type), deep, and organ space. They are determined based on their anatomic level. In addition, they differ in their risk factors, pathophysiology, and treatment. Deep and organ space SSIs are often categorized together as they represent similar processes in general surgery patients [7]. Lawson et al. and Blumetti et al. have shown that the predictors for deep/organ space SSIs vary from the predictors for superficial SSIs [7,9]. For example, open surgery (vs laparoscopic) is a predictor of all SSIs, whereas increased body mass index (BMI) is a stronger predictor of superficial SSIs than of deep or organ space SSIs. As a result of their findings, Lawson et al. proposed considering the different SSI types independently when developing prevention strategies as each type requires a different targeted solution [7].

Predictive models for SSIs have been in existence since the 1990's. Often, they are scoring systems derived from a multivariate logistic regression analysis. One of the most commonly used SSI risk models is the National Nosocomial Infections Surveillance (NNIS) Basic SSI Risk Index [10,11]. It uses 3 predictors to generate a score between 0 and 3, making it easy to use, but has limited discriminatory ability. More recently, van Walraven and Musselman developed the Surgical Site Infection Risk Score (SSIRS), a logistic regression model, to predict any SSIs within 30 days of surgery. However, the model includes Current Procedural Terminal (CPT) codes, which are not immediately available during an operation. These codes are usually administratively assigned days to weeks following surgery [12].

Our goal has been to determine SSI risk at the time of completion of the surgical procedure, including features of the operation itself, so that alternative wound management strategies and care protocols can be evaluated in the highest risk population. In this paper, we develop and test predictive models that can be used in the operating room in real-time, with high discriminatory power to detect general surgery patients at risk for all SSIs or superficial SSIs, within 30 days of surgery. Specifically, we develop naïve Bayes (NB) and support vector machine (SVM) models to predict 1) any SSI vs no SSI and 2) superficial SSI vs no superficial SSI. We believe that predicting superficial SSIs, in addition to all SSIs, allows for more tailored prevention interventions and is therefore a more cost effective quality improvement strategy.

Furthermore, we examine the relative importance of predictors of surgical site infections by mutual information, normalized mutual information, and chi squared statistics, and we show the differences in SSI rates in select predictor categories, and continuous variable intervals generated from ChiMerge discretization.

2. DATA COLLECTION

The surgical dataset was extracted from the University of Iowa Hospitals & Clinics EHR (Epic, Verona, WI) and entered into a datamart created in Microsoft SQL Server (Microsoft Inc., Redmond, WA) using an extract, transform, and load (ETL) process. This process is automated through scheduled Structured Query Language (SQL) queries on the server. This data was then combined with outcomes data obtained from the American College of Surgeons National Surgical Quality Improvement Program (ACS-NSQIP), a validated, institution-based surgical database of patient risk factors and 30-day postoperative outcomes [13]. The study was approved by the University of Iowa Institutional Review Board.

Our datamart contains patients who have undergone colorectal surgery, minimally invasive surgery, bariatric surgery, vascular surgery, and acute care surgery. The training set was created using data from patients who had undergone an operation between January 1, 2011 and September 30, 2013, and the validation set contained patient data from October 1, 2013 to December 31, 2013. The rates for all SSIs and superficial SSIs are shown in Table 1. Figure 1 shows the SSI rate per month for all, superficial, and deep/organ space SSIs. The SSI rates vary considerably from month to month, with the most common SSI being the superficial SSI during most months.

Table 1. SSI rates in the full dataset, training set, and validation set

Set	Dates	Number of Cases	SSI rate (All SSIs)	SSI rate (Superficial SSIs)
Full dataset	1/1/2011 – 12/31/2013	2211	0.084	0.049
Training set	1/1/2011 – 9/30/2013	2085	0.084	0.047
Validation set	10/1/2013 – 12/31/2013	126	0.087	0.071

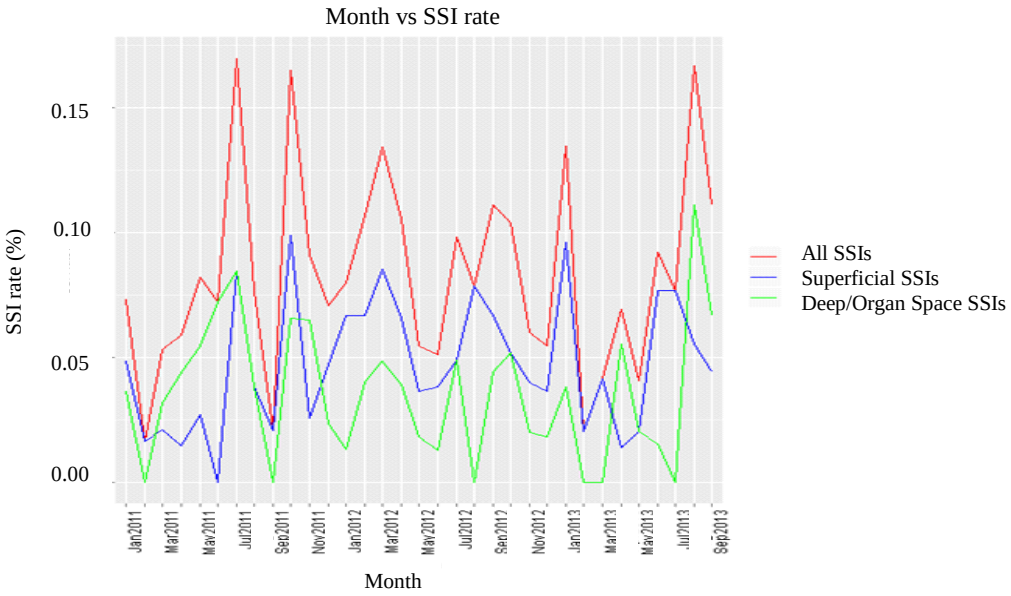


Figure 1. SSI rate over time for all SSIs, superficial SSIs, and deep/organ space SSIs (Training Set)

3. PREDICTOR VARIABLES

Predictor variables were constrained to those extractable from the hospital EHR and available prior to the completion of an operation. This constraint allows for a risk prediction to be made prior to the end of the operation so that an intra-operative intervention can be implemented by the surgeon in real-time. The predictor variables included demographic data (age, sex, body mass index (BMI), ethnicity, zip code), insurance company, hospital location prior to operation, total number of surgical operations during the hospital encounter, presence of an ostomy, American Society of Anesthesiologists physical status classification (ASA) score, preoperative hemoglobin, wound class, surgical apgar score (SAS) [14], estimated blood loss (EBL), blood transfusion volume, minimum intraoperative temperature, operating room, duration of operation, procedure category, and whether the procedure was laparoscopic/robotic or an open operation. Many of these predictors have been shown to be risk factors for SSIs [7,9]. Table 2 summarizes the variables used for the classifier training.

Table 2. Variable description

Feature Name	Feature Type/Description
Age	Numeric
Sex	Male, female
Ethnicity	Hispanic, non-Hispanic, unknown
Zip code	Categorical
Surgical apgar score (SAS)	Numeric, from 0 to 10; Risk score for postop morbidity and mortality; lower score associated with worse outcome
Preoperative hemoglobin (Preop Hb)	Numeric
Estimated blood loss (EBL)	Numeric
Blood transfusion volume (Transfusion)	Numeric
ASA score	Numeric, from 1 to 5; Score for health status; higher score indicates sicker patient; (1=healthy; 5 = moribund)
Body mass index (BMI)	Numeric
Minimum intraoperative temperature (Min Temp)	Numeric
Wound class	Clean (Cl), clean-contaminated (Cl-Co), contaminated (Co), dirty-or-infected(Di-I), unknown (U)
Surgeon	Categorical
Insurance company	Categorical
Hospital location prior to operation (Location)	Categorical
Total number of surgical operations during the hospital encounter (Total Procedures)	Numeric
Presence of ostomy (Ostomy)	Categorical (0=no,1=yes)
Operating room	Categorical
Procedure duration (Duration)	Numeric
Procedure category	Categorical
Laparoscopic/robotic surgery vs open operation (Laparoscopy)	Categorical (0 = open, 1 = laparoscopic/robotic)

4. PROCEDURE CATEGORIZATION

There are two groups of variables needed to use our model in real-time, before the patient leaves the operating room. The first group is automatically obtained from the hospital EHR and entered into our datamart. The second group of variables is obtained at the time of the operation and is entered into a web interface by the user before being transferred to the datamart. These two groups of variables are then entered into the model to generate a prediction in real-time.

The procedure type is an example of the second group of variables. It is not immediately available in the EHR and must be entered by the user. In order to simplify the data entry by the user, the procedure type was categorized into 9 groups: colon, appendix, gallbladder, stomach, hernia, pancreas, small intestines, colonoscopy, and other. In addition, the procedure is specified by the user as either laparoscopic/robotic or open.

Regular expressions were used to categorize 126 unique CPT codes in the dataset into the 9 aforementioned groups. For example, the CPT code "CRS ROBOTIC SEGMENTAL COLON RESECTION S SYSTEM" was converted to the procedure category *colon* if the term "colon", "ostom", "colect", "procto", or "CRS" was present in the procedure name. Table 3 summarizes the stems used to assign a procedure to each category and the order in which they were prioritized. Table 4 shows the total and superficial SSI rates associated with each procedure category.

Table 3. Procedure Categorization Using Regular Expressions (Training Set)

Order of Assignment	Text Present in Procedure Name	Assigned Procedure Category
1	"gastro"	stomach
2	"nissen"	stomach
3	"gastrect"	stomach
4	"pancreas"	pancreas
5	"cholecyst"	gallbladder
6	"hernia"	hernia
7	"small bowel"	small intestines
8	"append"	appendix
9	"ostom"	colon
10	"colect"	colon
11	"CRS"	colon
12	"colonoscopy"	colonoscopy
13	If none of the above is present	other

Table 4. Procedure Category and SSI rate (Training Set)

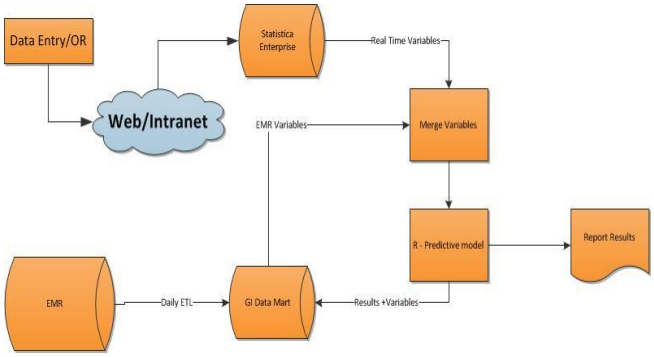
Procedure Category	Total cases	SSI rate (All) (%)	SSI rate (Superficial) (%)
Colon	758	16.1	8.8
Other	335	9.3	4.8
Appendix	103	3.9	3.9
Gallbladder	261	2.7	1.5
Stomach	210	2.4	1.9
Hernia	411	1.5	1.0
Colonoscopy	1	0	0
Pancreas	1	0	0
Small intestines	5	0	0

5. WEB INTERFACE

The web interface was developed using STATISTICA Enterprise Platform (StatSoft Inc.). As noted earlier, users submit variables obtained at the time of operation that are not immediately available in the EHR. This information is then transferred to the datamart, where it is combined with variables that were extracted

directly from the EHR. The data is then accessed from within R (R Foundation for Statistical Computing, Vienna, Austria), and used by the classifiers to make predictions of SSI risk. The entire process from intraoperative data gathering to obtaining predictions takes less than 10 minutes on average. The overall design of the web interface as well as a screen shot is shown in Figure 2.

a)



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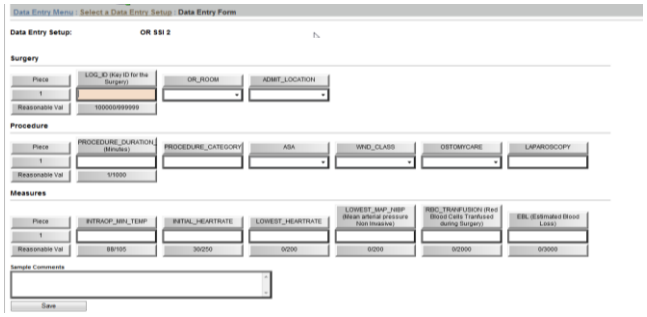


Figure 2. Web interface a) design and b) screen capture

6. VARIABLE DISCRETIZATION

Compared to other discretization methods, ChiMerge [15] has been shown to better improve classifier performance when applied to electronic medical record (EMR) datasets [16]. In the ChiMerge algorithm, each distinct value is treated as a separate interval, and the values are sorted. Adjacent pairs of intervals are then merged if the class labels in those intervals are not statistically significantly different from each other (alpha = 0.05). Our class labels were all SSIs. We applied the ChiMerge method to our dataset to improve classifier performance. We also used the discretization output to find predictor intervals associated with high SSI risk. Table 5 shows the discretization output. The total SSI rates of the continuous variable intervals with at least 20 patient cases are shown in Figure 3. Higher SSI rates in patients with lower preoperative hemoglobin, lower minimum intraoperative temperature, higher EBL, longer procedure duration, and larger transfusion volume were expected findings. Interestingly, there was a non-linear relationship between age and SSI rate. We observed higher SSI rates with increasing age intervals until interval 4 (age≥66.5), wherein the SSI rate was low. Lawson et al. also found a lower odds of SSIs (OR 0.85, p<0.01) in patients 65 years and older [7]. The SSI rates in the BMI intervals were also surprising. We expected the SSI rates to increase with increasing BMI; instead, there was a bimodal distribution, with high rates found in intervals 2 (BMI 14.0-39.4) and 4 (BMI>41.5). This unexpected finding may be due to the fact that the BMI intervals generated from the ChiMerge discretization are not concordant with established clinical categories. For example, interval 2 contains patients who are underweight (BMI<18.5), normal weight (BMI 18.5-24.9), overweight (BMI 25 – 29.9), and obese (BMI >30). In this case, the inclusion of 4 different clinical categories into one interval may have skewed the analysis of SSI rates. In the case of procedure duration, note the duration intervals alternate between low and high SSI rates between intervals 6 and 19. This highlights the limitations of ChiMerge discretization as it only evaluates consecutive values for similarity, resulting in local optimization, whereby if two very similar intervals are separated by any size interval that is statistically different, the two similar intervals are not merged.

Table 5. ChiMerge discretization of continuous variables

Variable	(Interval Number) Variable Intervals			
Age	**(1)** 18-35.4	**(2)** 35.5-65.4	**(3)** 65.5-66.4	**(4)** 66.5-100
Preop Hb	**(1)** 6-11.54	**(2)** 11.55-15.94	**(3)** 15.95-16.04	**(4)** 16.05-18.04
EBL	**(1)** 0-31.4	**(2)** 31.5-33.9	**(3)** 34.0-112.4	**(4)** 112.5-177.4
	(5) 177.5-189.9	**(6)** 190.0-587.4	**(7)** 587.5-7100	
Transfusion	**(1)** 0-312.4	**(2)** 312.5-1712.4	**(3)** 1712.5-3900	
BMI	**(1)** 13.0-13.9	**(2)** 14.0-39.4	**(3)** 39.5-41.4	**(4)** 41.5-84
Min Temp	**(1)** 87.8-87.94	**(2)** 87.95-88.04	**(3)** 88.05-90.74	**(4)** 90.75-90.84
	(5) 90.85-94.14	**(6)** 94.15-94.24	**(7)** 94.25-98.24	**(8)** 98.25-101.3
Duration	**(1)** 6-41.4 …	**(36)** 567.5-675	…. Total of 36 intervals	

7. PREDICTOR IMPORTANCE

Mutual information (MI) is a symmetric measure of the information shared between two variables. It is used as a variable ranking method for feature selection and has been shown to improve model performance in clinical datasets [17,18]. The normalized mutual information (NMI) more easily facilitates the comparison of variables however, as it ranges from 0 to 1, whereas MI has no upper bound and favors variables with many possible values. Two commonly used normalization methods are the Kvalseth method (K-NMI) [19] and the Strehl and Ghosh method (S&G-NMI) [20]. In table 6, we show the variable rankings (i.e. predictor importance) from the K-NMI method, and include the S&G-NMI, MI, and chi squared statistic for comparison. The top 5 predictors that had the highest K-NMI and that were statistically significant by chi squared analysis were ostomy presence, EBL, procedure duration, procedure category, and total procedures. Ranking features could allow us to prioritize interventions to specifically address the most important variables. For example, we may aim to shorten the procedure duration knowing that it is an important predictor of SSIs.

We show the SSI rates for some of the important categorical variables in Figure 4. The SSI rates are higher in patients with an ostomy, larger number of total procedures, dirtier wound class, lower surgical apgar score (SAS) and higher ASA score (both signify sicker patients), and in patients who had an open operation (vs laparoscopic). These findings support our current understanding of risk factors for SSIs. Interestingly, we found certain zip codes to be associated with higher SSI rates. These regional differences are likely multi-factorial, and may be due to socioeconomic status, distance from the main hospital, access to care, and the overall environmental burden.

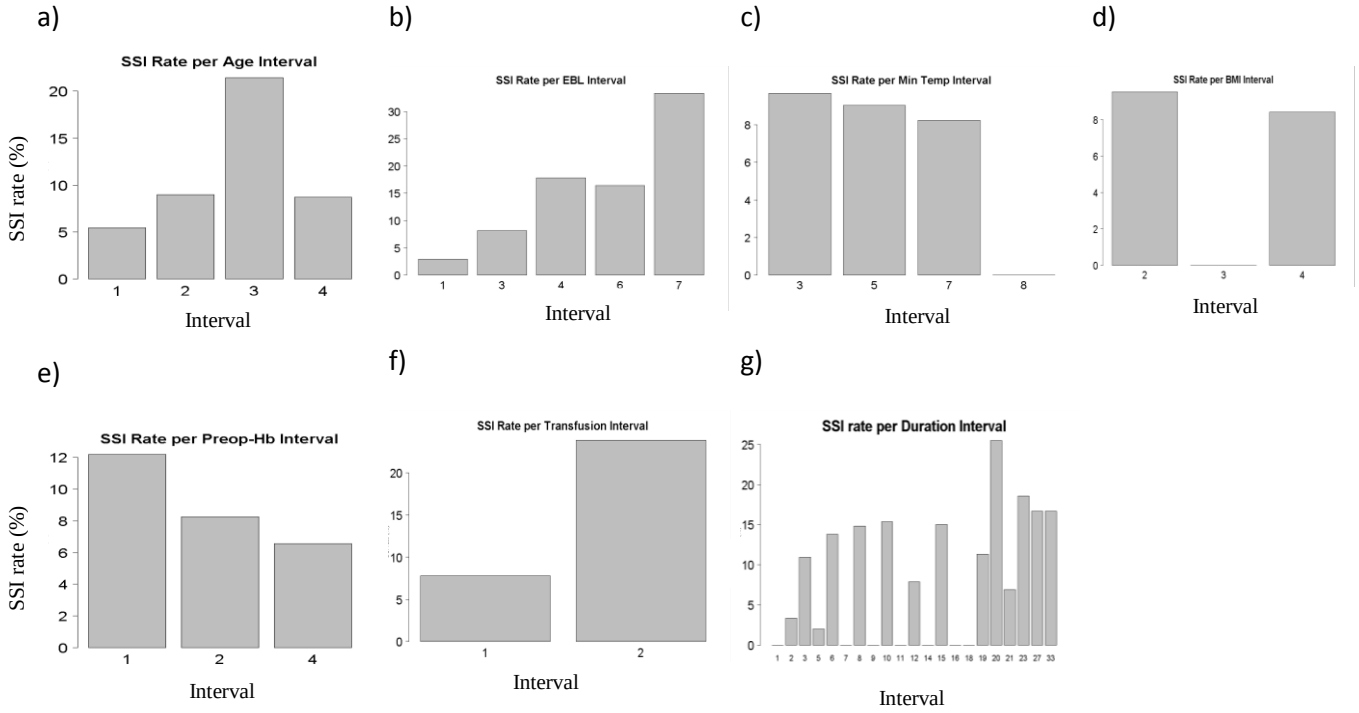


Figure 3. SSI rates of discretized continuous variables that contain at least 20 patient cases (Training Set)

8. MODEL DEVELOPMENT

We compared the performance of naïve Bayes (NB) and support vector machine (SVM) classifiers, with and without ChiMerge discretization, in predicting all SSIs and superficial SSIs. These two classifiers were chosen for further study as they were the best performing models in our previous work predicting hospital readmissions, which in surgical patients, are often due to SSIs.

All of the experiments were performed using R language version 2.15.1. The NB and SVM classifiers were available in the *e1071* package. For the SVM model, a linear kernel and C=0.1 was chosen after a tuning analysis. In addition, class weights were assigned according to the proportion of positive to negative cases in the training set, because of the asymmetric class sizes in the dataset.

Missing continuous variables in the testing set were imputed with the mean or median value from the training set. Missing categorical variables were imputed with the mode value from the training set. New categorical variable values that were not present in the training set and therefore not used to train the model were imputed with the mode values from the training set. The training set was evaluated using 10-fold cross validation.

The F-score is the harmonic mean of the sensitivity and positive-predictive value for a given threshold [21]. The maximum F-score and its associated probability threshold were obtained for each fold of a 10-fold cross-validation of the training set. This threshold (CUTOFF) was then used to classify patients at risk for an SSI. The median threshold generated from the 10-fold cross-validation of the training set was used as the final model threshold in the validation studies.

If the median threshold was greater than 0.50, it was replaced with 0.50 to maximize the sensitivity (this only occurred in the NB(+ChiMerge) prediction of superficial SSIs).

The calibration of a model describes how closely the predicted probabilities agree with the observed outcomes [22]. The calibration error (CAL) is the difference between the observed and predicted risk of SSIs. We determined the calibration error for the top quintile of predicted risk for the NB and SVM models.

The *ROCR* package was used to obtain the model area under the curve (AUC). In addition, the model accuracy (ACC), sensitivity (SEN), specificity (SPEC), positive predictive value (PPV), and negative predictive value (NPV), were obtained using the probability threshold associated with the maximum F-score.

The NB and SVM model performances are shown in Tables 7 and 8. ChiMerge discretization improved the performance of the NB model in predicting superficial SSIs and all SSIs, and the SVM model in predicting superficial SSIs, but had no effect on the SVM model's prediction of all SSIs. Both models performed better when predicting all SSIs than when predicting superficial SSIs. In regards to model sensitivity, an important metric for detecting at risk patients and performing interventions in a cost-effective manner, the SVM(+ChiMerge) outperformed the NB(+ChiMerge) model in predicting superficial SSIs and all SSIs (Tables 7,8,9). In the validation set, both models performed worse in predicting superficial SSIs. This may be due to the difference in superficial SSI rates between the training set (0.047) and the validation set (0.071). Finally, the SVM model had lower calibration error than the NB model, making it a more reliable model in supplying accurate risk probabilities.

Table 6. Normalized mutual information, mutual information, and chi squared statistic for the a) most and b) least important predictors (ranking is ordered by K-NMI)

a)

Variable	K-NMI	S&G-NMI	MI	Chi squared statistic
SSIs	1	1	0.416	2072.0, df=1 , p-value= 0
Ostomy	0.055	0.057	0.031	109.4, df=1, p-value= 1.32e-25
EBL	0.043	0.055	0.047	173.5, df=6, p-value= 8.09e-35
Duration	0.035	0.058	0.073	260.2, df=35, p-value= 3.29e-36
Zip code	0.032	0.072	0.128	485.5, df=452, p-value= 0.13
Procedure category	0.029	0.041	0.041	108.9, df=8 , p-value= 6.69e-20
Total procedures	0.028	0.030	0.019	72.7, df=12, p-value= 9.86e-11
Transfusion	0.028	0.029	0.009	43.7, df= 2, p-value= 3.26e-10
Surgeon	0.021	0.035	0.045	115.1, df=22, p-value= 1.36e-14
Wound class	0.014	0.017	0.014	38.2, df=4, p-value= 9.97e-08
Location	0.013	0.016	0.013	45.4, df= 35, p-value= 0.11

b)

Variable	K-NMI	S&G-NMI	MI	Chi squared statistic
Insurance company	0.011	0.019	0.025	77.8, df=93, p-value= 0.87
BMI	0.010	0.011	0.006	17.8, df= 3, p-value= 0.0005
Min Temp	0.010	0.012	0.009	30.2, df=7, p-value= 8.88e-05
SAS	0.009	0.013	0.013	44.4, df=8, p-value= 4.85e-07
Operating room	0.007	0.013	0.018	54.1, df= 38, p-value= 0.04
Preop Hb	0.007	0.008	0.005	17.0, df=3, p-value= 0.0007
Ethnicity	0.007	0.007	0.003	4.60, df=2 , p-value= 0.10
ASA score	0.006	0.007	0.006	17.5, df=4, p-value= 0.002
Age	0.004	0.005	0.004	11.6, df=3, p-value= 0.009
Laparoscopy	0.003	0.004	0.002	6.1, df=1, p-value= 0.01
Sex	0.002	0.002	0.002	4.0, df=1, p-value= 0.04

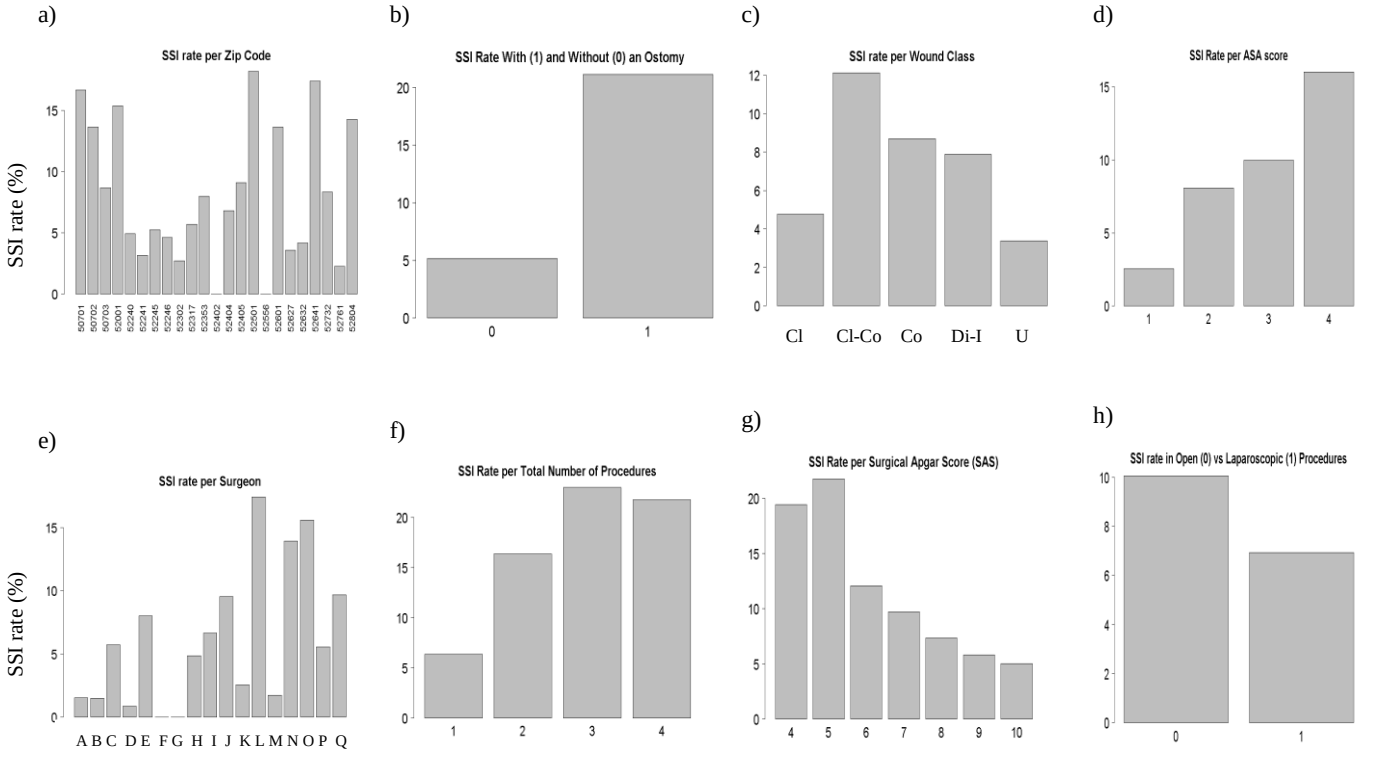


Figure 4. SSI rates (%) of select categorical variables that contain at least 20 patient cases (Training Set)

Table 7. Naïve Bayes model performance in predicting all SSIs and superficial SSIs (+/- ChiMerge discretization); SD = standard deviation

Set	Classifier	Class label	AUC (SD)	MAX F-SCORE	CUTOFF	SEN (SD)	SPEC	PPV	NPV	ACC	CAL
Training	NB (-ChiMerge)	All SSI	0.76 (0.05)	0.34	0.06	0.63 (0.09)	0.80	0.24	0.96	0.79	0.34
Training	NB (+ChiMerge)	All SSI	0.81 (0.04)	0.40	0.44	0.57 (0.17)	0.88	0.34	0.96	0.86	0.48
Training	NB (-ChiMerge)	Superficial SSI	0.70 (0.12)	0.23	0.50	0.44 (0.23)	0.82	0.26	0.97	0.78	0.43
Training	NB (+ChiMerge)	Superficial SSI	0.78 (0.07)	0.34	0.69	0.42 (0.17)	0.93	0.39	0.97	0.91	0.32
Validation	NB (+ChiMerge)	All SSI	0.75	---	0.44	0.55	0.77	0.18	0.95	0.75	---
Validation	NB (+ChiMerge)	Superficial SSI	0.67	---	0.69, imputed with 0.50	0.11	0.89	0.07	0.93	0.83	---

Table 8. SVM model performance in predicting all SSIs and superficial SSIs (+/- ChiMerge discretization); SD = standard deviation

Set	Classifier	Class label	AUC (SD)	MAX F-SCORE	CUTOFF	SEN (SD)	SPEC	PPV	NPV	ACC	CAL
Training	SVM (-ChiMerge)	All SSI	0.79 (0.03)	0.38	0.14	0.64 (0.13)	0.84	0.28	0.96	0.82	0.04
Training	SVM (+ChiMerge)	All SSI	0.79 (0.03)	0.39	0.14	0.58 (0.16)	0.87	0.34	0.96	0.85	0.04
Training	SVM (-ChiMerge)	Superficial SSI	0.71 (0.08)	0.24	0.09	0.46 (0.28)	0.87	0.23	0.97	0.85	0.05
Training	SVM (+ChiMerge)	Superficial SSI	0.76 (0.09)	0.27	0.11	0.42 (0.20)	0.87	0.38	0.97	0.83	0.13
Validation	SVM (+ChiMerge)	All SSI	0.71	---	0.14	0.64	0.70	0.17	0.95	0.69	---
Validation	SVM (+ChiMerge)	Superficial SSI	0.64	---	0.11	0.22	0.88	0.13	0.94	0.83	---

Table 9. Confusion matrix of a) NB(+ChiMerge) and b) SVM(+ChiMerge) for prediction of all SSIs (Validation Set)

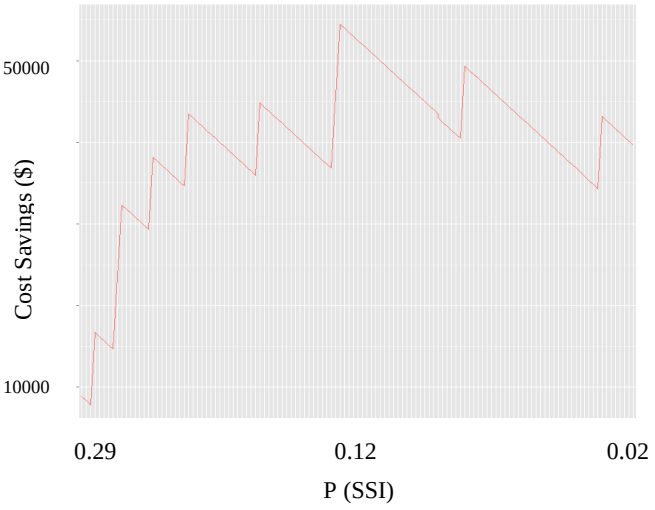
a)

		OUTCOME	
		No SSI	SSI
PREDICTION	No SSI	TN=88	FN=5
	SSI	FP=27	TP=6

b)

		OUTCOME	
		No SSI	SSI
PREDICTION	No SSI	TN=80	FN=4
	SSI	FP=35	TP=7

Figure 5. Profit curve of SVM(+ChiMerge) prediction of all SSIs (Validation Set)



9. DISCUSSION AND CONCLUSIONS

In this paper, we have discussed a framework for designing a predictive model that can be used for real-time intra-operative decision making. To our knowledge, our work is the first to present a model that can be used directly from the operating room. We designed models that can detect patients at risk for all SSIs, and patients at risk for superficial SSIs. The results from our experiments suggest that naïve Bayes and support vector machines can indeed do this with high discrimination.

Previous studies have investigated the risk factors for SSIs. Here, we have outlined the relative importance of those common predictors using the Kvalseth NMI. The top 5 predictors for SSIs that are also statistically significant after a chi squared statistic analysis are ostomy presence, EBL, procedure duration, procedure category, and total procedures.

In our hospital, we have estimated the cost of an SSI to average $28,000 per patient. If the cost of an intervention (eg. a wound management system) is around $500, we would be able to afford 56 false positives for every 1 false negative to break even financially. Given that our SVM(+ChiMerge) model has 9 false positives for 1 false negative (Table 9) we believe using this model in a clinical setting will offer substantial cost savings. We demonstrate this further using a profit curve. We show that when the SVM(+ChiMerge) model is applied to the validation set, a maximum cost savings of over $50,000 can be achieved when a probability threshold of 0.12 is used, assuming our intervention is effective 33% of the time, which is a conservative estimate compared to what has been reported in the literature [23,24] (Figure 5).

A limitation of our study is not including pre-existing conditions in our models. Co-morbidities such as renal failure, diabetes, chronic obstructive pulmonary disease (COPD), hypertension, steroid use, disseminated cancer, and radiation therapy have been shown to be associated with SSIs but were not included in our models [7]. The current implementation of the hospital EHR is not yet conducive to obtaining reliable co-morbidities, nor does it provide diagnostic or procedural coding in real-time. We plan to include co-morbidities in our future models as advancements in the EHR system are made.

These models can be easily extended and generalized to predict other outcomes (eg. hospital readmissions) in other patient populations (eg. Internal Medicine patients), by substituting the outcomes variable, and by adding pertinent predictors to the model. In future work, we will determine if the use of these predictive models in the operating room targeting high risk patients for SSI preventative strategies is effective in preventing SSIs. This will be done in the context of a randomized controlled clinical trial.

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