Predicting Hospital Readmissions Using AI

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The Problem

The readmission of patients who have recently been discharged poses a substantial financial burden to healthcare systems because most readmissions are avoidable and indicate low quality healthcare.

To crackdown on hospitals with high readmission rates and to improve patient healthcare, the Centers for Medicare and Medicaid Services (CMS) apply payment penalties to hospitals with higher than expected readmission rates. As a consequence, about 82 percent of CMS organizations will receive reduced reimbursements under the Hospital Readmissions Reduction Program in 2019 (*Fontana, 2018*).

One of the biggest challenges to prevent readmissions is identifying patients who are at risk of readmission. Early identification of these patients would enable hospital staff to provide the right level of care during their initial admission before they are discharged.

In this whitepaper, we present a brief overview of the current approach used to identify patients at risk of readmission, describe a new approach, conduct a side-by-side comparison of the approaches, compare readmission predictions within different patient population/conditions, and discuss the business outcomes in terms of improving patient care and reducing patient readmission costs.

The Current Approach

Today, the LACE score is used by many hospitals to identify patients at risk for readmission. The score takes into account four variables: the Length of stay, whether the patient was admitted through the emergency department or came voluntarily (Acuity), whether or not the patients have more than one disease or disorders (Comorbidity), and the number of Emergency department visits in the previous 6 months before admission. The sum of these variables is used to predict the rate of readmission or death within 30 days of discharge. A patient with LACE score of greater than 10 indicates a high risk of readmission.

There are conflicting views on the usefulness of the LACE score. Some studies show accurate discrimination for patients with risk for readmission (*van Walraven et al., 2010*), while others suggest the LACE score has poor discriminating capability *(Dadiomov et al., 2018; Robinson and Hudali. 2017; Low et al. 2017; Cotter et al., 2012)*. To determine the utility of this readmission score, we used two independent sets of hospital records (a total of 31,885 records) to analyze how well the LACE score discriminates between patients that are readmitted (True Positives) versus those that are not (True Negatives). Before the assessment, we knew that 12.3% of the patients (n=3,929) in the combined hospital records were readmitted after discharge. The accuracy of LACE score was assessed by comparing the predicted readmissions of the model to the actual readmissions using the following formula:

$$\text{Accuracy} = \frac{\text{TruePositives} + \text{TrueNegatives}}{\text{TruePositives} + \text{FalsePositives} + \text{TrueNegatives} + \text{FalseNegatives}}$$

We found that 50.6% of the patients were flagged as probable readmission candidates (False Positives) when in fact they were not actually readmitted within 30 days (*Table 1*). This result would affect hospital profitability because false positives require the hospital system to expend more resources to these patients. In addition, 2.3 % of the patients were flagged as NOT probable readmission candidates (False Negatives) when in fact they were readmitted within 30 days. This result affects hospital profitability in two ways: the readmission would mean that the hospital would not receive reimbursement for the cost incurred, and the hospital would be subjected to downward payment adjustment up to 3% for Medicare patients cared for by the hospital the following year.

Table 1. CONFUSION MATRIX OF READMISSION STATUS PREDICTIONS USING THE LACE SCORE

DATA SET: 31,885 PATIENTS; ACTUAL CLASSIFICATION INCLUDES 3,929 PATIENTS WITH KNOWN READMISSION STATUS (*YES*) AND 27,956 PATIENTS SERVED AS NEGATIVE CONTROLS (*NO*). LEGEND: *ACTUAL* – ACTUAL CLASSIFICATION; *PREDICTED* – LACE SCORE PREDICTION; *TP* - TRUE POSITIVE; *TN* - TRUE NEGATIVE; *FP* - FALSE POSITIVE; *FN* - FALSE NEGATIVE;

n=31,885	Predicted Yes	Predicted No	Row Sum
Actual Yes	TP=3,240	FN=743	3,929
Actual No	FP=16,159	TN=11,797	27,956
Column Sum	19,399	12,540	

Only 47.1% of readmissions were accurately classified (15,037/31,885) by the LACE Score. Hence, we conclude that the LACE score poorly discriminates between patients at risk of readmission from those who are not and developing an approach that accurately predicts patient readmission risk is highly desired.

Predicting Patient Readmission Status Using a New Approach

Electronic hospital medical records contain a treasure trove of information that can be mined for patterns such as patient age, the previous number of hospital visits, and patient diagnosis and procedural codes. These patterns can be used to develop mathematical models for identifying patients at risk for readmission.

Prior to designing a model, the hospital records were split into training, testing and validation sets. The training data set was used to build the model, the testing dataset was used to assess the model's performance, and the validation dataset was used to verify the model's performance. One of the two hospital data sets was used for training and testing of the model, while the other was used for validation.

The data in the training and testing datasets were balanced in order to prevent over fitting of the model; meaning, the datasets contained equal number of patients with the readmission status of Yes and the readmission status of No (i.e., 2460 patients in each group). We chose an artificial neural network (ANN) approach to model the data because they better deal with the inherent variability (non-linearity) associated with electronic healthcare data as demonstrated by *Futoma et al. (2015)*.

Improved Predictions of Readmission Status

The confusion matrix of the training and testing dataset and the validation dataset yielded highly accurate predictions of 94.9% (*Table 2*) and 98.2% (*Table 3*), respectively.

Table 2. CONFUSION MATRIX OF READMISSION STATUS PREDICTIONS USING THE ANN MODEL ON "TRAINING DATASET"

DATA SET: 4,920 PATIENTS; ACTUAL CLASSIFICATION INCLUDES 2,460 PATIENTS WITH KNOWN READMISSION STATUS (*YES*) AND 2,460 PATIENTS SERVED AS NEGATIVE CONTROLS (*NO*). LEGEND: *ACTUAL* – ACTUAL CLASSIFICATION; *PREDICTED* – ANN MODEL PREDICTION; *TP* - TRUE POSITIVE; *TN* - TRUE NEGATIVE; *FP* - FALSE POSITIVE; *FN* - FALSE NEGATIVE;

n=4,920	Predicted Yes	Predicted No	Row Sum
Actual Yes	TP=2186	FN=274	2460
Actual No	FP=0	TN=2460	2460
Column Sum	2186	2734	

Approximately 94.4% were accurately classified (4,646/4,920) by the ANN model.

Table 3. CONFUSION MATRIX OF READMISSION STATUS PREDICTIONS USING THE ANN MODEL ON "VALIDATION DATASET"

DATA SET: 11,161 PATIENTS; ACTUAL CLASSIFICATION INCLUDES 1,469 PATIENTS WITH KNOWN READMISSION STATUS (*YES*) AND 9,691 PATIENTS SERVED AS NEGATIVE CONTROLS (*NO*). LEGEND: *ACTUAL* – ACTUAL CLASSIFICATION; *PREDICTED* – ANN MODEL PREDICTION; *TP* - TRUE POSITIVE; *TN* - TRUE NEGATIVE; *FP* - FALSE POSITIVE; *FN* - FALSE NEGATIVE;

n=11,161	Predicted Yes	Predicted No	Row Sum
Actual Yes	TP=1271	FN=198	1469
Actual No	FP=1	TN=9691	9692
Column Sum	1272	9889	

Approximately 98.2% were accurately classified (10,962/11,161) by the ANN model.

ANN Model Performance by Patient Populations/ Conditions

The Centers for Medicare and Medicaid (CMS) Hospital Readmission Reduction Program (HRRP) assesses penalties for hospitals by evaluating readmission rates for six patient populations/conditions (a.k.a Cohorts) that have higher than expected readmission rates – a national benchmark (*Table 4)*. Given that there are different numbers of readmission rates for each population/condition, we assessed the performance of the new ANN model using the Receiver Operating Characteristic (ROC) and the area under the curve (AUC) analysis.

ROC-AUC is a performance measurement for classification problems. The ROC is a probability curve and the AUC represents a measure of discrimination, such as discriminating between a patient with a readmission status of 1 (Yes) or 0 (No). While an AUC close to 1 indicates an excellent model with high predictability, an AUC of 0.5 indicates that the model has no predictability.

Table 4. COHORTS (*) USED TO ASSESS PENALTIES BY CMS HRRP

Cohorts	Code
Acute myocardial infarction*	AMI
Stroke	STK
Chronic Obstructive Pulmonary Disorder*	COPD
Heart Failure*	HF
Pneumonia*	PN
Coronary Artery Bypass Grafting*	CABG
Total Hip Arthroplasty/Total Knee Arthroplasty*	THA/TKA

We found that the readmission status was accurately predicted for patients with Acute Myocardial Infarction, Stoke, Chronic Obstructive Pulmonary Disorder, Heart Failure, Pneumonia, and Coronary Artery Bypass Grafting (AUC>=0.93) (*Table 5*), but poorly predicted for patients with Total Hip Arthroplasty/Total Knee Arthroplasty (AUC=0.51). The putative reason for this poor predictability is the THA/TKA cohort had a lower number of readmission patients (42 out of 1470; 2.9%) than the other cohorts.

Table 5. RESULTS OF READMISSION ANN MODEL BY CMS HRRP COHORT

Cohort	Size	Readmission rate (%)	AUC	95% CI
All	11,161	13.2	0.93	92.4-94.5
AMI	1,128	9.7	0.95	91.9-98.5
STK	1,331	11.3	0.93	89.5-96.1
COPD	1,628	19.7	0.97	95.5-98.6
HF	2,499	17.5	0.94	91.6-95.5
PN	2,679	14.0	0.95	93.6-97.0
CABG	426	8.2	0.98	94.4-100.0
THA/TKA	1,470	2.9	0.51	41.6-60.6

While readmission predictions were highly accurate for most cohorts, the model does not accurately predict readmission for patients in the THA/TKA cohort.

Coherence with Other Readmission Studies

A survey of the recent papers on studies predicting readmission status using electronic medical records (*Table 6*) revealed that most models have ROC-AUC values ranging from 0.70 to 0.78. This range indicates modest or acceptable discriminative ability.

Table 6. COMPARISON OF OUR ANN MODEL'S ROC-AUC ANALYSES OF READMISSION STATUS AGAINST PRIOR PUBLISHED STUDIES

Cohort	Futoma et al. 2015	Yang et al. 2016	Our study
AMI	0.65	0.67	0.95
COPD	0.71	0.72	0.97
HF	0.68	0.68	0.94
PN	0.73	0.72	0.95
THA/TKA	0.64	0.72	0.51

Except for the THA/TKA cohort, our study yielded better readmission status predictions by population/condition. Of note, the *Futoma et al. (2015)* and *Yang et al. (2016)* studies yielded better predictions for the THA/TKA cohort than our model (Table 6). Re-training the ANN model with a different dataset with more THA/TKA readmission patients might improve upon its performance.

Also note, the highest ROC-AUC value for a readmission model was 0.85 -- but was not included in *Table 6* because the study (*Rahimian et al., 2018*) was based on emergency room readmissions, not hospital readmissions.

The fact that our study yielded an overall ROC-AUC value of 93.5% (*Figure 1*) suggests that the validated ANN model is far superior to all known readmission prediction models.

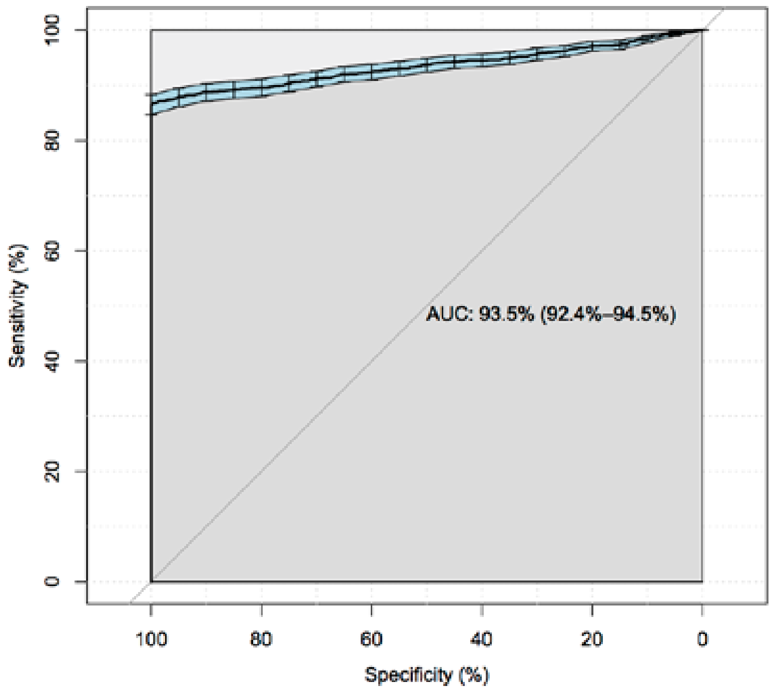


Figure 1. ROC-AUC FOR READMISSION STATUS PREDICTIONS USING THE ANN MODEL ON A VALIDATION DATASET (N=11,161 PATIENTS). THE 95% CONFIDENCE INTERVALS ARE BLUE.

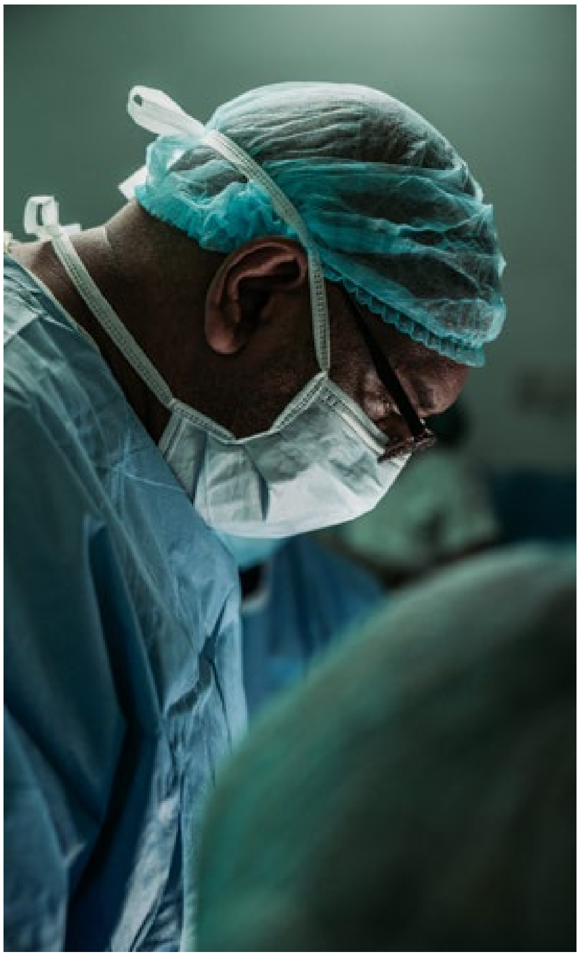
Patient and Business Outcomes

We can directly compare the predictive power of the LACE score to our ANN model (henceforth referred to as the Predictive Readmission Calculator, PRC) by constructing an Intersection Matrix of the 31,885 patient health records. We know beforehand that exactly 3,929 patients were identified as being readmitted within 30 days of an initial discharge (re-admission status as Yes) and 27,956 patients were identified as not readmitted (re-admission status as No).

Interestingly, when contrasted with the LACE score, hospitals using the PRC model would be able to reduce the allocation of additional resources and costs towards care for 4,512 patients – the difference in values tagged as (a) in *Table 7* below. Furthermore, hospitals using the LACE score would risk reimbursement from the potential readmissions for 583 patients - values tagged as (b) in *Table 7* - that were incorrectly predicted.

Table 7. INTERSECTION MATRIX OF READMISSION STATUS PREDICTIONS USING THE LACE SCORE AND THE PRC

n=31,885	PRC Predicted Yes	PRC Predicted No
LACE Predicted Yes	2876	16469[a]
LACE Predicted No	583[b]	11957[a]



Although readmission costs vary by medical condition, we calculated the potential cost savings of hospitals using the PRC over the LACE score by using the average cost of an all-cause readmission, which is $11,200 (*Anonymous, 2013*). By identifying 4,512 patients that should not be readmitted, the PRC could potentially save the hospital systems additional costs of care that impact their bottom line directly. While there is no published figure available for additional cost of care to prevent readmissions, it is reported that CMS healthcare payments are below actual costs - as much as 12 cents on every dollar - incurred by hospitals for patient care (*LaPointe, 2016*). By accurately identifying 583 patients that should be readmitted, the PRC approach can potentially save the hospital systems $6.5 million.

The high price tag associated with the inaccuracies of the LACE score result in significant cost burdens for these hospitals that use the LACE score as a readmission risk stratification method. In contrast, the PRC provides superior predictive power in terms of identifying patients that should not likely be readmitted versus those that should likely be readmitted. By utilizing the PRC, hospitals can improve patient care and reduce patient readmission costs.

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