RISK PREDICTION FOR UNPLANNED HOSPITAL READMISSION FOR ACUTE MYOCARDIAL INFARCTION WITH COST-SENSITIVE APPROACH

Junar Arciete Landicho

Department of Computer Science, University of Science and Technology of Southern Philippines,

Cagayan de Oro City, Philippines

Email: junarlandicho@ustp.edu.ph

ABSTRACT: *Acute Myocardial Infarction (AMI) is one of the leading diseases with a high hospital readmission rate; this adds to the cost of treatment. However, it is potentially preventable. Though several predictive models have been developed over the years to enable early identification of AMI patients who are at a high risk of readmission, only a few of these consider the cost factor. The goal of this study was to build and compare predictive models for patient readmission within one year. It aimed to help hospitals to understand the risk factors and application of a cost-sensitive element. A retrospective observational cohort study was conducted to evaluate AMI admissions between June 2017 and December 2018 in a single hospital setting. A resampling technique and misclassification error cost was used to develop a cost-sensitive classifier. The models were validated with Logistic Regression, Support Vector Machine, C5.0 Decision Tree and CART Algorithm. A total of 200 patients were included and 42 (21.0%) of those were readmitted within one year of the previous discharge. The results showed that the C5.0 Decision Tree gave the best overall performance when using evaluation metrics as it caused the least misclassification cost. Predictors which had a highly significant association with AMI readmission were: number of outpatient visits, number of comorbidities, red blood cell, ceratinise, respiratory rate, sodium and blood sugar counts. Incorporating cost and resampling techniques could minimise misclassification errors and improve the model's performance in developing predictions for within-one-year readmission of AMI patients. Risk factors for readmission found in our study were consistent with previous studies.*

Keywords: Acute Myocardial Infarction; Machine Learning; Hospital Readmission; Cost-Sensitive Learning; Risk Prediction

1.0 INTRODUCTION

Unplanned hospital readmission is common for patients with Acute Myocardial Infarction (AMI). It remains one of the most expensive diagnoses, with frequent readmission, is potentially avoidable and is associated with higher mortality and morbidity among the elderly population [18-22]. It accounts for half of the 17 million worldwide annual deaths from cardiovascular disease [25]. In the United States, approximately one in six patients diagnosed with AMI has unplanned readmission within 30 days of discharge, costing over $1 billion annually in healthcare [18,19]. In Spain, the readmission rate for an adult patient is 20.2% at one year after discharge with AMI [26]. Furthermore, in developing countries such as South Africa, Nigeria, and the Philippines, hospital readmission problems are much more pronounced due to limited resources and lack of funding with which to grapple the problem; additionally, in these countries, there is insufficient information about population-based data [10,14]. Therefore, identifying patients with a high readmission risk, and lowering the cost to help healthcare providers direct their resources and services to those patients to prevent avoidable readmissions should be considered a priority.

Hospitals are known to have different characteristics in their patient populations, and the one-model-fits-all strategy may not work optimally [23]. By understanding the risk factors, strategies to reduce AMI readmission can be guided. The factors that influence a patient's risk for one-year readmission with recurrent AMI are still not known [24]. One of the strategies used to identify risk factors and reduce AMI readmission rates is to apply classifiers and predictive models, including Logistic Regression and machine learning algorithms [15,16]. The currently available AMI readmission risk prediction model has poor-to-modest predictive ability, and some of the models are not readily actionable in real-time. These models have been applied to an almost balanced dataset where the number of cases which have not been readmitted is equal to or more than readmitted cases [27]. In addition, only a few predictive models for hospital readmission incorporate readmission costs and ignore misclassification costs [5]. The misclassification cost is an essential factor in evaluating the performance of a predictive model that applies cost-sensitive learning using imbalanced datasets.

For a potentially small number of patients, an appropriate method may be needed to meet target rates, and traditional statistics may produce an incomplete model. It is suggested that the cost and probability of readmission need to be considered [12]. Furthermore, a few studies have been published regarding hospital readmissions in developing countries, including the Philippines [5,6].

In this study, we evaluated different machine learning models for the prediction. We identified predictors for one-year AMI readmission using administrative and clinical datasets in a hospital-specific setting using the cost-sensitivity learning approach.

2.0 MATERIALS AND METHODS

2.1 Study Design, Population and Data Sources

The patient data was obtained from the Northern Mindanao Medical Centre (NMMC), Cagayan de Oro City, Philippines, and the study was approved by the Research Ethics Board. We conducted a retrospective cohort study using administrative and clinical data. The study cohort consisted of patient demographics, services, diagnosis and charges codes, procedures, and admission characteristics for the hospital or physician visit. We retrieved data relating to all admissions of patients with AMI from the hospital between June 2017 and December 2018. The initial dataset comprised 338 patients with AMI. We used the International Classification of Disease, Ninth Edition (ICD-9) codes to identify AMI admission, including I20.0 and I21.9. We considered patients with a primary or secondary diagnosis of AMI, who were aged 18 years or older and had an index inpatient admission. Patients who died during their hospitalisation, transferred to another medical institution or had a scheduled readmission were excluded. We also removed inconsistent data such as age discrepancies, or a discharge date that preceded the admission date.

2.2 Study Objective and Outcome

The objective of this study was to explore the potential of predictive models in the area of cost-effectiveness in order to help decision-makers to provide effective intervention strategies and optimise available hospital resources. The primary outcome was a performance comparison of predictive models and identification of unplanned readmission within one year. We calculated all the payments reported as the measure for patient spending during admission to the hospital.

2.3 Data Preparation

Based on the initial list of hospital admissions, some data acquired were inconsistent and incomplete. Constant features or duplicated records in the dataset were removed to ensure unique information on admission and avoid error in the models. We applied multiple imputation techniques with five imputations using predictive mean matching (PMM) to identify missing data. Feature selection was used to reduce dimensionality and select the most relevant features of the dataset [28]. We ranked and found the most important features using the Learning Vector Quantization (LVQ) algorithm [33].

2.4 Cost-sensitive Classification

In this study, four common models were used: Logistic Regression (LR), Support Vector Machine (SVM), C5.0 Decision Tree, and the Classification and Regression Tree (CART) algorithm [8,29,30]. Cost-sensitive learning takes the costs of different misclassification errors into consideration when building the model. The minority class is assigned as the positive class, and the majority class is assigned as the negative class. This can be shown in a cost matrix where cost associated with the four outcomes is provided: false positive (FP), false negative (FN), true positive (TP) and true negative (TN), as shown in Table 1. We did not assign a cost to correct classification, so the cost of TP and cost of TN were set to 0. The data were randomly divided into a training dataset (70%) for the development phase and a testing dataset (30%) for validation of the model [7]. To address the class imbalance problem in medical datasets, the training set was modified using a hybrid resampling technique and included misclassification cost [9,31].

To further enhance the performance of the models, tuning was undertaken to find the best parameters, and a repeated 10-fold cross-validation was used on the training set. Cost sensitivity depends on the cost value, so we used a varied cost range ∈ {0.1,1,10,100} and selected the final cost values. The effectiveness of each model was evaluated using the area under the curve (AUC), accuracy, recall, precision, f-measures, and total cost.

Table 1. Cost Matrix for the Cost-sensitive Classification

	Actual Negative	**Actual Positive**
Predict Negative	C(0,0) or TN	C(0,1) or FN
Predict Positive	C(1,0) or FP	C(1,1) or TP

3.0 RESULTS

3.1 Baseline Characteristics of Patients Hospitalised with AMI

Of the 338 patients with AMI during the study period, 200 records met the inclusion criteria and were included in the analysis. Overall, 42 (21.0%) patients were found to have been readmitted within a year. The baseline characteristics of patients are shown in Table 2. On average, patients who were readmitted were older (65.02, ±10.35) and the majority of them were males (57.1%). Hypertensive Cardiovascular Disease (40.0%), Diabetes Mellitus (18.50%), and Pneumonia (15.50%) were common comorbidities. A higher proportion of readmitted patients had a diagnosis of AMI-NSTEMI (66.7%) and a medical history of hypertension (61.9%). It was observed that readmitted patients stayed in the hospital for no less than seven days (7.09, ±2.72). Most patients with AMI had almost no records of previous admissions (0.69, ±1.55) but most of them visited the hospital more than four times as outpatient (4.59, ±7.64) and others had attended the Emergency room at least three times (3.35, ±3.43).

Table 2. Baseline Patient Characteristics of Patients with One-year Readmission.

Variables	All Patients (N = 200)	No Readmission (N = 158)	Readmission (N = 42)	p-value
Age, years, mean (SD)	62.12 (11.66)	61.37 (11.86)	65.02 (10.35)	0.059
Sex, n (%)				0.239
Male	126 (63.0)	102 (64.6)	24 (57.1)	
Female	74 (37.0)	56 (35.4)	18 (42.9)	
Marital Status, n (%)				0.029
Single	27 (13.5)	24 (15.2)	3 (7.1)	
Separated	1 (0.5)	1 (0.6)	-	
Widowed	33 (16.5)	20 (12.7)	13 (31.0)	
Married	136 (68.5)	111 (70.3)	26 (61.9)	
Social Services Classification, n (%)				0.198
C1	20 (10.0)	17 (10.8)	3 (7.1)	
C2	5 (2.5)	5 (3.2)	-	
C3	42 (21.0)	35 (22.2)	7 (16.7)	
D	124 (66.5)	101 (63.9)	32 (76.2)	
Clinical Records, mean (SD)				
No. of Operations	0.14 (0.45)	0.15 (0.48)	0.11 (0.32)	0.289
No. of Medications	11.14 (3.76)	11.26 (3.95)	10.67 (2.97)	0.164
No. of Laboratory Tests	14.24 (9.05)	14.41 (9.69)	13.61 (16.11)	0.615
Comorbidities, n (%)				0.050

Hypertensive Cardiovascular Disease	80 (40.00)	62 (39.24)	18 (42.86)	
Diabetes Mellitus	37 (18.50)	29 (18.35)	8 (19.05)	
Pneumonia	31 (15.50)	24 (15.19)	7 (16.67)	
Pulmonary Congestion	14 (7.00)	11 (6.96)	3 (7.14)	
Left Bundle Branch Block	13 (6.50)	8 (5.06)	5 (11.90)	
Initial Lab Test, mean (SD)				
Creatinine (mg/dl)	1.82 (3.95)	1.75 (4.25)	2.13 (2.41)	0.328
Hematocrit (%)	37.78 (6.47)	38.07 (6.64)	36.63 (5.67)	0.043
Hemoglobin (g/dl)	13.20 (2.99)	13.34 (9.69)	12.62 (2.00)	0.33
Blood Urea Nitrogen (mg/dl)	38.7 (28.87)	38.34 (29.86)	40.00 (25.39)	0.598
Potassium (mmol/L)	4.80 (10.29)	5.03 (11.44)	3.83 (0.84)	0.297
Type of AMI, n (%)				0.518
STEMI	72 (36.0)	60 (38.0)	12 (28.6)	
NSTEMI	119 (59.5)	91 (57.6)	28 (66.7)	
Other	9 (4.5)	7 (4.4)	2 (4.8)	
Medical History, n (%)				
Hypertension	135 (67.5)	109 (69.0)	26 (61.9)	0.234
Diabetes Mellitus	44 (22.)	37 (23.4)	7 (16.7)	0.409
PTB Treatment	12 (6.0)	8 (5.1)	4 (9.5)	0.509
Bronchial Asthma	7 (3.5)	6 (3.8)	1 (2.4)	0.345
Arthritis	14 (7.0)	12 (7.6)	2 (4.8)	0.593
Personal and Social History, n (%)				
Smoker	75(37.5)	60 (38.0)	15 (35.7)	0.805
Alcoholic	47 (23.50	37 (23.4)	10 (23.8)	0.296
Family History of Hypertension & Heart Disease	123 (61.5)	103 (65.2)	20 (47.6)	0.049
Hospital Utilisation, mean (SD)				
Length of Stay	7.33 (4.19)	7.39 (4.50)	7.09 (2.72)	
No. of Previous Admissions	0.32 (0.93)	0.22 (0.65)	0.69 (1.55)	0.050
No. of Previous Outpatient Visits	1.74 (4.49)	0.98 (2.76)	4.59 (7.64)	0.004
Utilisation of Emergency room	1.94 (2.15)	1.57 (1.46)	3.35 (3.43)	0.002

3.2 Identified Risk Factors for One-year AMI Readmissions

The results for feature selection ranked by the LVQ algorithm are shown in Figure 1. As seen in this figure, the number of outpatient visits, number of comorbidities, red blood cell, creatinine, respiratory rate, sodium and blood sugar counts are considered the most important features in identifying AMI patients at high risk of one-year readmission based on the threshold set in this study. It can also be observed that most of the important features are detailed in the initial laboratory test, clinical records, and hospital utilisation.

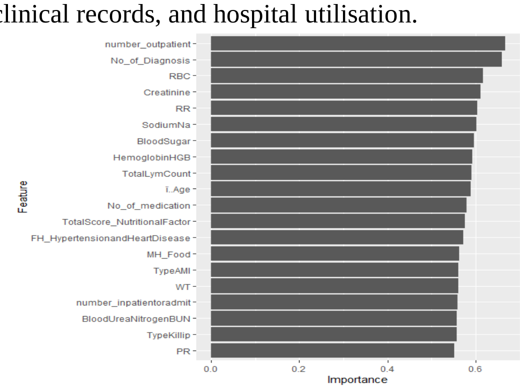

Figure 1. Important Variables in AMI Readmission

3.3 Performance of Predictive Models

In Figure 2, we display the AUROC curve for all the predictive models. The C5.0 Decision Tree is the best performing algorithm (0.611) followed by the Regularized Logistic Regression (0.535) and CART Algorithm (0.444); SVM Linear (0.410) was the least impressive model in this case. It is observed that when high-value cost is used, the performance of Regularized Logistic Regression is decreased while that of SVM Linear is improved. There are no significant changes for the C5.0 Decision Tree and CART Algorithm regardless of cost value. Other performance metrics for the predictive model for one-year AMI readmission are summarised in Table 3. C5.0 Decision Tree consistently outperforms the other models in terms of accuracy, precision and f-measure metrics. It is observed that SVM Linear does not outperform any other model.

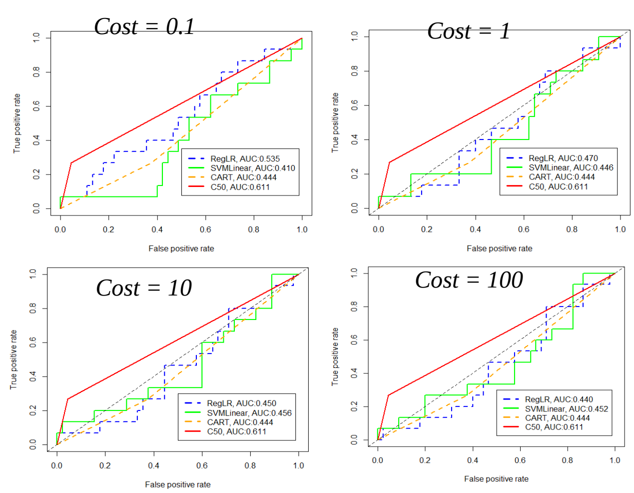

Figure 2. Comparison of Area Under the Receiving Operating Characteristic (AUROC) for Different Costs for AMI Readmission Risk at One Year.

Table 3. Summary of Performance Metrics of Cost-Sensitive Predictive Models Based on Best Cost Value.

Predictive Models	AUC	Accuracy	Recall	Precision	F-measure
RegLogistic Regression	0.535	0.583	0.273	0.400	0.324
SVM Linear	0.456	0.500	0.333	0.200	0.250
C5.0 Decision Tree	0.611	0.783	0.267	0.667	0.381
CART Algorithm	0.444	0.700	0.533	0.421	0.471

3.4 Cost Analysis

By using the actual cost of readmission, a cost analysis was conducted to calculate the possible savings if the model were to be implemented. We calculated the average cost of readmission for patients with AMI using the data provided by the hospital. The estimated cost of readmission for AMI patients was Php 43,159.87 for 200 patients representing the total readmission data, where the average length of stay was 7.09 days. Therefore, the estimated cost per day for admission was calculated to be Php 6,087.43 (43,159.87/7.09). Therefore, the cost of FP and FN were Php 6,087.43 and Php 6,598.68, respectively. The misclassification cost from different models using the cost matrix is given in Table 4. C5.0 Decision Tree obtained the lowest mean misclassification cost (Php 75,434.88) among the predictive model.

Table 4. Comparison of Misclassification Cost for Different Predictive Models.

Predictive Model	Misclassification Cost for 60 patients
Regularized Logistic Regression	Php 149,491.25
SVM Linear	Php 179,680.71
C5.0 Decision Tree	Php 75,434.88
CART Algorithm	Php 107,444.41

4.0 DISCUSSION

This is the first study to predict which patients with AMI would be readmitted within one year of discharge in the Philippines. We chose to focus on one-year readmission instead of any shorter time period, such as 30-day readmission, because it was observed that most readmissions occur over a longer period. The readmission rates reported in this study were lower than those in some previous literature [34-36].

We examined the ability of various prediction models to identify high readmission risk with hospitalisation costs using administrative and clinical data. The C5.0 Decision Tree emerged as the best algorithm for 10-fold cross-validation compared to Regularized Logistic Regression, SVM Linear, and the CART Algorithm. These results are in line with various existing studies undertaken previously. Although our model had better AUC values, it is difficult to compare it with previously developed readmission models because it relies mostly on risk scores or prediction of mortality [37-39,41].

There are many factors that can affect readmission rates for AMI cases. Some of these factors include hospital utilisation, initial laboratory test and comorbidities that confirm previous findings, and others are newly reported [40,42,43]. In this study, the number of outpatient visits, number of comorbidities, red blood cell, creatinine, respiratory rate, sodium and blood sugar counts are important features to consider when predicting readmitted AMI patients.

There were a few limitations of this study. The AMI cases were collected based on administrative and clinical data, and we did not analyse the chart reviews and other medical information. It was a hospital-specific study and, as such, the results may not be applicable to patients who are admitted or transferred to other hospitals. This study only focused on readmission outcomes for the adult and elderly population and it did not include death and paediatric records.

5.0 CONCLUSION AND FUTURE WORKS

In this study, we developed and compared four predictive models. All the models were evaluated based on several performance metrics. It was found that C5.0 Decision Tree performs better when predicting readmissions with the lowest mean misclassification cost by a large margin. In this study, it has been demonstrated that cost-sensitive approaches can be used to tune and allow predictive models to be more precise. The number of outpatient visits, number of comorbidities, red blood cell, creatinine, respiratory rate, sodium and blood sugar counts were considered to be important predictors associated with one-year readmission using a feature ranking technique. The use of the predictive model may be a great tool in providing insights to design disease-specific interventions and decrease the readmission of high-risk patients in developing countries. Incorporating the cost-sensitive learning approach and resampling technique helps the predictive models to address class imbalance and to minimise cost.

This research could be extended to other cohort studies related to planned readmission and the results may be more interesting and informative. Several critical features in the medical records such as health history, lifestyle and other social factors could also be considered in similar studies in the future. These factors may have significant effects on the performance of models for predicting hospital readmissions and may obscure the detection of important disparities in post-discharge care. Other statistical methods or machine learning algorithms such as Neural Network and Random Forest, that may provide better results or improve the accuracy of results, could also be explore

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