Predicting 30-days All-cause Hospital Readmissions Considering Discharge-to-alternate-care-facilities

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Abstract: Hospital discharge is a decision based on several data points including diagnostic, physiological, demographic and caretaker information. Readmissions days after discharge are costly in addition to negative impact on capacity and service quality of hospitals. 30-days readmission (30DRA) literature remains focused on above variables and medical conditions paying little attention to the role of alternate-care-facilities (such as skilled nursing facilities and hospices) on reduction of 30DRA rates. To the best of our knowledge, there is negligible research considering alternate care variables for predicting readmissions even when physicians have actively started considering discharge-to-alternate-care during discharge planning. This paper develops a classification model for predicting patients who are likely to be readmitted within 30 days of discharge-to-alternate-care. Several machine-learning approaches, such as multi-logistic regression, Naïve Bayes, random forest, and neural networks were tested on the model to find the one with highest predictive power. The model was trained and tested on MIMIC-III, a large anonymized electronic health records (EHRs) database from US hospitals. Results suggest discharge-to-alternate-care reduces 30DRA. Moreover, neural networks and logistic regression techniques show better precision and accuracy in identifying the patients likely to be readmitted in 30 days.

1 INTRODUCTION

An increase in hospital readmission rates has been burdening the US healthcare system in the form of unnecessary medical expenses. Jencks et al. (2009) noted around 20 percent of Medicare patients were readmitted within 30 days. It is not surprising hospital readmissions are increasingly being considered an indicator of care quality, resource utilization and health outcomes (MedPAC, 2013, Halfon et al., 2006). Medicare started reporting hospital readmission rates in 2009 and launched the Hospital Readmission Reduction Program (HRRP) in 2012 lowering payments to hospitals with excess readmissions (CMS, n.d.-a). Main goals of these programs include lowering treatment costs for patients while preventing inefficient use of scarce healthcare resources and improving patient health outcomes.

Discharge planning is a key process preceding readmission. Alternate care, which is additional primary or secondary care prescribed for patients when discharged from acute care, as a complement ensures healthcare continuity ultimately avoiding poor health outcomes and 30-days readmissions (30DRA) (Naylor et al., 2011, MedPAC, 2013). Many researchers and policy organizations consider alternate or transitional care as the next frontier to deal with disease progression (Mechanic, 2014). To that end, clinical decision support systems (CDSS) have become an important part of discharge planning. Modern CDSS present EHR, diagnostic, labs and comorbidity data to healthcare providers for making effective discharge planning decisions. Based on above data, these CDSS provide valuable support in the form of risk scores and indices predicting mortality, diseases based on co-morbidities, and re-admissions. However, to the best of our knowledge,

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research is negligent on predictive models that consider alternate care as predictor variables for 30-days readmissions.

This paper builds and tests a predictive model for all-cause 30DRAs incorporating history of discharge locations prior to current readmission. We used a subset of MIMIC-III EHR database containing anonymized acute in-patient records (Johnson et al., 2016). The model was trained and tested on several machine-learning (ML) approaches including multi-logistic regression, Naïve Bayes, random forest and neural networks. The results show precision and accuracy of the predictions improves when considering previous discharge locations along with demographics, current admissions and care levels, and disease severity and comorbidity levels during discharge planning. Neural networks turn out to be the best predictive approach here followed by random forest with high evaluations on their ROC, Precision, Recall and F1 scores. The model will be refined further on each of the category of variables.

Rest of the paper is organized as follows. Next section covers relevant literature on hospital readmissions, alternate care and predicting 30DRAs. Section 3 introduces the predictive model and variables at some length before discussing research methods and data mining from MIMIC-III database. It is followed by training and testing results. Final section 4 presents conclusions and plans for future research.

2 LITERAURE ON HOSPITAL READMISSIONS AND ALTERNATE-CARE-FACILITIES

2.1 Hospital Readmissions and Healthcare Costs

Two major economic issues related to hospital readmissions are volumes and costs (Zohrabian et al., 2018). Around 20% patients in US hospitals are re-admitted within 30 days of discharge costing Medicare around 17 billion dollars (Jencks et al., 2009) of which $12 billion are go to potentially avoidable readmissions (Shulan et al., 2013). As per 2017 reports, US healthcare systems is already spending around 17% of its GDP on healthcare, way higher than any other developed OECD nation; most of them spending around 10% of their GDPs (OECD, n.d.). That explains the rationale behind Affordable Care Act (ACA) of 2010 introducing 30-days readmissions reduction as a key policy target. Ensuing to that, Hospital Readmissions Reduction Program (HRRP) was operationalized in 2012 when CMS started financially penalizing Medicare-funded hospitals with high readmission rates (CMS, n.d.-a).

While discussing ACA, Orszag and Emanuel (2010) note, “hospital discharges has been identified as a particular problem in the health care system overall. More than half of these readmitted patients have not seen their physician between discharge and readmission, and a recent study suggests that better coordination of care can reduce readmission rates for major chronic illness. The policy provides $500 million over 5 years to manage care for 30 days after hospital discharge and also imposes payment penalties on hospitals with high risk-adjusted readmission rates for certain conditions.”

These penalties and incentives focused on reducing hospital readmissions have deeply motivated practitioners and researchers to investigate possible ways for reductions in hospital readmissions; see following systematic literature reviews (Kansagara et al., 2011, Leppin et al., 2014, Ross et al., 2008). The research findings have emphasized, inter alia, better discharge planning and transitionary (alternate) care interventions.

2.2 Role of Discharge Planning and Alternate Care in Reducing Hospital Readmissions

A hospital discharge decision is complicated and it needs to be well-informed (Pearson et al., 2004). Besides medical history, current medical conditions, and comorbidities data, it is also based on demographic and external variables such as patient’s physical abilities to independently carryout daily life functions, cognitive abilities, the living quarters and availability of family or caregivers to help the patient, etc. (Allaudeen et al., 2011, Kassin et al., 2012, Maali et al., 2018). Physicians and care providers have to consider these variables during discharge planning since they may lead to premature discharges, poor transitions between different care settings, or poor information exchanges during hand-offs, that are all major reasons behind readmissions (CMS, 2013, Hameed, 2019), which have big implications for well-being of patients, their family members, and professional caregivers.

CMS’s (Centers for Medicare and Medicaid Services) guidelines §482.43 define ‘hospital discharge planning’ as “a process that involves determining the appropriate post-hospital discharge destination for a patient; identifying what the patient requires for a smooth and safe transition from the hospital to his/her discharge destination; and beginning the process of meeting the patient's identified post-discharge needs" (CMS, 2013). Alternative terms are also used by other agencies and hospitals, such as "transition planning" or "community care transitions" especially if there exist post-acute-care healthcare needs of their patients.

Discharge planning is guided by professional bodies in several countries. CMS under Department of Health & Human Services (HHS), USA guides care providers on proper discharge planning and effective transition through post-acute-care needs or continued care needs (CMS, 2013). Similarly, The National Health Service and Community Care Act of 1990 established requirements for UK hospitals to duly consider community care as part of discharge decisions to improve patients' health and lower national healthcare system costs.

An inverse relationship has been proven between quality of post-acute-care and early hospital readmissions. Koehler et al., (2009) showed targeted care bundle delivered to high-risk elderly inpatients decreased unplanned 30-days acute admissions following discharge. Similarly, Naylor et al., (2011) found from several researches on transitionary care that of all the interventions, discharge management plus follow-up have the most significant effects on reducing readmissions. Garåsen et al., (2007) reported positive relationships between use of alternate-care-facilities and reduction of readmissions. Jones et al., (1999) stated that alternate care is comparatively cheaper than acute care in hospitals which constitutes for about 2.4 million hospital days per year (Sutherland and Crump, 2013). Despite affordable prices, alternate-care-facilities provide services that are not too lower in quality than acute care provided in hospitals (Wilson et al., 1997, Richards et al., 1998).

Rich et al., (1995) observed the readmission rate in elderly people with heart failure with ranges from 29 percent to 49 percent. He found improving transfer care after the discharge reduces the readmission rates in the elderly. Jack et al., (2009) also reported similar results for general population based on self-reported data in which the intervention group showed comparatively lower readmission rate than the control group not receiving any additional care. Naylor et al., (1999) went further in estimating reduction in readmission might decrease up to US$3000 per patient.

2.3 Alternate-care-facilities

Several forms of alternate care (also referred as transitionary or post-acute-care) can be provided after discharge. In this paper we define 'alternate care' as a prescribed medical intervention or benefit beyond self-administration of prescription or off-the-counter (OTC) medicines. Our definition of alternate care includes any type of primary or secondary care provided to anyone discharged from acute care or a hospital. Post-discharge interventions typically involve experienced professionals and therapists ensuring patients have all necessary assistance, equipment and help. Such post-discharge care is more common in elderly with relatively higher risk of readmission. Most common types of post-discharge alternate care in the US healthcare system include returning home with early supported discharge (ESD), returning home with social care reablement, transfer to a community hospital, or transfer to a residential (nursing) home (Waring et al., 2014).

Based on the location, the alternate care can be divided mainly into two subgroups; 1) primary or secondary care delivered at home, and; 2) primary or secondary care delivered at an alternate-care-facility outside home.

First subgroup includes 'home care with home intravenous (IV) provider' and general 'home healthcare'. Former means treatment at home with an intravenous (IV) medicine or fluid that is supervised by trained nurses or certified specialists. It provides all necessary support at home of the patient and partially covered by Medicare or government. Home healthcare is home based treatment that is relatively affordable with a designated agent who regularly visits the patients' home on appointment. Social care reablement covers patients needing personal care on a daily basis and lasts for about 6 weeks. It includes bathing and other essential activities for those who cannot help themselves and do not have family or relatives to take care (CMS, n.d.-b)

Second subgroup, care at an alternate-care-facility, includes Distinct Part Hospitals, Skilled Nursing Facility (SNF), Intermediate Care Facility (ICF), Hospice Medical Facility, Short-term Hospital, and Long-term Care Hospital. Rehabilitation Distinct Part Hospitals provide separated beds in specific locations with SNF services. SNF involves full medical services, nursing care as well as additional services such as meals, medications and social services provided by registered nurses, professional therapists and physicians (CMS, n.d.-b). Commonly, SNF is suggested for short-term rehabilitation after serious injuries and partially covered by hospital insurance and accounts for 15 percent of Medicare funding (Buntin et al., 2010). Short-term hospitals are specialized in providing active and short treatments after injuries or after surgery care. Long Term Care

Hospital (LTCH) focus on extended treatment (more than 25 days) and, commonly, functions as sanatoriums for patients with chronic diseases (CMS, n.d.). Compared to above noted alternate-care-facilities, ICF offers lower degree of care since it is a nursing home for those who do not require care given at hospitals or any other special nursing facilities. However, the degree of treatment that ICF patients need are greater than given at home and, thus, needs equipped nursing facilities. Hospice Medical facility is a specially equipped home that provides necessary care for those who have terminal illnesses with the life expectancy of less than 6 months. It is covered by Medicare, Medicaid, and most private insurance companies.

Based on the literature review above, it is quite sensible on healthcare providers' part to consider discharging high risk patients to alternate-care-facilities wherever needed instead of only discharging them to home. Alternate care interventions after discharge ensure patients are highly aware of and capable of taking care of their health or seeking and receiving essential care outside the settings of expensive hospitalization. The improved health behaviour and cheaper methods of receiving care on a regular basis reduces the number of readmissions.

2.4 Predicting Hospital Readmissions within 30 Days and Beyond

From the patient dataset standpoint, Demir (2014) identified three categories of readmission prediction tools; models using retrospective administrative data, models using real-time administrative data, and models incorporating primary data collection. He noted almost all the models he studied from numerous researchers have very poor predictive power.

From the modelling techniques point of view, there are two major approaches in 30DRAs predictions literature. Even though both these approaches involve supervised machine learning, in which independent and dependent variables are defined by the modeller, the first set of approaches mainly calculate probability of re-admissions as a continuous variable. They typically incorporate uni- or multi-variate regression analysis, decisions trees and Bayesian networks techniques for calculating the probability of readmissions using several independent variables. Subsequently, the variables depicting significant relationships with readmissions are weighted to build readmission risk scores and indices. See for example HOSPITAL score by Donzé et al., (2013) and LACE index by van Walraven et al., (2010). Kansagara et al., (2011) did a comprehensive systematic review of such studies.

Second set of prediction techniques are based on classification algorithms such as logistic regression, naïve Bayes networks, decision trees and random forests, etc. Rather than directly reporting probabilities of readmission, these classifiers categorize each record (admitted patient) into either 'likely-to-be-readmitted' or 'not-likely-to-be-readmitted' classes. Neural network techniques are also gaining much popularity in classification tasks.

From disease and conditions point of view, readmissions prediction literature can be broadly be seen focused either on all-cause-readmissions or very narrowly focused on specific diseases or conditions for instance heart patients, patients undergone surgery, or elderly patients, etc.

Maali et al., (2018) looked at all-cause readmission within 7 days, 30 days and 60 days at a Sydney hospital. They found stronger associations between more readmissions between 7-days and 30 or 60 days with old age and previously longer hospital stays. Similarly, Choudhry et al., (2013) calculated all-cause 30-days readmissions predictions in Chicago area at two points of time, i.e. admission and discharge. They tested a variety of variables like demographics, visits, history and physical exam, medications, conditions, past and present procedures, lab tests and exploratory. The ROC (Receiver Operating Characteristic) curves for all-cause admissions and all-cause-discharge models depict high AUC (area under the curves) above 0.75 depicting good sensitivity and precision. Billings et al., (2012) used NHS data to come with a generic all-cause 30-days readmission predictive model called PARR-30. The AUC of their model at 0.7 is also fairly good as it accounts for age, previous emergency discharges, deprivation band of residence area and history in prior 3 years and Charlson's comorbidity index. Building further on HOSPITAL score from his 2010 paper, Donzé et al., (2013) used a multi-logistic regression classifier to calculate potentially avoidable all-cause 30-days readmissions. His model depicts good discriminatory power with AUC value of 0.71.

Numerous other studies and predictive models for 3o-day readmission risk have been developed based on typical clinical data, see for example (Bottle et al., 2006, Kassin et al., 2012, Van Walraven et al., 2011, Allaudeen et al., 2011). They all demonstrated the significance of independent variables such as biomarkers, specific symptoms and conditions, administrative data, demographics (such as race, gender and age etc.) in predicting risk score of general populations.

It is important to note even though all-causea readmissions models, owing to their complexity and co-variances, are generally poor in predictive power when compared with specific disease models. However, they use simplistic and commonly available variables to make their models usable and practical for care providers in clinical settings especially on patient bed side. Shulan et al. (2013) added diagnoses related groups (DRG) codes and hierarchical condition categories (HCC) to demonstrate that increasing predictive power of all – purpose predictive models would require working with more sophisticatedly managed data and variables. Not surprisingly, one of their developed model's AUC reaches 0.8.

On the contrary, there are models focusing specific medical conditions or patient cohorts. For example, using NHS data of 930 patients with COPD and asthma, Demir (2014) comprehensively compared the predictive power of several different techniques from both regression and classifier groups using variables like prior outpatient accidents, emergency visits, and length of stays. He achieved the best predictive power for his models with AUCs in tune of 0.9s though regression and multiple regression classifiers performed better than generalized additive models (GAMs) and multivariate regression splines (MARS).

Desai and Stevenson (2012) showed significantly high rate of readmission in patients with heart failures - approximately 24 percent within only 30 days for patients with pulmonary artery diastolic pressure, chronic filling pressure elevation, ejection fraction, natriuretic peptides and cardiac troponins. (Sharif et al., 2014) suggested yet another model for elderly with chronic obstructive pulmonary disease (COPD).

It can be argued whether or not 30-day readmissions can be prevented entirely but several studies have established that nearly one-third of overall readmission rates might be predictable (Van Walraven et al., 2011, Ross et al., 2009). There is still much room for research on prevention of 30-days re-admissions through better predictions and interventions. Regardless, both the above noted predictive modelling research strands have not duly treated interventions involving transitionary care in alternate-care-facilities.

3 30-DAYS READMISSIONS PREDICTIVE MODEL WITH DISCHARGE-TO-ALTERNATE-CARE VARIABLES

3.1 Defining Target (Dependent) and Predictor (Independent) Variables

We have designed a simple classification problem with '30-Day Readmission' as a binary target dependent variable. A value of '1' means likely readmission within 30 days of discharge whereas '0' represents a patient not likely to be readmitted within 30 days. In addition to that, we have incorporated several categories of independent variables (features) i.e. demographics, current admission and care levels including DRG severity, prior discharge locations from previous readmission (i.e. discharges-to-alternate-care) and finally comorbidity levels. See Table 1 on next page for all the variables and their possible values.

3.2 Mining Data from MIMIC-III

Our dataset comprises of the MIMIC-III database which is freely accessible de-identified database of about 40,000 critical care patients at Beth Israel Deaconess Medical Center between 2001 and 2012 (Pollard, 2016, Johnson et al., 2016). It contains 125557 unique admission records which includes several readmissions, many under 30 days. The clinical database contains variables on patient demographics, diagnosis (ICD-9 codes), labs, procedures, medications, admissions and discharge history and more. Both available and extracted variables included in this study are depicted in Table 1 along with the values they assume.

The database was loaded on an open source PostgresSQL database server. SQL queries were written to mine variables/features for patients who were readmitted ever in the hospital. 12379 extracted records were then subjected to further processing in Microsoft Excel to identify patient records with under 30 days readmissions and matching their discharge location data from their previous admission records. Comorbidity levels for each of the records were then also extracted from DRG_CODE DESCRIPTIONS as 'none', 'with comorbid conditions', and 'with major comorbid conditions'. 3191 readmissions records were available for analysis. In order to ensure class balance, a block of around 3600 records for non-admitted patients was appended. That brought the test and training dataset sample size to 6773 records.

After random sorting the records, it was further broken down into two datasets comprising 5078 records (75%) for model training and 1695 records (25%) as hold-out dataset for testing. Figure 1 elaborates the whole data preparation process.

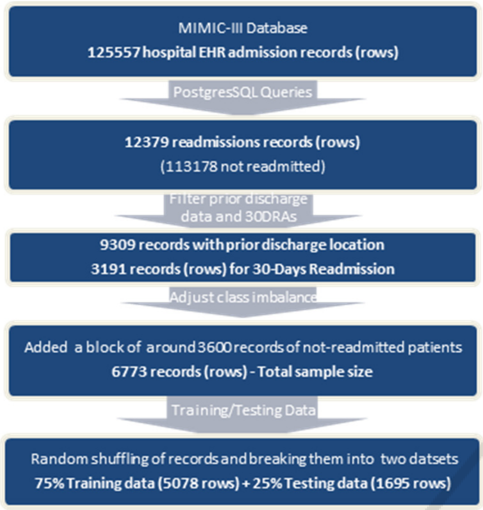

Figure 1: Step-wise data mining and processing.

Table 1: Variables (Features) included in the predictive model with their values (available or extracted).

Category	**Predictor Variables**	**Values**
Demographics	Gender	Male, Female
	Marital Status	Single, Divorced, Widowed, Married, Life Partner Separated, Null, Unknown
	Age	< 89 years
	Ethnicity	7 types Asian (e.g. Chinese, Cambodian, etc.), 4 types Black (e.g. Black African, Black Haitian, 10 types Hispanics, 4 types White, American Indian/Alaskan Native, Native Hawaiian, Portuguese, Multi-Racial, Middle Eastern, Unable to obtain, Declined to Answer, Other
Current Admission and Care Level	Admission Type	Elective, Emergency, Urgent
	Admission Location for Current Admission	Clinical Referral/Premature, Emergency Admit, Phys Referral/Normal Deli, Tranf from Hosp/Extram, Transf from Other Healt, Trans
	Length of Stay	Number of Days
	Discharge Location for Current Admission	SNF, Hosp, Home, Home Healthcare, Home with Home IV Providr, Hospice – Home, Hospice – Medical Facility, ICF, Long Term Care Hospital, Short Term Hospital, Rehab/Distinct Part Hospital 1, Rehab/Distinct Part Hospital 2 **Not Included:** Dead/Expired, Disc-Tran to Psyc Hosp, Disc-Tran to Children/Cancer, Left Against Medical Advi, Other Facility,
	Diagnosis_DRG_CODE	ICD-9 Codes
	Diagnosis_DESCRIPTION	Detailed textual description of Diagnosis including comorbidity notes - **Not included here**
Discharge Location for Previous Admission	Previous Discharge Location	SNF, Hosp, Home, Home Healthcare, Home with Home IV Providr, Hospice – Home, Hospice – Medical Facility, ICF, Long Term Care Hospital, Short Term Hospital, Rehab/Distinct Part Hospital 1, Rehab/Distinct Part Hospital 2
Comorbidity Conditions	Drug Severity	4 levels: 1,2,3,4
	Drug Mortality	4 levels: 1,2,3,4
	None	0,1 **(extracted from text of Diagnosis_DESCRIPTION)**
	With Comorbid Conditions	0,1 **(extracted from text of Diagnosis_DESCRIPTION)**
	With Major Comorbid Conditions	0,1 **(extracted from text of Diagnosis_DESCRIPTION)**
	SAPS II Score	**Not included**
	SOFA Score	**Not included**

The final dataset comprising 6773 patient-admission records is fairly dispersed on gender, ethnicity, and marital status making it a good sample patient wise. Class balance of readmissions is near to perfect after adjustments. The sample is slightly skewed for 'previous discharge location' variable towards discharge-to-alternate-care but since that alternate care is also well dispersed over several different alternate-care-facilities, it appears to work fine, especially in the wake of around 1500 discharge-to-home records. Figure 2 highlights all the descriptive of the final dataset for testing and analysis.

3.3 Model Training and Testing Results and Analysis

Considering the size of the dataset and the variety of predictor variables in the above model, it was trained and tested on four different classification techniques i.e. multi-logistic regression, Naïve Bayes, random forest and a neural network. Ridge 2 regularization was used for multi-logistic regression with a strength C value set at 65. For random forest 2 number of trees were specified with 5 attributes at each split. Limit depth of individual trees was left at default 3 while as the algorithm was configured not to split individual subsets smaller than 5. The neural network with 100 neurons was activated using most common ReLu function. Adam solver was used while regularization alpha was set at 0.005. One hundred iterations were requested of the neural network.

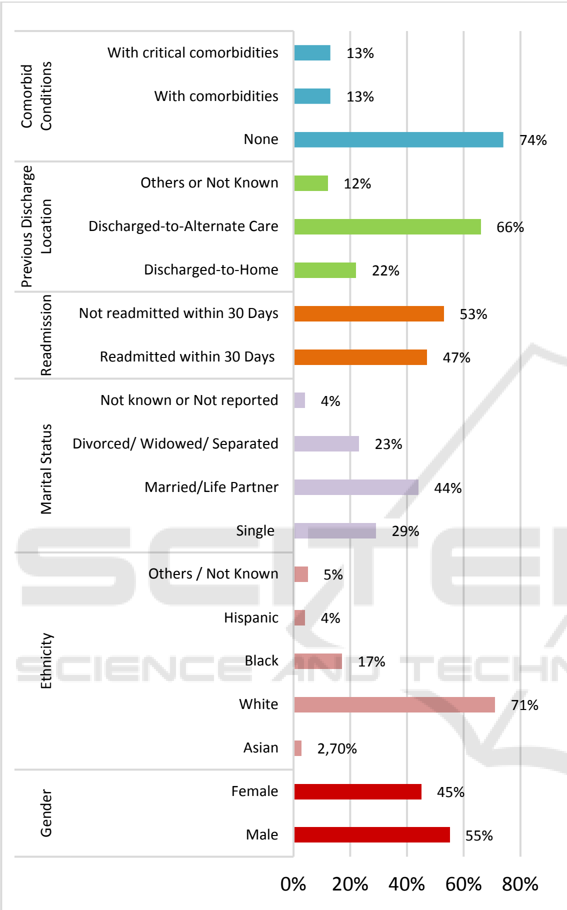

Figure 2: Description of Finalized Dataset.

Figure 3 depicts a process flow developed and executed in open source Orange software for testing and training the model. 75% of the 6773 records were set for training dataset while the testing was performed on the rest 25% records in the same dataset. A higher number of 20 folds were set for better cross-validation. Classification results were calculated mainly as average over both classes but also for target classes 0 and 1 respectively.

After obtaining the predictions several performance evaluation metrics have been used to analyse and interpret the model performance including confusion matrices, AUC - ROC curves, sensitivity, Recall and F1 scores of each machine learning model.

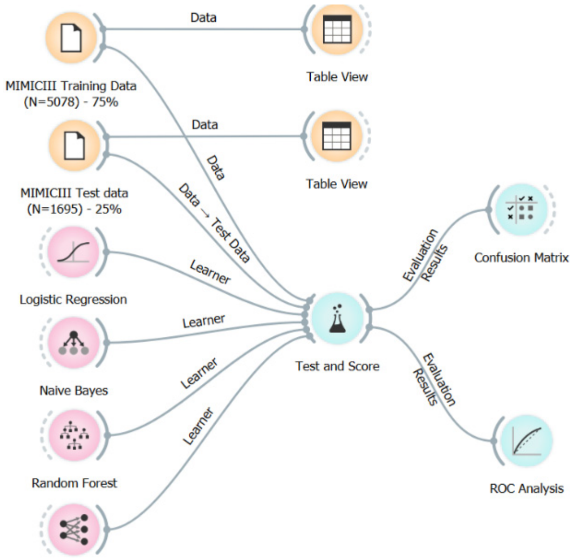

Figure 3: Process flow for training and testing the predictive model (developed in open source 'Orange' ML and visualization software': https://orange.biolab.si/).

Table 2: Confusion Matrices for all ML models including both discharge-to-home and discharge-to-alternate-care variables; 0 represents no-30-days readmission while 1 represents readmission within 30 days.

			Predicted	
			0	1
Logistic Regression	Actual	0	86.60%	13.40%
		1	51.00%	49.00%
Naïve Bayes	Actual	0	72.00%	28.00%
		1	45.80%	54.20%
Random Forest	Actual	0	75.10%	24.90%
		1	48.10%	51.90%
Neural Network	Actual	0	82.80%	17.20%
		1	45.80%	54.20%

Confusion matrices in Table 2 highlight the fact, overall Random Forest and Naïve Bayes classifiers did not perform as good as Logistic Regression and Neural Networks. The true positive (TP) predictions of Random Forest and Naïve Bayes are at 51.9% and 54.2% percent respectively while their true negatives (TN) predictions are at 75.1% and 72% respectively. Consequently, their accuracy and precision both are not the best for consideration even though it could be called fair. The same is apparent in the ROC and AUC curves (see figure 4) where both Random Forest and Naïve Bayes are not the best performers.

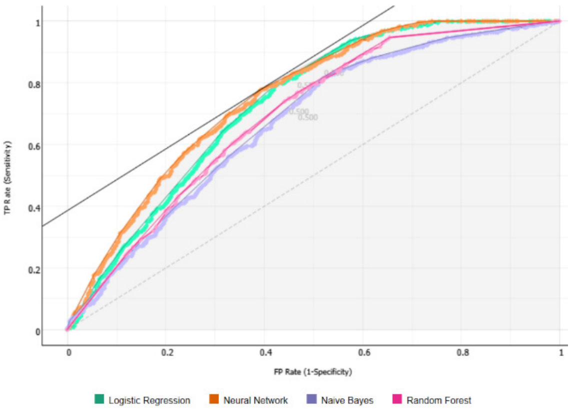

Figure 4: AUC-ROC curves (Target class: 0, Costs: FP = 500, FN = 500 Target probability: 50.0 %).

However, confusion matrices, and performance metrics scores (see Table 3) of neural networks and logistic regression algorithms appear to have predictive power in terms of accuracy as well as precision. With an AUC of 0.75 for the neural network and 0.73 for random forest, it is clear that alternate care has a role in correctly predicting 30-days readmissions. With high Recall scores nearing 0.7 both of these models can be used to help healthcare providers correctly predict the potential 30-days readmissions during discharge planning.

Table 3: Performance of different machine learning models including discharge-to-home as well as discharge-to-alternate-care variables.

Model	AUC	CA	F1	Precision	Recall
Logistic Regression	0.729	0.683	0.670	0.707	0.683
Naive Bayes	0.669	0.633	0.630	0.635	0.633
Random Forest	0.691	0.651	0.648	0.654	0.651
Neural Network	0.750	0.688	0.682	0.701	0.688

In order to differentiate the contribution of discharge-to-alternate-care-facilities from the original model, the variables related to alternate care were temporarily excluded from the model. These excluded variables comprised Home Healthcare, Home with Home IV Providr, Hospice – Home, Hospice – Medical Facility, Long Term Care Hospital, Short Term Hospital, ICF, Rehab/Distinct Part Hospital 1, Rehab/Distinct Part Hospital 2 and SNF. The resulting models were trained and tested again. Around 10 point/percent increase in the prediction power of neural networks and logistic regression models was noted owing to alternate care variables. Overall, Neural Networks outperformed all other models.

4 CONCLUSIONS AND FUTURE RESEARCH

This research developed and tested a supervised predictive model for 30-days readmissions. Based on the considered discharge location of the patient during discharge planning process, health care providers can find this decision support quite valuable. It is especially valuable in the wake of financial penalties imposed by CMS on Medicare-funded hospitals. Previous all-cause 30-days hospital readmissions prediction research had been poor in terms of predictive power with few exceptions (Demir, 2014, Shulan et al., 2013). However, there are no models using alternate care or transitionary care variables for such predictions. This paper contributes by developing a simple yet good predictive power neural network model for all-cause 30-days readmissions.

Such predictive models considering pathways and transitions between alternate-care-facilities should be very interesting for insurance providers due to their coverage and cost implications. The intentions and benefits of insurance companies may be studied further in this context.

Another area of work is stratification and predicting alternate-care-pathways for patients with most common but critical diseases and conditions. Their numbers and desired care levels might differ from general all-cause readmission patients.

Future work is being carried out to improve it into a formal 30-days readmissions risk model duly considering alternate care variables by also systematically incorporating comorbidity scores, such as SAPS II and SOFA, as well as current lab results, procedures, previous admissions and medical history. It is expected that the final predictive model can achieve an accuracy of above 90%. Once completed, it will go into creation of a clinical decision support app/tool that can be linked with most typical hospital EHR systems for use on patient bedside and clinical settings during discharge and transitionary care planning.

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