Objective: To develop a new and different machine learning model to predict the risk of hospital readmissions within 30 days of discharge and then to compare the result of the newly built model with a pre-existing famous model i.e. LACE Index.

Data Source: Two years (2015 and 2016) of data which was gathered from Waitemata District Health Board (WDHB) was used in this research. The dataset includes six months of retrospective data and one month of prospective data.

Methods: We performed a retrospective analysis of 213439 patients, out of which 17549 were true readmissions, 162568 were false readmissions and rest were not applicable records. The dataset went through deep pre-processing and feature engineering before applying various machine learning models which were Decision Table, AdaBoost, Random Forest, SVM and REPTree. Bagging technique was applied on the best model among these.

Results: The actual readmission rate for the given WDHB's data was 9.83%. The readmission rate for pre-existing model, LACE Index, on the same data was 10.90%. The readmission rate for the newly built model, RHR-30, was 9.83% with the score threshold of 0.02.

INTRODUCTION

When a patient is admitted as an acute admission into a hospital within a short period of time post the discharge from the hospital is considered as an unplanned hospital readmission. These unplanned hospital readmissions are burden to patients as well as the healthcare system. An increasing unplanned readmissions are not only costly for healthcare providers however are also perceived as an indicator for the quality of care that is being provided by the hospital and are also costly for the healthcare (Chassin, Loeb, Schmaltz, & Wachter, 2010; Zhou, Della, Roberts, Goh, & Dhaliwal, 2016)

In 2016, acute readmission rate within 28-days of discharge for all the District Health Boards (DHBs) nationwide was 7.8%, Canterbury having the highest readmission rate of 8.9% (*District Health Board Sector Financial Performance for year to date 30 September 2016.*). In the United Kingdom, the emergency 30-days readmission rate between 2004 and 2010 was 7% and it was estimated that 2% were potentially preventable (Blunt, Bardsley, Grove, & Clarke, 2014).

There are many factors other than medical information which adds to unplanned readmissions for example social and culture factors. Hence, not all readmission can be prevented and estimating of how many can be avoided remain controversial (Glass, Lisk, & Stensland, 2012; Joynt & Jha, 2013)

The research aims to conduct an in-depth pre-processing of the Waitemata District Health Board (WDHB) data and building a machine learning model to predict the risk of hospital readmissions within the 30 days of discharge of the patient. It also aims at comparing the results of the newly built model with an existing and popular model, LACE Index model.

LITERATURE REVIEW

Machine learning algorithms are popular tools for predicting hospital readmissions (Krumholz et al., 2011; Stiglic, Wang, Davey, & Obradovic, 2014). Some researchers have created models which aims to predict hospital readmissions in default population settings. Research suggests these models have been used and have significantly established over time. LACE Index model is one of the popular model to detect high readmission risk patients. LACE Index model uses four attributes which are length of stay ("L"), acuity of the admissions ("A"), comorbidity index score ("C") and emergency department use which measured as the number of visits in the six months before admission ("E") (van Walraven et al., 2010).

Design of the study is more important than the analysis as a poorly analysed study can usually be reanalysed however a badly designed study can never be retrieved. It's the design of the study which will govern how the data are to be analysed (Swinscow & Campbell, 1997). Majority of the research have performed cohort retrospective study. A cohort retrospective study is comparing groups of individuals who are alike in many ways but differ by a certain characteristic in terms of the outcome (Institute, 2016). The data is collected from a health organization for each patient from the existing records and is be analysed through machine learning models to determine the relative risk of the cohort compared to the control group. Two of the studies which were reviewed in this literature review also included prospective study with a retrospective study. Prospective cohort study follows over time and compares the predicted outcome (Institute, 2016).

Key Features for "Readmission":

Different research has different definition for unplanned hospital readmission i.e. different inclusion and exclusion criteria were used in each study. The significant inclusion and exclusion criteria were extracted from the 13 studies included during literature review for this research are shown in Table 1.

Table 1. A summary of design of study and significant inclusion and exclusion criteria on 28-day or 30-day unplanned hospital readmission

References	Design of Study	Inclusion Criteria	Exclusion Criteria
(Choudhry et al., 2013)	12 months of retrospective data		• Psychiatry admissions • Skilled nursing admissions • Hospice admissions • Rehabilitation admissions • Maternal and newborn visits • Patients died during the index hospitalization
(Berry et al., 2018)	Retrospective data	• Newborns • Children • Cancer patients • Mental health patients	
(Khan, Malone, Pagel, Vollbrecht, & Baumgardner, 2012)	Retrospective data	• Age: 65 and older	• Outpatient stays • Patient died during the hospital stay
(van Walraven, Wong, & Forster, 2012a)	Retrospective data	• One admission per patient • Age: 18 and older	• Patients died during the hospital stay • Psychiatric or obstetric admissions • Discharge to long-term care, rehabilitations or other hospitals
(van Walraven, Wong, & Forster, 2012b)	Retrospective data	• One admission per patient • Age: 18 and older	• Patients died during the hospital stay • Psychiatric or obstetric admissions

			• Discharge to long-term care, rehabilitations or other hospitals
(Escobar et al., 2015)	Retrospective data	• Overnight stay hospitalization • Age: 18 and older • Post-delivery complications	• One-day surgeries which didn't result in overnight stay • Hospitalization for childbirth
(Maali et al., 2018)	12 months of retrospective data + 2 months of prospective data	• Index hospitalization • Initiated via ED	• Patient died during the index hospitalization
(Shulan, Gao, & Moore, 2013)	Retrospective data	• Index hospitalization	• Patients transferred from other hospitals
(van Walraven, Wong, Forster, & Hawken, 2013)	Retrospective data	• One observation per patient	• Patients died during the hospital stay • Psychiatric or obstetric admissions • Discharge to long-term care, rehabilitations or other hospitals • Urgent hospitalization occurring within 30 days of previous
(Yu et al., 2015)	2 years, 6 years and 10 years of retrospective data for Hospital 1, Hospital 2 and Hospital 3 respectively	• Index hospitalization • If patient had multiple visits within 30days, only first one was considered as readmission • Age: 65 and older	• In-hospital mortality visits • Patients not insured by Medicare/Medicaid
(Wakefield & Mehr, 2013)	Retrospective data	• Age: 18 and older • Psychiatric conditions requiring temporary acute care such as alcohol detoxification,	• Outpatient stays • LOS 0 days • Maternal and newborns • Psychiatric or obstetric admissions • Planned readmissions unless it was from the ED

		drug detoxification or stabilization following a suicide attempt	
(Lee, 2012)	Retrospective data	• When a patient had multiple visits, each visit evaluated separately	
(Baillie et al., 2013)	24 months of retrospective data + 12 months of prospective data	• All adult admissions	• Short procedure admissions • Hospice admissions • Rehabilitation admissions

Data and Model Settings:

Table 2 summarizes the characteristic of the final included studies in this literature review. The studies conducted is from various parts of the world like USA, Canada, UK and Australia. The duration of the retrieved data source ranged from one single day data collected across ten hospitals to data collected for 6 years from four health database in Ontario. Every study had a different sample size and accordingly a different derivation and validation split, for example (Shulan et al., 2013; van Walraven et al., 2012a, 2012b) has 50-50 split in derivation and validation split, on the other hand (Lee, 2012) has 70-30 split, (Choudhry et al., 2013) has 75-25 split and (Wakefield & Mehr, 2013) has 90-10 split keeping the higher number as a derivation sample percentage and smaller number as validation sample percentage. A total of 29 models were derived or validated using administrative and/or clinical/medical data. The sample size varied from 227 patients to 31729762 patients. The unplanned hospital readmission rate for 28-days or 30-days ranged from 6.60% (*n*= 62255) to 23% (*n*=2441), '*n*' being the sample size for the respective study. Table 2 also includes all predictive models made/used in the respective studies and compares its performances. In logistic regression, the result variable is the log of the odds of the event ie readmission probability/ 1- readmission probability. After determining the final model, the multi-variable logistic regression allows for the calculation of cohort studies' readmission probability. The majority of the studies reported c-statistic (also known as ROC area) which is a measure for model discrimination and Hosmer-Lemeshow value as a measure for calibration (Steyerberg et al., 2010). The discriminative ability for all-cause unplanned hospital readmission ranged from 0.55 to 0.80 and calibration ranged from 15.11(p=0.0569) to 40.14(p<0.0001)

Table 2 Characteristics and performance of predictive models of 13 included studies on 28-day or 30-day unplanned hospital readmission predictive models

Ref.		Model Name	Results

	• Data Source • Time Period • Sample Size		
(Choudhry et al., 2013)	• 8 Hospital, Chicago • 1 March 2010 – 31 July 2012 • 126479	ACC Admission Model	• Discrimination: 0.75 • Calibration: 23.5 (p=0.003)
		ACC Discharge Model	• Discrimination: 0.77 • Calibration: 19.9
(Berry et al., 2018)	• US Agency for Healthcare Research and Quality Nationwide Readmissions Database • 2013 • Index Admissions: 31729762	Logistic Regression Model	Odds ratio for readmission: • Age 16-20: (range 0.70 (95% confidence interval 0.68 to 0.71) to 1.04 (1.02 to 1.06)) • Age 21-45: (range 1.02 (1.00 to 1.03) to 1.12 (1.10 to 1.14)) • Age 46-64: (range 1.02 (1.00 to 1.04) to 0.91 (0.90 to 0.93)) • Age 65 & above: (0.78 (0.77 to 0.79))
(Khan et al., 2012)	• 10 Hospitals/ EMRs • 26-Jan-11 • 227	Rehospitalisation Risk Score	• Cutoff: 7 • Sensitivity: 61% • Specificity: 22% • PPV: 12% • NPV: 77% • p=0.001
(van Walraven et al., 2012a)	• 4 Health Database, Ontario • 1 April 2003 - 31 March 2009 • Random Patients: 200000	CMG score (case-mix groups)	• Discrimination: 0.65 • Calibration: 15.11 (p=0.0569)
		LACE index (validation)	• Discrimination: 0.735 • Calibration: 21.19 (p=0.0067)
		Combined CMG score and LACE index	• Discrimination: 0.759 • Calibration: 40.14 (p<0.0001)
(van Walraven et al., 2012b)	• 4 Health Database, Ontario • 1 April 2003 - 31 March 2009 • Random Patients: 500000	LACE+	• Discrimination: 0.759
		LACE+ with CMG Score	• Discrimination: 0.771
(Escobar et al., 2015)	• 21 Hospitals EMRs • 1 June 2010 - 31 Dec 2013 • 360036	ED 30	• R square: 0.158 • Discrimination: 0.739
		Discharge Day 30	• R square: 0.174 • Discrimination: 0.756

		LACE	• R square: 0.145 • Discrimination: 0.729
(Maali et al., 2018)	• 1 Hospital, Australia • 1 July 2008 - 31 Dec 2012 • 62255	RETURN 30 (gradient tree boosting algo: XGBoost) (95% CI) (10-fold CV)	• Cutoff: 12 • Sensitivity: 52.9% • Specificity: 77.4% • PPV: 14.8% • Discrimination: 0.71
		Logistic Regression (selected variables) (10-fold CV)	• Sensitivity: 59.0% • Specificity: 73.3% • PPV: 16.5% • Discrimination: 0.72
(Shulan et al., 2013)	• Veterans Healthcare Network Upstate New York • 2011 • 8718	Unnamed (losgistic regression)	• Discrimination: 0.8
(van Walraven et al., 2013)	• Centralised Database, Ontario • 2004 – 2009 • Patients: 499996; Index Admissions: 858410	LACE+ (extension of a validation index) (95% CI)	• Discrimination: 0.73
(Yu et al., 2015)	• 3 Hospitals, USA • Not Reported • Hospital 1: 2441; Hospital 2: 26520; Hospital 3: 45785	Generic Model	• Discrimination: 0.85
		Admission: Linear SVM	Hospital2 • Recall: 0.36(0.02) • Precision: 0.18(0.01) • Discrimination: 0.60 Hospital3 • Recall: 0.34(0.01) • Precision: 0.19(0.01) • Discrimination: 0.64
		Discharge: Linear SVM	Hospital2 • Recall: 0.68(0.02) • Precision: 0.34(0.01) • Discrimination: 0.74 Hospital3 • Recall: 0.54(0.01) • Precision: 0.30(0.01) • Discrimination: 0.72
		Admission: Poly SVM	Hospital2 • Recall: 0.31(0.02) • Precision: 0.15(0.01) • Discrimination: 0.57 Hospital3 • Recall: 0.31(0.02) • Precision: 0.17(0.01)

		Discharge: Poly SVM	Hospital2 • Recall: 0.67(0.01) • Precision: 0.33(0.01) • Discrimination: 0.70 Hospital3 • Recall: 0.52(0.01) • Precision: 0.29(0.01) • Discrimination: 0.69
		Admission: Cox PH	Hospital2 • Recall: 0.34(0.02) • Precision: 0.17(0.01) • Discrimination: 0.59 Hospital3 • Recall: 0.26(0.06) • Precision: 0.15(0.03) • Discrimination: 0.57
		Discharge: Cox PH	Hospital2 • Recall: 0.66(0.02) • Precision: 0.33(0.01) • Discrimination: 0.73 Hospital3 • Recall: 0.49(0.04) • Precision: 0.27(0.02) • Discrimination: 0.67
		Discharge: LACE	Hospital2 • Recall: 0.31(0.02) • Precision: 0.15(0.01) • Discrimination: 0.55 Hospital3 • Recall: 0.27(0.01) • Precision: 0.15(0.01) • Discrimination: 0.60
(Wakefield & Mehr, 2013)	• 91 Hospitals - Health Facts Database • 1 October 2008 - 31 August 2010 • Index Admissions: 463351	Unnaned (logistic regression)	• Discrimination: 0.657
(Lee, 2012)	• 1 Tertiary Hospital • Jan 2009 - Dec 2009 • Patients: 11951	Logistic Regression Model	• Root ASE (Asymptotic Standard Error): 0.385 • Misclassification Rate: 0.180
		Decision Tree	• Root ASE (Asymptotic Standard Error): 0.369 • Misclassification Rate: 0.177
		Neural Network	• Root ASE (Asymptotic Standard Error): 0.383

			• Misclassification Rate: 0.211
(Baillie et al., 2013)	• 3 Hospitals • August 2009 - Sept 2012 • 120396	Prediction Model	• F-score: 0.339 • Discrimination: 0.614

METHODS

Data Source, Data Description and Data Insight:

The data used for this project is gathered from Waitemata District Health Board (WDHB). The WDHB data includes admission instances of two years i.e. 2015 and 2016.

The dataset also includes six months of retrospective data and one month of prospective data. The dataset includes six months of retrospective data is included so the number of emergency department visits can be studied for previous six months if the admission date is in early January 2015 and it includes one month of prospective data to check for readmissions for the patients whose initial admission happened in late December 2016.

The readmission rate of the given 2 years of WDHB data is 9.83%. Out of 17713 patients in the WDHB data for 2015 and 2016, who were readmitted in the hospital within 30-days of the initial discharge, 9768 (55.15%) were females and 7945 (44.85%) were males.

Inclusion and Exclusion Criteria for “Readmission”:

The inclusions and exclusion criteria for readmission for this research was influenced by several previous research.

The inclusion criteria for readmission are:

1. Only acute (non-elective) admissions are considered i.e. only unplanned admissions are considered.
2. The discharge location of the index admission should be “Home” (van Walraven et al., 2012a, 2012b; van Walraven et al., 2013)
3. The patient who are 18 years old or above at the time of readmission (Escobar et al., 2015).
4. If the patient has multiple visits within 30 days of index hospitalization, only first visit was considered as readmission (van Walraven et al., 2012a, 2012b; van Walraven et al., 2013; Yu et al., 2015)

The exclusion criteria for readmission are:

1. Hospital visits which did not result in overnight stay in the hospital (Escobar et al., 2015; Khan et al., 2012; Wakefield & Mehr, 2013)
2. Arranged admissions i.e. elective admissions (Khan et al., 2012)
3. Psychiatric admissions returned from leave (Choudhry et al., 2013; van Walraven et al., 2012a, 2012b; van Walraven et al., 2013)

Model Building and Evaluation:

The dataset of total valid records of 180117 instances, were split into train set and test set with the ration of 70:30. The train set has 70% of the total records i.e. 126081 and test set has rest 30% of the records i.e. 54036.

Various machine learning models like Decision Table, AdaBoost, Random Forest, SVM and REPTree were applied on training set. These algorithms were chosen as they are quite popular in the previous studies done on prediction problems. All these models were performed with 10-fold cross validation. The accuracy and root mean square error of the following algorithms are quite similar to each other. However, we cannot rely on the accuracy as it can be considered as misleading due to nature of the real-time data, where instances of readmissions are evidently very low compare to the patients who were not readmitted, the accuracy of the model will be a result of highly imbalanced data.

The receiver operating characteristic (ROC) analysis is used to quantify the accuracy in discrimination between two states, in this case we can refer to 'readmitted' and 'not-readmitted'. A ROC curve is based on the notion of a 'separator' scale, on which readmitted, and not-readmitted results forms a pair of overlapping distribution. The complete separation of the two underlying distributions implies a perfectly discriminating test while complete overlap implies no discrimination (Hajian-Tilaki, 2013). The discrimination score (c-statistic or ROC area) for all these models (see Table 3) were greater than 0.5, which means all the models were performing better than a random guess. Out of these five, REPTree showed the best discrimination score of 0.717 ROC area.

Table 3 Comparation of discrimination score and time taken on the train dataset by different models

	Decision Table (train)	**Ada Boost (train)**	**Random Forest (train)**	**SVM (train)**	**REP Tree (train)**	**REP Tree + Bagging (train)**
ROC Area	0.712	0.707	0.687	0.666	0.717	0.721
Time Taken (seconds)	7.04	1.81	16.51	58.15	0.86	6.19

In order to make reliable decisions, numerous learning techniques are combined to form an ensemble of models. Bagging is one of the most effective computationally intensive procedures to improve on unstable estimators or classifiers, useful especially for high dimensional data set problems (Bühlmann & Yu, 2002). Bagging is a simple and effective way to reduce the error rate of many classification learning algorithms (Domingos, 1997). Therefore, bagging technique was combined with REPTree model and applied on the data, which gave better discrimination score i.e. 0.721 ROC Area.

As REPTree + Bagging performed significantly better than other models on the train set. The same model (REPTree + Bagging) was applied on test set which has imbalanced class and compared it with the score obtained on the train set (see Table 4). The ROC area for the test set was similar i.e. 0.728 hence, REPTree + Bagging was selected as the best model and named **RHR-30** (Risk of Hospital Readmission within 30-days).

Table 4. Comparation of discrimination score and time taken on the train and test dataset by the best model, RHR-30 (Risk Of 30-days Hospital Readmissions) Model

	REP Tree + Bagging (train)	**REP Tree + Bagging (test)**
ROC Area	0.721	0.728
Time Taken (seconds)	6.19	24.76

RESULTS

Confusion Matrix and ROC Curve:

The confusion matrix for RHR-30 model (see Figure 1), describes the performance on the test data for which readmitted instances are known. Out of 54,036 records in the test data: 297 records were predicted positive and were true (True Positive), 48431 records were predicted negative and were true (True Negative), 328 records were predicted positive but were false (False Positive – Type 1 Error), 4980 records were predicted negative but were true (False Negative – Type 2 Error).

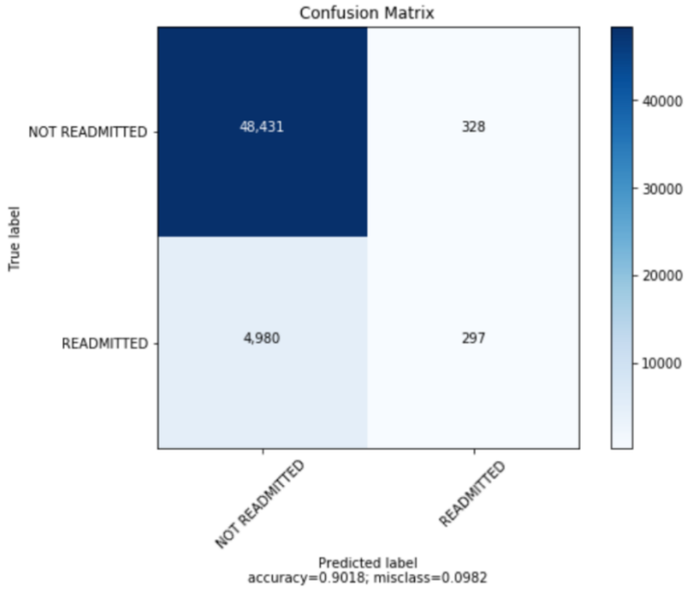

Figure 1 Confusion Matrix shows actual and predicted readmitted and not readmitted patients

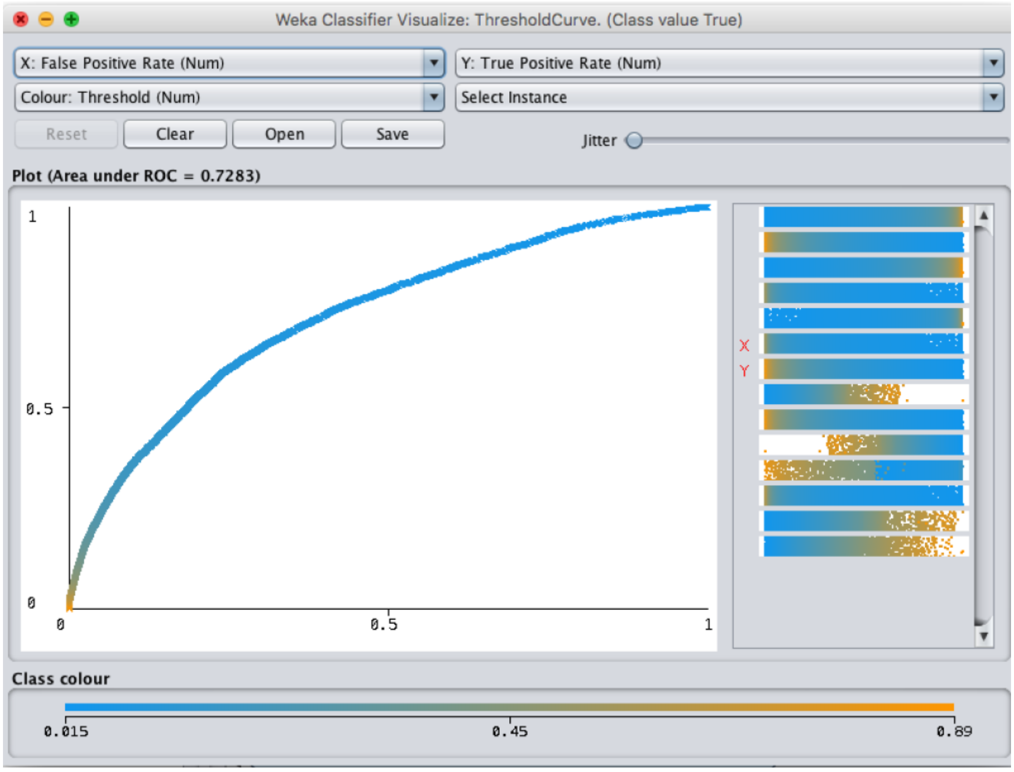

Figure 2 ROC curve for RHR-30 model (using WEKA)

The ROC curve shows the relation between the true positive rate (sensitivity) and false positive rate (1- the specificity). These results are plotted against each other at all risk cut off levels and the area under the curve which is also known as curve statistic (C-statistic), is a value that lies between 0 and 1 so one can compare the sensitivities and specificities between models. For RHR-30, the ROC curve is 0.7283 (see Figure 2), which is the best performance so far in this project.

RHR-30 Significant Attributes:

In order to analyze which attributes, contribute more for RHR-30, Information Gain attribute evaluator with ranker method was applied in Weka. The weightage of top 20 significant attributes can be seen in Figure 3. The top four significant attributes were:

- Count of Emergency Department visits in the six months before admission
- Length of the stay
- Age
- Acuity of the admission

The emergency department visits count attribute dominates the most. It is interesting to consider that the intervention which will reduce re-admissions will also end up reducing emergency visits slightly if not considerably. We can observe the dependable changes once the model is in use for months in a healthcare.

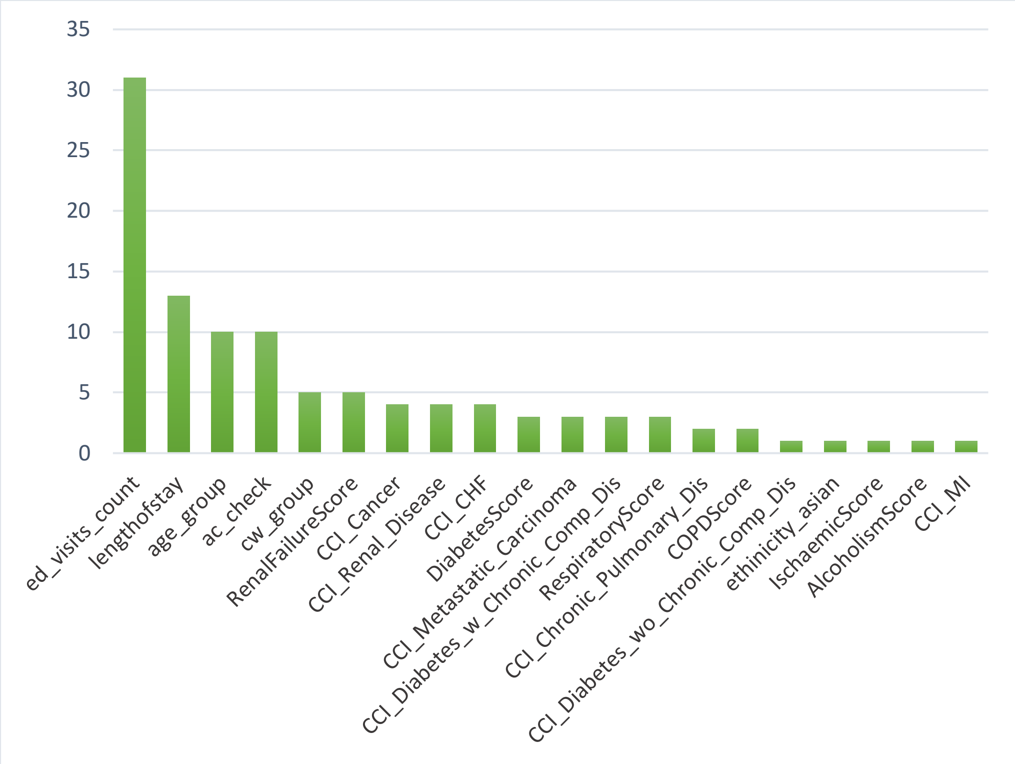

Figure 3 Pareto chart of significant variables includes in the predictive model, RHR-30

RHR-30 v/s LACE INDEX MODEL

ROC Area:

LACE Index model was developed on data from Ontario (van Walraven et al., 2010), Canada hence three models' results were compared: LACE on Canada's data, LACE on WDHB's data and RHR-30 on WDHB's data. Table 5 shows the comparison in the discrimination score (ROC area) and Figure 4 shows the bar graph for the compared scores.

Table 5 Comparation of discrimination score of LACE Index on original data i.e. Canada's healthcare's data, LACE Index on WDHB data and RHR-30 model on WDHB data

	LACE on original (Canada's) data	LACE on WDHB data	RHR-30 on WDHB data
ROC Area	0.68	0.64	0.72

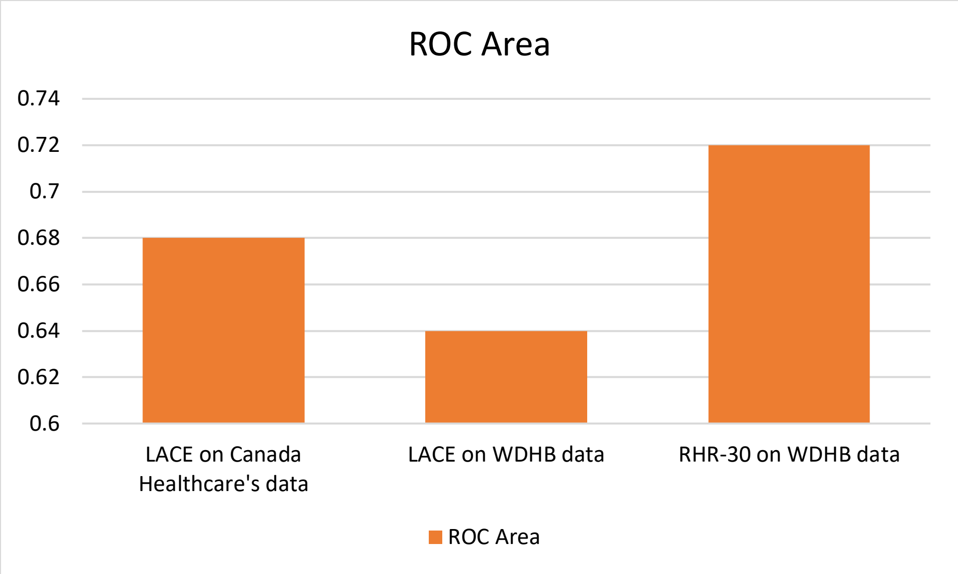

Figure 4 Bar graph of discrimination score of LACE Index on original data i.e. Canada's healthcare's data, LACE Index on WDHB data and RHR-30 model on WDHB data

As seen, performance of LACE Index model on WDHB's data was poorer than LACE Index model on original data. It can be justified as LACE Index model was developed on Canada's data whereas applied on New Zealand's data.

Readmission Rate:

As mentioned before, the actual readmission rate for the given WDHB's data is 9.83%. After applying LACE Index model and RHR-30 model, the readmission rate was calculated keeping the best threshold of given WDHB's data (see Table 6). The readmission rate for LACE index model was 10.90% with the threshold of 10 with the minimum and maximum threshold score of 0 and 19 respectively. Similarly, for RHR-30 model the readmission rate was 9.83% with the score threshold of 0.02 with the minimum and maximum threshold score of 0 and 1. It is important to note that the threshold for different healthcare will be different. The fact that we were aware of the readmission rate for WDHB's data in 2015 and 2016, the threshold was adjusted to get the accurate result. However, while doing the real-time prediction on real-world data, it will be important to study the different threshold and continue with the best one.

Table 6 Comparison of LACE model's and RHR-30 model's readmission rate with actual readmission rate

	Actual	**LACE**	**RHR-30**
Readmission Rate	**9.83%**	10.90%	9.83%

CONCLUSION

The unplanned readmissions are those which are acute (non-elective) admissions. Elective admissions are those admissions when a doctor requests a bed be reserved for a patient on a particular day, hence acute admissions excludes planned admissions. Readmissions are unplanned overnight stay in the hospital within a specific period of time from an initial admission. Hospital readmissions are upsetting to patients and costly to the healthcare systems too. Some of the readmissions that do occur are avoidable, hence whether its New Zealand or any other country in the world, readmission rates are one of the very important health quality measure. There are various ways to identify patients at the high risk of hospital readmissions which are, clinical knowledge, threshold modelling and predictive modelling (Purdy, 2010). This project report focuses on developing a prediction model for unplanned hospital readmissions within 30 days of discharged using Waitemata District Health Board (WDHB) records. The time period of 30 days was chosen because it is considered the most likely time setting that the two occasions can be relatable. As the time frame increases the chances of picking up admissions unrelated to the initial admission also increases.

There are several factors that can contribute to unplanned readmissions. These factors can be divided into following categories (Holloway & Thomas, 1989) :

- Medical factors: the data is accessible from secondary sources (e.g., discharge abstracts and claims forms) whenever needed, such as sex, age, diagnosis, and practices performed.
- Other medical factors: e.g., self-reported global and functional health status.
- Nonmedical factors: e.g., living arrangements, marital status, care accessibility, social factors, cultural factors and insurance coverage.

Preventable factors i.e. factors which was under the control of the hospital, include: surgical complications, errors related to medication and poor discharge measures which do not properly involves patients, their relatives, general practitioners or aged-care worker (Maali et al., 2018).

In this research, a general structure for hospital-specific and all-cause model for risk of hospital readmission prediction was developed and investigated. The real-world hospital data structure has the advantage that it can take all attributes the hospital has collected for its patient’s population. Five machine learning algorithms were applied, and all five algorithms achieved the prediction accuracy rate around 65%. However, considering the real-world data is highly imbalance in nature, hence, choosing the best model on their accuracy rate would be misleading. Therefore, the best model was selected on the bases of discrimination score i.e. ROC area. Most of the studies included in the literature review, also selected discrimination score as their performance metrics.

RHR-30 model was built on WDHB’s data for calculating risk of hospital readmission within 30 days of discharge. RHR-30 out-performs all the other machine learning algorithms applied in this project and also out-performs LACE model, by having the highest ROC area (discrimination score) and performs much better compare to the well-known pre-existing risk of readmission model i.e. LACE. The model yielded a ROC area of 0.72 – a modest value for a clinical predictive rule.

The LACE Index model is based on length of stay, acuity of admission, comorbidity index score and emergency department visits in previous six months. It was observed that RHR-30 model’s top attributes are quite similar to LACE Index model’s attributes,

as the top four attributes on which RHR-30 is dependent are emergency department visits in previous six months, length of stay, age and acuity of admission. The emergency department (ED) visits counts dominates the most compare to all other attributes. Other than ED visits, the two attributes: the length of stay and the admission acuity, holds the most important role in building a model for calculating risk of hospital readmissions.
It was also found that applying a mixed-method approach was valuable and extra efforts are needed during selection of risk factors/features that are of high-quality data, certainly accessible, and can be generalized across multiple populations. To create a good accurate predictive model which is multidimensional and responsible is dependent on several factors, including, however not limited to, the quality and accessibility of data, the power to reproduce the findings beyond training dataset, and the balance between a tight and comprehensive prediction model.

However, we cannot blindly rely on 30-days hospital readmissions model for several reasons (Joynt & Jha, 2012; Purdy, 2010; Shulan et al., 2013).

1. Some proportion of readmissions at 30 days after the initial discharge are avoidable. Community-level factors which are outside the hospital's control are also responsible for hospital readmissions rates.
2. It is a debate whether readmissions always suggest poor hospital quality, as hospital readmission rates can also be the result of low mortality rates or good access to hospital care.
3. It is worth improving care coordination, implementing personalized health care programs, structured discharge planning and focusing on making more aimed and effective policies for achieving the goal.
4. Applying models from one healthcare system to another healthcare system could result in misspecification as the same model will shows different results for two completely different data. Though in our project when the LACE Index was generated on Canada's data the discrimination score was 0.68 whereas when the same LACE index model was applied on New Zealand's data the score was 0.64, which is remarkably close however still not the same. Also, RHR-30 shows much better results on New Zealand's data compare to LACE model.

FUTURE WORK

An interesting investigation that can be done with the information that we have within this project is to check the day of discharge and the day of readmission and observe the probability of discharging a patient on Friday and readmitting the same patient on the following Monday. Also, doing a primary diagnosis by spotting top five discharge diagnoses common within the readmissions, to discover and get familiar with common traits in those specific conditions' readmissions cases.
The next plan in continuation to the extend the project is to increase this structure to other risk modeling such as death, hospital-acquired infection, etc. It would be interesting to have more informative dataset which includes attributes like insurance data, mental health data, social determinacies like smoking, drinking, etc. in the data and observe their significance in hospital readmissions. Furthermore, to note all the discharges who had a behavior health condition and who didn't and comprehend if there is an important difference.

Another stage that we can include in future is to understand, according to the healthcare when is the best time to activate the model; whether it's at discharge or after discharge or prior to discharge. If healthcare prefers to active the model prior to discharge, it should be considered that data for some comorbidity factors will not be available, hence have to plan a strategy to deal with that limitation.
The best practice to use predictive modelling to calculate risk of hospital readmission is to refresh the analysis and fill in the gaps periodically.

CONFLICT OF INTEREST STATEMENT

Authors declare no conflict of interest.

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