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Predicting the Readmission of Heart Failure Patients through Data Analytics

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Abstract. Reducing the costs and improving the quality of treatment in hospital systems as well as demands for better treatment from patients in order to keep them away from readmissions are two main issues healthcare systems have faced. In order to solve such challenges, predicting the occurrence of re-hospitalisation with data mining techniques would be so worthwhile. In this study, we are seeking to predict the occurrence of re-hospitalisation of the heart failure patients in two time-horizons (1-month and 3-month) via deployment of classification algorithms (i.e. decision trees, artificial neural networks, support vector machines and logistic regression). Two criterions (as main criterions) such as AUC (area under curve) and ACC (accuracy) have been calculated and assessed for classifying the prediction-power of the models in each time-horizon (outcome/target). We also have calculated some other criterions such as recall, precision and F1-Score. Then, we identified the importance and contribution of the variables for each outcome. Therefore, the variables whose contribution/importance changes over time are differentiated. It is noteworthy to say that this study is done under the scrutiny of an expert cardiologist. Trained nurses and expert cardiologist monitored the dataset every day, which was a hard and valuable measure to conduct. Finally, the dataset does not have missing values and noises. This research can be the basis for prospective medical studies and projects.

Keywords: Data mining; classification algorithms; heart failure; healthcare analytics; decision support systems; readmission; re-hospitalization; expert cardiologist; factor importance.

1. Introduction

Information technology has played a key role as a facilitator in various industries. One of the most important fields that recently moves towards using IT with an increasing acceleration is healthcare systems. Most of the developed countries are keen on finding new methods and approaches in modernising their healthcare systems as well as investing on such potential areas (Cowie *et al.*, 2014). The main goal of these approaches is to apply information technology in order to improve the health systems, patient safety, and quality of treatment as well as reduce the costs of treatment. Applying Decision Support Systems (DSSs) (Reynolds *et al.*, 2015) or using data mining techniques (Stewart *et al.*, 2002) in hospitals whereas Patients data have been archived electronically could be a good example. This has brought many advantages for patient treatment. Modernising healthcare systems with IT has led this industry to make significant breakthroughs in medical researches. Therefore, let medical researchers overcome some crucial challenges such as the following:

- The ability of monitoring the effectiveness of a particular treatment for a statistical society of particular patients.
- Determining the side effects of taking a particular medicine.
- Predicting the occurrence of diseases in early stages.

One of the major challenges in healthcare systems is the occurrence of re-hospitalisation/readmission in hospitals, which can bring negative consequences for patients and hospitals as well. This could also be costly for both public and private payers.

Annual hospitalisations pertaining to acute heart failure (AHF) in USA and Europe have exceeded one million in each side (Miró *et al.*, 2017). HF programs and initiatives also have distinguished diminishing the rate of early readmissions as a main goal (Núñez, 2016).

In 2011, Medicare paid for about 60% of all re-hospitalisations followed by private insurance. A great portion of all spending in Medicare is for readmission costs. About 40 percentage of total Spending in Medicare belongs to inpatient care. However, about 20% of all inpatient hospitalisations (which paid by Medicare systems) is for early re-hospitalizations (within 30 days). Further admissions (readmissions) put patients in dangerous circumstances (stress, hospital infection, ect.).

Although, the great portion of readmissions are for services, which are not surgical. It seems that readmissions are not economically and non-economically profitable for hospitals (Fingar and Washington, 2006).

About 5% of all urgent hospitalisations in USA and Europe are because of AHF and AHF is threatening lives of millions of peoples around the universe. With a high percentage (about 10) HF patients would come up with in-hospital death through admission (Leong, 2017).

As such, hospital systems are seriously commanding multitude strategies to make sure that discharged patient would not be readmitted within a short period after their first hospitalisation. Many of the more popular are:

- Increased patient education of the care regime that needs to be followed.

- Scheduling a follow-up appointment with their primary physician before the patient has been discharged.
- Follow-up calls to the patient to verify that the patient is maintaining their care routines as well as home visits to verify the healthcare regime is being followed and giving more information and education (Natale and Wang, 2013).
- Stratifying the risk of the patient re-hospitalisation.

With the belief of "An ounce of prevention is worth a pound of cure", the treatment methods and approaches have been thoroughly changed during the last decades. In fact, if hospital systems could measure the risk of the re-hospitalisation and (somehow classifying the patients by their risk of readmission) they will be able to command significant treatment strategies in the preferable form by letting the right patients take the right treatment.

One of the measurements of classifying the patients (with high and low risk of re-hospitalization) that should be conducted in healthcare systems is applying information technology and its approaches such as data mining techniques. The data, which has been recorded before the discharge of AHF patients from the hospital, are valuable for predicting their re-hospitalisation occurrence.

As our goal is to find the target class of patients (who are more likely to get readmitted to the hospital), predictive techniques and classification models need to be developed. There are many data mining classification models available to us such as the most powerful ones like Decision Trees (DTs), Support Vector Machine (SVM), Artificial Neural Network (ANN) and Logistic Regression (LR).

This study is based on the said four powerful and significant models and keen to help hospital systems to reduce their costs and also AHF patients to get treated in more suited manner and hopefully preventing them from further re-hospitalisations. The Software that we used through achieving the goal is IBM SPSS Modeler Version 18.0, which was really helpful and supportive (basically, for designing and managing the project).

2. Background

Studies of predicting the risk of HF patient readmissions have been done for many years. However, applying data mining techniques and using machine learning for such purpose is not as old as the statistical studies.

In this phase, we focus on most recent and similar studies to our research and then mention our benefit to them.

In 2013, Natale and Wang (2013) predicted the risk of HF patient readmission with DT algorithm. The final accuracy was about 83%. In addition, the important factors (among the others) have been presented.

In another study, Meadem *et al.* (2013) worked on the same problem within a short period of time (early readmission). They mainly focussed on preprocessing (data balancing, missing value imputation and feature selection) of the dataset in order to achieve the best results. They applied LR, Naïve Bayes (NB) and SVM

(RBF kernel function) as classification algorithms through using 10-fold cross validation. The highest reached accuracy was 79%.

Zolfaghar et al. (2013), (Yu et al., 2015) used a multi-layer approach in predicting the risk of HF patient readmissions with dividing the problem into three layers predicting if patients: (1) will be ever readmitted, (2) will be readmitted in 60 days and (3) will be readmitted within 30 days.

The missing value imputation was done only for the "Ejection Fraction" factor because of its importance in former studies. All of the features (with missing values) other than "Ejection Fraction" were discarded from the study. They applied NB and SVM as classification algorithms. Using multi-layer approach in their study was helpful in improving the True Positive (TP) of the models.

In 2015, Yu et al. (2015) believed that the majority of the former researches had not achieved the reliable accuracy for being applied in the real healthcare environment. They applied classification algorithms (cox regression and SVM) on three different datasets pertaining to three different hospitals. Eventually, they compare the final results with the Lace method. Their purposed model also worked better than the LACE method. They obtained different results in each dataset (pertaining to each hospital). The highest AUC was for all-cause readmission (86%) from Hospital 1 (dataset).

In 2016, Shameer et al. (2016) worked on predicting the risk of readmission by using machine-learning algorithms. They used NB for classification. The interesting thing in the study is the number of fields/features of the primary data warehouse (about 4205). In order to build the proper model feature selection methods such as PCA and LR were used by them. They ran the NB model on each group of variables, then on most important of them (105 variables — Composite model). The highest amount of ACC and AUC was about 84% and 0.78 respectively for the purposed Composite model.

In 2017, Leong et al. (2017) worked on predicting the risk of 30-day readmission of the HF patients. LR was applied to the dataset and the AUC with the amount of 0.76 was presented as the final result. Eventually, seven features were reported as the most important ones.

All of the above researches generally can be assessed in four terms:

(a) Methodology
Four phases were available in all methodologies (data understanding, preprocessing phase, modeling and evaluation).
(b) Target variable
Most of them used 30-day or early readmission for the target variable. (Only one of them used 60-day as another target point).
(c) Validation and assessment of the models
Five or 10-fold cross validation were used.
Generally, for the assessment of the models, the ACC and AUC were used as a performance indicator.

(d) Classification algorithms
The classification algorithms used were (NB, LR–Mostly used ones), SVM and DT (only used in one of the above studies).
(e) Variables
The researchers used four major groups:
Demographics, clinical information, ICD-9 Codes and Comorbidities.
(f) Data gathering

In this study, we faced a risk stratification challenge or a classification problem, which simply had two target points: (1) Readmitted patients, (2) Non-readmitted patients over particular time horizons (early readmission within 30 days or readmission within 90 days). All past literatures have faced somehow the same classification problem and used the most typical classification algorithms such as DTs, SVMs and LR. As we mentioned (in introduction part) no previous similar studies have been done in the whole country (to our knowledge). Therefore, we just wanted to do this for the first time and did not seek to reinvent the wheel or do something extremely different from such studies in other countries. Hopefully, we could add some values to them.

We wanted to look through the problem from different aspects. As mentioned in Table 1, past researches mainly focussed on different areas such as:

(1) Data preparation phase (for example missing value imputation or feature selection)
(2) Classification algorithms (with evaluation — ACC or AUC)
(3) One Target point (30 day-readmission)

They just used the prepared and raw data, which health systems gave to them (with multiple deficits such as missing values).

We can also mention some other aspects, which we focussed on as follows:

- Accurate data gathering projects which is conducive to results that are more valid. To our knowledge, none of the previous literature mentioned the process of the data gathering. Although none of them considered this phase (data gathering) as a critical step which even needs to run a project including daily monitoring by an expert team included trained nurses (headed by an expert cardiologist), accurate follow-ups and so on. Some said that they could not find out either patients were admitted to another hospitals or not.
- None of them used multitude classification algorithms like what we did using multitude data mining classification algorithms such as SVM (with different Kernel functions), ANN (Multi-layer Perceptron (MLP) and Radial Basic Function (RBF)), DT and LR.
- They barely used two time horizons for the target class.
- Assessment of the factor importance and their changes over time (from 1 month to 3 months).
- We reached the highest ACC among other researches ($\sim$90) in predicting RH1M (Re-hospitalization in 1 month).

Table 1. Quick review of what past literatures have focussed on.

Year of publish	AUC	ACC	Number of records	Number of variables	Number of important variables	Classification algorithms used	Preprocessing	Target	Factor importance assessment	Data gathering project*
2013	—	83	499	37	20	DT	—	30 days readmission	No	No
2013	64	79	1800	49	—	NB-SVM(RBF)-LR	Feature Selection-Missing Value Imputation-Under/Over Sampling	30 days readmission	No	No
2013	—	—	1477	50	—	NB-SVM	Feature Selection-Missing Value Imputation	30 and 60 days readmission	No	No
2015	74	86	23000	18	—	SVM(Linear)-SVM-(Poly)	—	30 days readmission	No	No
2016	83	78	1068	4205	105	NB	PCA-LR	30 days readmission	No	No
2017	—	76	1475	30	7	LR	—	30 days readmission	No	No

- We have run this research as a preliminary step of building a risk predictor system in real hospital environment.

With no particular intention, we thought that rule induction can be done in further complementary studies in the future and the whole content seems sufficient for a paper.

3. Methodology

Thanks to the methodology used by Dag *et al.* (2017) for applying data mining techniques in predicting the survival of heart transplant patients, we also propose a data analytics methodology, which consists of four sequential phases depicted in Fig. 1. The previously mentioned methodology has been changed slightly and is customized for our research. However, the overall framework remains steady.

The first phase (Data Preparation) consists of three main parts: (a) data source description, (b) data cleaning: eliminating intra- and post-operative factors as well as fields with no prediction power, assessing the missing values, erroneous and duplicated records, (c) data selection: where each patient's readmission was coded into two binary outcomes indicating whether the patient gets readmitted in 1 month or 3 months.

In the second phase, data mining classification models were applied to the dataset through a 5-fold cross validation procedure in order to achieve a desirable classification performance and rank the predictor variables based on their importance level, i.e. each model provides its own set of important variables for each of the two outcomes (re-hospitalization in 1 month (RH1M) and re-hospitalization in 3 months (RH3M)).

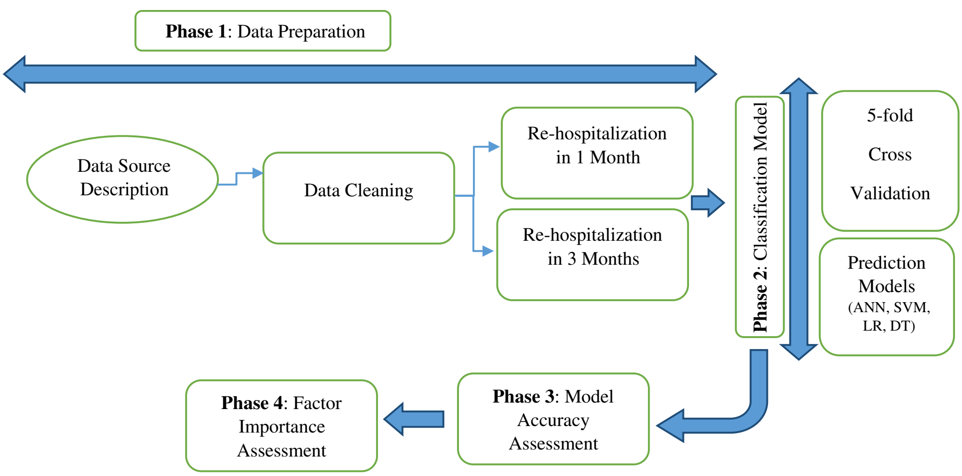

Fig. 1. An overview of the proposed methodology.

In the third phase, the accuracy of the classification models has been assessed. Finally, in the last phase, the comparison of the important variable sets leads us to distinguish the variables whose importance change over time (from 1 month to 3 months).

The data used in this study were for AHF patients were admitted in Rajaie Cardiovascular Medical and Research Center, one of the three important centres for AHF and heart transplantation programs in Tehran, Iran.

The patients were enrolled for 10 months from March 2015 to February 2016. The data have 230 records (pertaining to AHF patients with signs of AHF in accordance with accepted guidelines) which archived electronically McMurray *et al.* (2012).

3.1. *Data preparation*

3.1.1. *Data source description*

The expert registry team collected the dataset used in this study, on admission and throughout the hospital course. All the patients were subsequently followed for 3 months for re-hospitalization or death. During admission, a comprehensive medical and drug history was taken and an expert cardiologist performed thorough physical examination and echocardiography. Moreover, the laboratory data including Complete Blood Count (CBC), blood sugar, Blood Urea Nitrogen (BUN), serum Cr, sodium (Na), potassium (K), magnesium (Mg), liver enzymes and bilirubin were recorded on admission. BUN and Cr levels were recorded on a daily basis until the discharge day. All laboratory tests were performed in the clinical laboratory of Rajaie Cardiovascular Medical and Research Center using routine standard laboratory methods. Then, the data were recorded in the software designed by the medical Information Technology (IT) team of Rajaie Cardiovascular Medical and Research Center. Trained nurses and an expert cardiologist controlled the recorded data every day.

The Institutional Research and Ethics Committee of Rajaie Cardiovascular Medical and Research Center has approved this study.

Developing a data-driven model in order to predict the re-hospitalisation in 1 month or 3 months is one of the main objectives of this study. Hence distinguishing the cause of readmission is also important. Is it related to heart failure or some other problems? The follow-ups have been performed accurately in order to distinguish this main issue. Eventually, 230 records remained in the dataset for purpose of this study.

3.1.2. *Data cleaning*

In this paper, firstly, we eliminated all the intra- and post-operative factors (since the Research questions are related to outcome prediction prior to readmission). Secondly, the variables/factors, which almost have not any prediction power (e.g. patient registry code number), were eliminated from the dataset. Thanks to the accurate data collection by the expert registry team, subsequent daily observation as well as control by trained nurses and expert cardiologists, the final dataset, which has been given to us for applying data mining classification models, had no erroneous and duplicated records as well as missing values. At the end of this stage, we had 230 data with 39 variables/fields.

3.1.3. *Data selection*

In this phase, the only patients who only were readmitted to the hospital for the cause of heart failure were separated from the others who have not readmitted due to their heart failure problem. This non-mathematical phase (depicted in Fig. 2) was performed during accurate follow-ups and in some suspicious cases; the RASHF follow-up team has reviewed the data. Finally, the two desirable outcomes (RH1M and RH3M) were specified in the dataset.

3.2. *Machine learning models*

In this study, we apply three popular data analytic models (SVMs, ANNs, and DTs) and a conventional statistical method (logistic regression). We selected these four algorithms due to: (a) good performance in several readmission papers (see e.g. Del Rizzo, 1999; Drakos, 2007; Hong, 2011; Oztekin, 2011; Kilic, 2012; Nakayama, 2012) short description has been provided for each popular model in the subsections below.

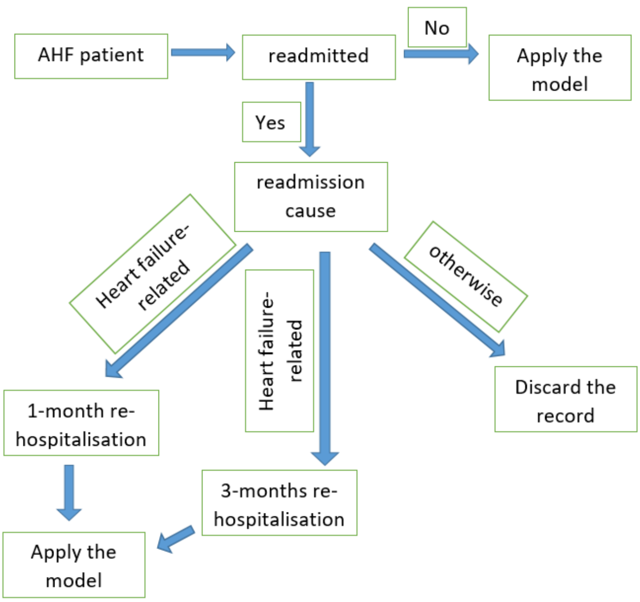

Fig. 2. Data selection phase.

3.2.1. *Artificial neural networks*

ANNs are so popular while they are not only being used as classification techniques but they can also solve other problems such as optimisation and pattern recognition. ANNs are also computing systems related to biological neural networks and they are based on collection of some connected units named artificial neurons just like axons in a brain (biological brain). Neurons can transmit signals to each other through connections (synapse). Then the neuron, which receives the signal, can also process it and then signal other connected neurons. Neurons generally represent a real number (typically between 0 and 1). Neurons and synapses have weights, which can affect the strength of signal sent downstream. Usually neurons are organised in layers. Different kinds of transformations can be performed on inputs by different layers. The ANNs can solve problems as human brains do. In this study, we used MLP and RBF (Han *et al.*, 2011).

3.2.2. *Decision trees*

DTs are one of the most understandable methods used through data mining and machine learning for creation and development of predictive models, which also can be applied for predicting re-hospitalisation of the heart failure patients (Natale and Wang, 2013). Not only DTs are not considered as black-box models but also, they can generate rules for their prediction method, which makes the interpretation of the model much easier and understandable. There are supervised methods, which can be separated in to two wide groups: Classification and Regression Trees (C&RT).

The Trees go from the observations (branches) to conclusions (target values or leaves). Where the leaves or target values can be discrete set of values, they are known as Classification Trees and in some cases that the target values or leaves are continuous values they are considered as Regression Trees.

They also make a tree structure, where leaves are labels of the classes and the branches are the conjunctions of features. Wide variety of DT algorithms are being used in data mining methods such as C4.5, C5, and ID3 (Quinlan, 2014) and C&RT (Breiman *et al.*, 1984). In this study, we applied some DT algorithms, which have been provided in IBM SPSS Modeler Software Version 18. The said algorithms are CHAID, C5, C&RT, and Tree-AS and QUEST. Some algorithms like C&RT and QUEST did not work properly on our dataset and somehow poor results were found but others have shown better accuracies.

3.2.3. *Logistic regression*

LR or Logit Regression is a statistical method, which is used when the dependent variable (DV) is categorical. The binary DV can take only two values (0 and 1) which represents results/outcomes such as pass/fail, occurrence/non-occurrence whereas in this case, this is pertaining to readmission or no readmission of the patients. In this technique, the linear combination of the predictive variables is modeled so that it can estimate the probability of the outcome response based on its predictors or features (Dag, 2017). In this study, we applied Stepwise, Forwards, Backwards, Backwards–Stepwise and Enter LR, which have been provided in IBM SPSS Modeler Software Version 18.

3.2.4. *Support vector machines*

SVMs are supervised learning models and also used through developing a predictive model or regression analysis and typically they are considered as a subset of classification algorithms (Gunn, 1998). This discriminative classifier defined by a separating hyperplane, which is applicable for datasets that are linearly and nonlinearly separable. Through enhancing the dimensionality of the space, nonlinear cases can also transform into linear one. This can be done by using one of the kernel functions (Han *et al.*, 2011). In this study, we used the radial basis, sigmoid, linear and polynomial kernel function.

4. Results and Discussion

4.1. *Data analytic model results*

In this study, we run the 5-cross validation data mining approach through a stream made in IBM SPSS Modeler Software Version 18, which has been illustrated in Fig. 3.

Table 2 illustrates the area under curve (AUC) and accuracy (ACC) value of all classification models for two time-points (RH1M and RH3M).

In this study, we calculated the AUC and the ACC of the models with the analysis node in the IBM SPSS Modeler Software Version 18. We used AUC as the primary performance criterion. The second metric (ACC) is also provided for medical practitioners to facilitate their interpretation of the models. As AUC (in evaluating the model performances) is likely more powerful than ACC, we sorted the table by AUC metric. There are several observations can be made from Table 1.

(A) The performance criterions of the classification models through RH1M category are higher than RH3M, which makes them more reliable. The maximum AUC of the RH1M models is 0.78 for Tree-As (CHAID or Exhaustive CHAID) model while in RH3M models it is 0.63 from ANN–MLP model. RH1M models have also indicated greater results in terms of ACC in comparison with the RH3M category. The maximum ACC is for C5 model ($\sim$90%) which also belongs to RH1M category while in RH3M models it did not exceed 70% (As-Trees). This greater efficiency in terms of AUC and ACC in RH1M category may have two potential explanations: Firstly, all of the patients were taking their treatment and medicines through the follow-ups, so that the patients in RH3M category had more time to complete their treatment after their discharge from the hospital. Secondly, this could also happen because of the low amount of data, which have been archived electronically and available for the study. The models may need more records in order to show better performance in predicting readmissions in 3 months.

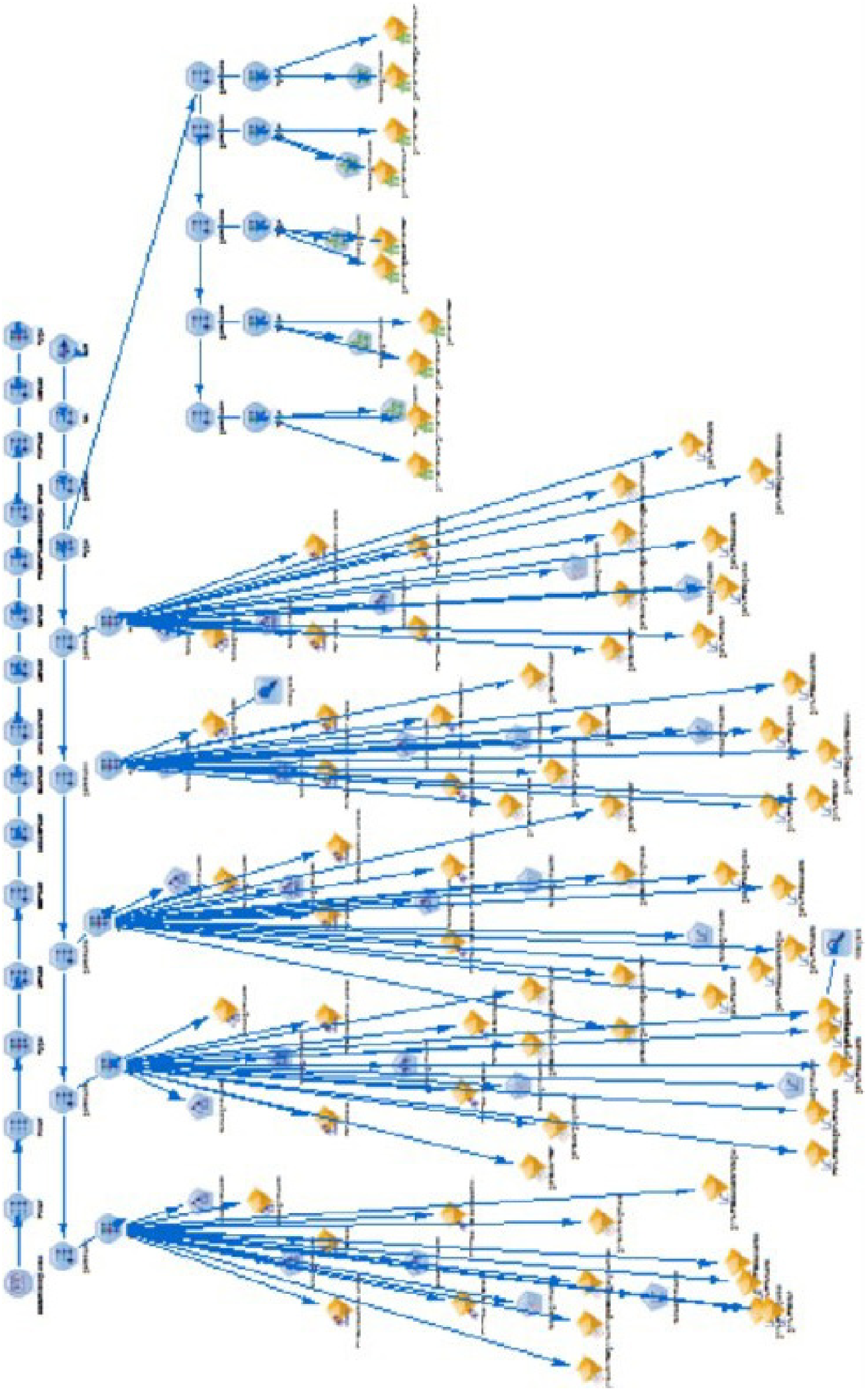

Fig. 3. An overview of the stream made for data mining project (proposed methodology) in SPSS Modeler Software Version 18.

Table 2. AUC, ACC, Recall, Precision and F1-Score of the classification models for two outcomes (RH1M, RH3M).

Time frame	Model	AUC	ACC	Recall	Precision	F1-Score
RH1M	Tree-As (CHAID)	0.78	88.7	∞	0	∞
	Tree-As (Exhaustive CHAID)	0.78	88.7	∞	0	∞
	CHAID	0.76	89.1	0.61	0.31	0.41
	SVM-Polynomial	0.74	88.3	∞	0.11	∞
	SVM-RBF	0.74	87.4	∞	0	∞
	C5	0.72	89.6	0.57	0.42	0.48
	LR-Forwards	0.72	88.3	∞	0.29	∞
	LR-Stepwise	0.72	87.8	∞	0.20	∞
	ANN–RBF	0.68	87.4	∞	0.16	∞
	ANN–MLP	0.68	85.7	∞	0.11	∞
	SVM-Linear	0.62	81.3	0.18	0.15	0.17
	Exhaustive CHAID	0.61	84.4	∞	0.12	∞
	LR-Enter	0.54	74.8	0.16	0.25	0.19
	LR-Backwards	0.54	74.8	0.16	0.25	0.19
	LR-Backwards-Stepwise	0.54	74.8	0.16	0.25	0.19
	SVM-Sigmoid	0.39	88.7	∞	0	∞
RH3M	ANN–MLP	0.63	64.8	∞	0.15	∞
	Tree-As (CHAID)	0.62	68.7	∞	0.20	∞
	Tree-As (Exhaustive CHAID)	0.62	68.7	∞	0.17	∞
	ANN–RBF	0.61	66.1	0.41	0.14	0.20
	Exhaustive CHAID	0.49	53.9	0.23	0.19	0.20
	C5	0.48	59.1	0.28	0.25	0.26
	SVM-RBF	0.47	60.0	0.22	0.11	0.14
	CHAID	0.46	53.0	0.26	0.24	0.25
	SVM-Sigmoid	0.46	67.8	∞	0	∞
	SVM-Polynomial	0.45	53.0	0.25	0.23	0.24
	LR-Stepwise	0.43	50.4	0.23	0.19	0.20
	LR-Forwards	0.40	50.4	0.25	0.19	0.21
	LR-Backwards	0.40	49.1	0.14	0.10	0.11
	LR-Backwards-Stepwise	0.39	49.1	0.14	0.10	0.11
	SVM-Linear	0.39	54.3	∞	0.08	∞
	LR-Enter	0.34	42.6	0.13	0.14	0.13

(B) For all two time-horizons (RH1M, RH3M), each model has set of important variables/factors which their factor importance is above 0.00).
Every variable can take part in some models as an important factor. For instance, the variable sex (gender) was only calculated as an important variable in only one model (C5) or the variable age was only calculated as an important variable in two models (ANN–MLP, ANN–RBF). By this criterion named NMFI (Number of Models that the Factor is Important) we divided all of the 34 variables into eight groups and assessed the changes of their importance over time (1 month to 3 months), as illustrated in Table 3.

A visual illustration of the importance of the variables is shown in Fig. 4.

Table 3. Division of the variables into eight groups and their average importance through time.

Group	NMFI	Mean of importance in models for predicting RH1M	Mean of importance in models for predicting RH3M
1	Max (16)	0.292	0.002
2	12, 13, 14 or 16	0.126	0.260
3	9, 10 or 11	0.037	0.002
4	7 or 8	0.029	0.015
5	6	0.020	0.027
6	4 or 5	0.011	0.008
7	1, 2 or 3	0.003	0.007
8	Min (0)	0	0.025

Figure 4 indicates the changes of each variable over time. Group 1 consists of the most important factor Worsening Renal Function (WRF) in predicting the RH1M; it was calculated as an important variable in all 16 models with mean of 0.292 but for predicting the RH3M its importance drastically decreases to 0.002.

Group 2 contains also a variable Chronic Renal Failure (CRF) with considerable mean of importance (0.126) in comparison with the others. Its factor importance in predicting RH3M increases to 0.260, which is the most increase among all of the factors. CRF has calculated as an important factor in 12 models.

Group 3 contains a variable (Uric Acid) which was important in 11 models and has mean of importance of 0.037 in predicting RH1M but in predicting RH3M, its importance decreases to 0.002.

In Group 4, the most important variables in predicting RH1M are Infection and Discharge Creatinine (CR) with mean of importance of 0.034 they both are calculated as important variables in eight models. The group importance in predicting RH1M is 0.029 while for RH3M it decreases into half (0.015).

In Group 5, the most important variable in predicting RH1M is Base-Cr (Base Creatinine) with mean of importance of 0.031 which has a slight change in predicting RH3M (0.027). Right Ventricular (RV) dysfunction with mean of importance of 0.014 has the most significant change among others while mean of RH3M importance is somehow quadrupled (0.057).

In Group 6, the mean of importance of the group from RH1M to RH3M has a slight change (0.011 to 0.008). In predicting the RH1M, the mean of importance of two variables named BUN and Tricuspid Regurgitation (TR) had considerable changes over time. (Lost 66% of its importance.)

The variables which shown importance in almost one model are gathered in Group 7. In predicting RH1M, the most important variable is Age with mean of importance of 0.01. Heart Rate (HR) importance has the most amount of change among the other variables of the group, which its RH3M importance is 17 times greater than its RH1M importance.

Group 8 are the factors that has no importance in predicting RH1M with the average importance of 0.0. However, in RH3M they show more importance in

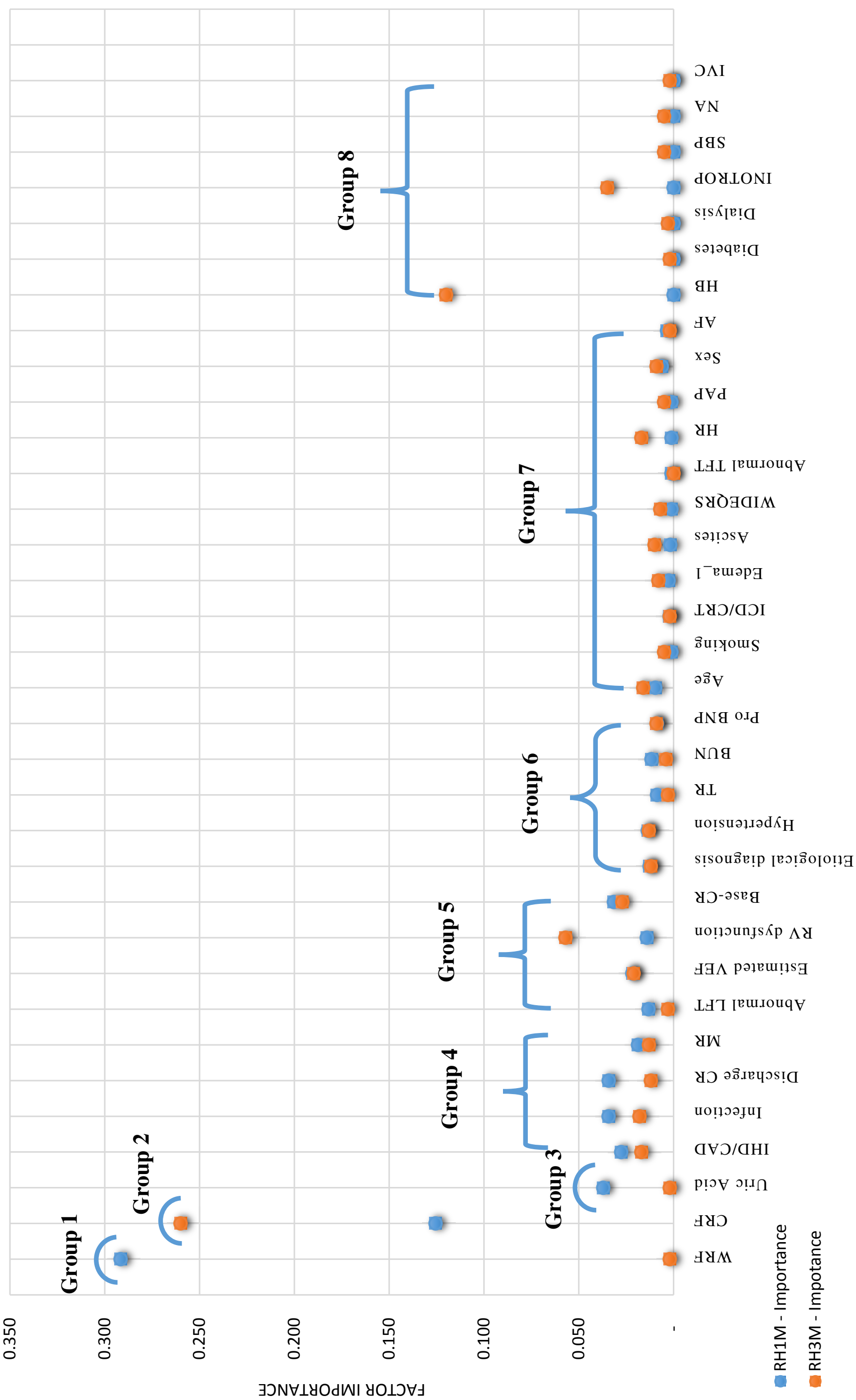

Fig. 4. The importance of the variables over time-horizons (RH1M and RH3M).

average of 0.025. Haemoglobin (HB) has the most amount of change (0.12) of importance, over time while Inotrope takes the second place with 0.035 amount of change.

4.2. *Limitations of the study*

- Poor amount of budget allocated to this project. Personal funding did it.
- Allocating an expert team (trained nurses headed by an expert cardiologist) to this project was a very difficult measure to conduct.
- Allocating resources for follow-up projects was very difficult to conduct.
- Low number of patient's records were achieved for the project with all difficulties (only 230 records).
- Low maturity in healthcare systems (or software) in the hospital.

5. Conclusions and Future Research Recommendations

In this study, the main goal was to develop a data-driven approach to predict the re-hospitalization of the heart failure patient's weather it will happen in 1 month or 3 months. Our second goal was to determine the amount of the importance of the variables in predicting the outcomes. How they change over these two time-points is also important.

In order to achieve these objectives, a data-mining project was performed through four phase's data analytic methodology. This method was used to investigate a small, feature-rich dataset acquired from RASHF registry center. The total number of 230 patients were enrolled into this study from 10 months from March 2015 to February 2016. Having the signs and symptoms of new-onset or worsening heart failure.

The following research questions regarding the re-hospitalisation of the heart failure patients have been addressed:

(1) Can we develop a DSS with high AUC for cardiovascular medical centres in order to help them distinguish the high-risk heart failure patients from low-risk ones?
(2) Can we extract the rules of the DTs models in order to help the medical personnel distinguish the high-risk patients in short time and conduct the necessary measures?
(3) Can we help such centres distinguish the factors with more importance and contribution in predicting the readmission of the heart failure patients?
(4) How does the importance of the factors change over time? (1 month to 3 months).
(5) Which classification models or algorithms performed better in predicting the readmissions?

In this study, we were working with an organised medical team, including expert cardiologists, nurses and registry team in order to start an IT-based project, which was just the first step to take. On the methodology of research, there are also other methods like design science and data science methods which are more comprehensive, but due to the scientific extent of which the research is conducted, the proposed research steps are of sufficient strength and validity according to international researches (Sohrabi and Raeesi Vanani, 2011; Raeesi Vanani and Jalali, 2017).

There are also many other re-hospitalisation research efforts conducted recently which can be considered as a good basis for future research (Jack *et al.*, 2009; Markota *et al.*, 2018) if such datasets are analysed through data mining approaches. We build models for predicting outcomes in two time-horizons (1-month and 3-month) the following performance results were obtained:

(A) Our approach can predict the 1- and 3-month outcomes with a mean AUC score of 0.67 and 0.47, respectively. The mean ACC score were 85.2 and 57.3, respectively.
Hence, this methodology can potentially assist the cardiologists and decision makers in heart failure medical centres in one month. Therefore, in order to predict readmission in 3 months, it is suggested that further records are needed in order to build more powerful and reliable models.
(B) We have identified the importance of the variables and how they have changed over time in predicting the outcomes, which can be shared with data science world and the business.
(C) Table 4 illustrates the mean ACC and AUC of the four major classification groups (DT, ANN, SVM and LR) applied in this study.

In order to prioritize the models in this study, it is better to combine the two criterions (ACC and AUC). As mentioned before, AUC is more powerful in assessing the model performance so we can propose a third criterion made through combination of the said two. We propose and name this criterion MA (Model Acceptance) and it is calculated as follows:

$$\bar{\text{MA}} = \frac{\sum_i^n \text{AUC}_i \cdot \text{ACC}_i}{\sum_i^n \text{ACC}_i}.$$

Table 4. ACC and AUC of the groups of classification algorithms in this study.

Group	Mean ACC in predicting RH1M	Mean ACC in predicting RH3M	Mean AUC in predicting RH1M	Mean AUC in predicting RH3M
DT	88.1	60.7	0.76	0.53
ANN	86.5	65.4	0.68	0.62
SVM	86.4	58.8	0.62	0.42
LR	80.1	48.4	0.61	0.38

Table 5. MA criterion calculated for all four major groups of classification algorithms used in this study.

Group	MA in predicting RH1M	MA in predicting RH3M
DT	0.73	0.54
ANN	0.68	0.62
SVM	0.62	0.42
LR	0.62	0.46

Table 5 illustrates the MA criterion for all of the four major groups used in this study.

It is obvious that this MA criterion has both ACC and AUC measures in it, which probably help us with choosing the best and most effective models in predicting RH1M and RH3M in this study (DT in RH1M and ANN in RH3M).

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