Predicting Short-term Mortality in Heart Failure patients

Rodriguez M 2021, January.

Abstract

Background

Despite advances in knowledge and technology, heart failure continues to pose a challenge to health care systems due to its complex nature. The field is ripe for application of Machine Learning (ML) techniques to work through this complexity and identify possible correlations that have not been detected by conventional research methods.

Methodology

A dataset comprising of 169 attributes from 2008 patients with heart failure admitted in a single institution from 2016 to 2019 was used. Data preparation, variable analyses and forecasting was done on a Jupyter platform using python language, pandas, scikit learn (Linear Regression, Random Forest Classifier/ Feature Importances) and statsmodels (Ordinary Least Squares).

Results

Most of the cohort were aged 69-89 years (67%), 42% were male, majority had chronic congestive heart failure, with both left- and right-heart failures, in NYHA III - IV. Comorbidities included diabetes (23%) and chronic kidney disease (24%). The mean left ventricular end-diastolic diameter (LVEDD) was normal at 53 +/- 9 (22-88 mm). Despite a low mean glomerular filtration rate of 68 ml/min/1.73m2, the median creatinine level was normal. The mean urea was mildly elevated 10 mmol/L. The mean brain natriuretic peptide level distribution was elevated (median 744 pg/mL). Majority (89%) stayed in the hospital for 1-2 weeks. The mortality rates were: 0.55% in-hospital, 1.25% on the first 7-days after admission, 1.84% at 28-days, and 2.84% at 6 months. The readmission rate was 40% by the 6th month, with a median time of 83 days from initial admission. Increased mortality was associated with male gender, low systolic blood pressure (BP), high NYHA classification, high Killip score, low Glascow coma score (GCS), elevated creatine kinase (CK), alanine transaminase (ALT), lactate dehydrogenase (LDH) and creatinine levels, and high O2 requirement. LVEDD did not show a trend with mortality. Modelling for 28-day mortality using GCS, Killip score, acute renal failure, ALT and FiO2 requirement showed a p <0..5, R squared 0.23 and predictive accuracy of 99%.

Conclusion

Of the numerous variables available to predict a patient's outcome, the most important ones can be selected using ML techniques. The approach yielded a working model with good predictive parameters.

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Introduction

Heart Failure (HF) remains a significant cause of ill health and death, with 26 million people affected worldwide.[1] North American population studies expect continued increase in numbers of patients affected with heart failure.[2] European study results show a risk of developing HF at 28-33% by age 55.[3] Less developed countries have even poorer HF prognoses compared to those of the developed countries in the Americas and Europe.[4]

HF continues to pose a challenge to the health care system due to its complex nature. Various approaches are implemented with the hopes of alleviating the disease - from the refining of diagnostic subtypes, development of new medications and interventions, and improving patient involvement in medical care. There have also been significant improvements in medical record keeping and data acquisition. The field is ripe for application of Machine Learning (ML) techniques to identify possible correlations that have not been detected by conventional research methods.

The objective of the study is to come up with a predictive model for short-term mortality, utilizing electronic health records. The study will characterize the patient subpopulation demographics, associated laboratory reports and outcomes. It will serve as a comparison population among other similar studies. The study will provide insights on steps for improvement towards unsupervised ML in helping solve HF dilemmas.

Methodology

The Physionet website was searched for heart disease-related data that contained relevant variables with a good cohort size and recent data collection. The 'Hospitalized patients with heart failure: Integrating electronic healthcare records and external outcome data' by Zhang et al[5] was chosen.

The dataset contained 168 attributes, with 2008 patients, having a few missing values. The data was collected from patients admitted with heart failure in a single institution in Sichuan, China between 2016 and 2019. The variables included demographics, vital statistics, blood laboratory exams, echocardiogram, and short-term to mid-term outcomes (mortality and readmission).

Limitations:

1. The data were collected retrospectively.
2. The data included an identifier.
3. The reason for admission was not explicit, but presumed to be for symptoms associated with heart failure.
4. Some important data could not be analyzed properly due to technicalities (definite age not given, EF values not available on most patients, incomplete follow-up data beyond the first 28 days, etc.).

The website provided a separate data table for medications administered, but the present analysis focused on admission data and did not include this in-hospital intervention.

The following were the questions that guided the present study:
1. What are the baseline characteristics of this specific cohort?
2. What are the mortality rates of this cohort (in-hospital, 1 month and 6 months)?
3. Which variables can predict mortality?

Based on the above questions, the following were the hypotheses generated:
1. The cohort is expected to comprise of patients with:
    a. advanced age,
    b. presenting with left-sided congestive heart failure (CHF) symptoms (NYHA 2-4), with distended left ventricles
    c. with significant cardiovascular comorbidities such as history of acute myocardial infarction (AMI), hypertension or diabetes
    d. laboratory abnormalities expected include a reduced ejection fraction, a distended LV, low hemoglobin, low serum sodium, elevated creatinine, high BNP, high LDH, deranged bleeding parameters (PT, PTT, INR), low albumin.
2. In-hospital mortality rate could range between 1 - 4% and 1-6 month mortality rate could rate in between 4 - 8% (Intrapolating from a cited 1-year mortality of 22%.[2]
3. Characteristics hypothesized to increase mortality risk include:
    a. advanced age, multiple previous admissions, needing emergent care
    b. hypotension, tachycardia, bradycardia, high O2 requirement
    c. distended LV, low EF
    d. low Hb, low Na, acidosis, high creatinine
    e. high BNP, high LDH, elevated AST and ALT, elevated INR
    f. low albumin

The exploration and analyses were done utilizing the Jupyter Notebook. Modules imported included pandas, numpy, statistics, matplotlib, seaborn, scikitlearn and statsmodels.

The comma separated values database was loaded as a DataFrame in Jupyter, taking care to not include identifying data. The column/ variables were checked for relevance and rearranged for easier interpretation into demographics, laboratories and outcomes. Individual variables were further arranged so as to group epidemiological and laboratory data in a meaningful manner. Laboratory names were updated (e.g. glutamic oxaloacetic transaminase to Aspartate transaminase (AST), and glutamic pyruvic transaminase to Alanine transaminase (ALT).

Columns that had more than 50% missing values were dropped. The retained variable with the highest percentage of missing value was LVEDD (45% null). There was incomplete data on mortality and readmission time, but this was expected as not all patients were dead or were readmitted - thus these variables were retained.

Columns that had missing values numbering >50 were filled using imputation based on NYHA class. The mean was imputed if there was no discrepancy. If there was a skew, the median was used for imputing. Otherwise, simple filling with mean or median (if with outliers) or mode was done. Previously mentioned null values for mortality and readmission outcomes were not filled.

DTypes were adjusted. For numerical values, integers were preferred unless warranted. Variable string values (e.g. male/female) were kept to facilitate plot labelling. These were converted to dummy variables prior to the forecasting analyses.

Univariate analyses were done using aggregate and plot functions. Values were expressed as frequency, means +/- standard deviation and range, or median, as appropriate. Binning was done on continuous variables to enable interpretation. Clinically-relevant binning was preferred to simple equal cutting. Categorical variables were expressed as frequencies and percentages.

Multivariate analyses were facilitated using groupby methods with the 28-day mortality as the base variable (shown to contain the most complete outcome data during the univariate stage). A correlation evaluation was utilized to identify the variables most associated with the 28-day mortality. Variables that were not evident on the correlation, but which has been previously identified in published reports[6] were also analyzed. Variables that are relevant to clinical practiced also underwent multivariate analysis. The values were expressed as percentages in relation to the mortality group, as well as to the whole cohort population.

LVEDD is a prominent factor in clinical decision-making. Thus, Linear Regression was done for LVEDD and select clinical variables.

Identification of variables for modelling was done using Statsmodels - Ordinary Least Squares (OLS). These were supported by Feature Importances of Random Forest Classifier, and validated using Logistic Regression.

Results

Univariate Analyses

Demographics

The cohort comprised of 2008 HF patients, mostly within the age range of 69-89 years, with a 42% male gender subpopulation. All of the patients has been admitted at least once prior to present admission. Almost half of the patients (48%) needed emergent care during present hospital admission

The mean heart and respiratory rates were normal (85 +/- 22 (0-198 bpm and 19 +/- 2 (0-36 bpm), respectively). The systolic BP was high normal at 131 +/- 24 (0-252 mmHg). The diastolic BP was normal. The mean mean-arterial-pressure (MAP) was high normal at 95 +/- 16 (0-181 mmHg). The mean weight and body mass index (BMI) were within acceptable range (53 +/- 11 (30-115 kg) and 21 +/- 4 (13-39), respectively). Majoriity were received alert with consciousness level GCS 15.

Most of the present admissions (93%) had a previous history of CHF. Majority (74%) had both left- and right-heart failures. More than half (52%) were of NYHA III classification and almost a third (31%) were in NYHA IV. (See Appendix A).

Although the patients were not suffering from AMI, the Killip scores were measured to further quantify CHF. Half (51%) were in Killip class II, 20% were in Killip 3, and 3% were in Killip 4 (See Appendix A).

There were no apparent dominant comorbidity (previous AMI, peripheral vascular disease, cerebrovascular disease, non-cardiovascular diseases). Only a quarter had diabetes (23%) or chronic kidney disease (24%). The Charlson Comorbidity Index score was low at 1-3.

Only a minority (2%) needed ventilatory support, however, 95% needed low-dose Oxygen supplementation (mean FiO2 33 +/- 5 (21-100%)).

Laboratory

The mean LVEDD was normal at 53 +/- 9 (range 22-88 mm).

Majority of the patients had normal CBC parameters, apart from a low mean eosinophil ratio of 0.02 (ref: 0.5-5). Almost a quarter (23%) had low to low-normal platelet counts (51-100).

The INR, APTT, TT, fibrinogen, CK and CK isoenzyme were within normal values (see Appendix B).

The CK-isoenzyme:CK ratio and median D-dimer levels were elevated (0.21 +/- 0.14 (0.01 - 1) and 1.17 mg/L, respectively).

The mean Glomerular Filtrate Rate was low at 68 +/- 36 (3 - 281 mL/min/1.73 m2). The median and mode creatinine levels were normal. The mean urea, uric acid and cystatin levels were mildly elevated (10 +/- 6 (2-46 mmol/L), 482 +/- 169 (62-1409 umol/L), 1.8 +/- 1 (range 0.2 - 10 mg/L), respectively).

The mean BNP level distribution was irregular and elevated (mean 1271, median 744, mode 5000 pg/ml).

The CO2 binding capacity, serum Na, K, Cl and Ca, HBD, LDH, HBD : LDH ratio, nucleotidase, fucosidase, albumin, globulin and white globulin ratio, AST, ALT, GTP , TB, DB, IB, AP, bile, TP, cholesterol, LDL, HDL and triglyceride had normal values (see Appendix B).

Outcomes

<u>In-hospital mortality and discharges</u>
Majority of the patients (89%) stayed in the hospital for 1-2 weeks and the in-hospital mortality rate was 0.55%. Of those who were discharged alive, the majority (69%) went home and almost a quarter (22%) went to live in a healthcare facility. There were patients who were discharged against advice, accounting for 5% of the discharges (see Table 1, Figure 1).

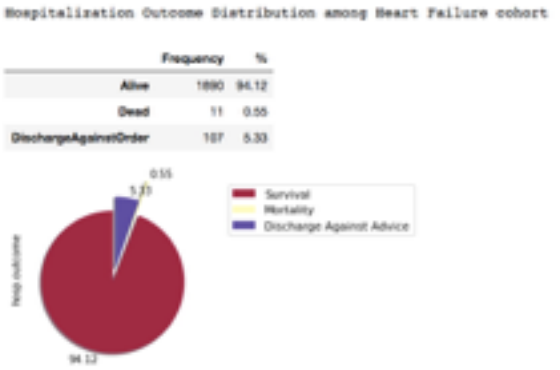
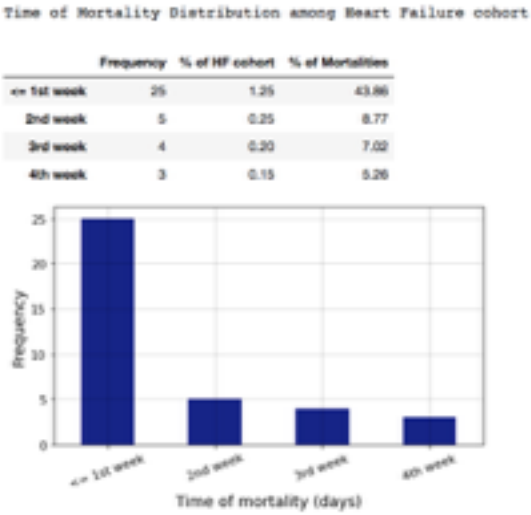


Table 1 and Figure 1. Hospitalization Outcomes



<u>1st month mortality</u>
Among the cohort admissions, 1.25% died within the first seven days, whether in- or outside the hospital. Approximately 1.84% died within the first 28 days (Figure 2).

It is possible that the mortality rates are higher due to the fact that some early deaths occurred soon after being discharged alive. Likewise, there was a good number of discharges against discharge, with poor subsequent follow-up/ unknown outcome. It was not appropriate to presume outcome in such cases.

Figure 2. Percentage and Timing of Mortality, 1 month

<u>6th month mortality</u>
Of those who were discharged alive, almost 1.4% would succumb to death within 6 months of initial admission. The cohort 6th month mortality was 2.84% (Figure 3).

<u>Readmission</u>
The rate of readmission increases rapidly from 7% during the 1st month, to almost 40% by the 6th month. The median time was 83 days from initial admission. Almost all of these readmissions were done through the emergency route.

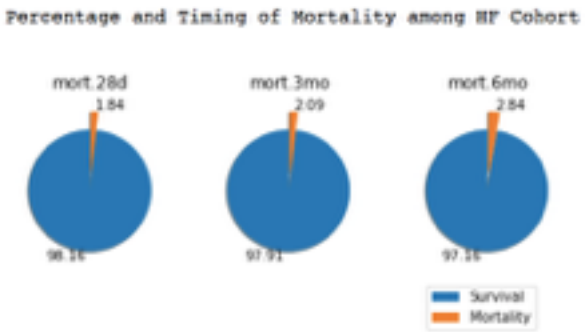


Figure 3. Percentage of Mortality, 1-6 months

Multivariate Analyses

Based on Correlation of Cohort data

While there was no strong correlation of the study variables with the outcome of 28-day mortality, smaller-group evaluations of variables with correlations > | 0.2 | revealed a trend of increased mortality associated with low GCS scores 3-4, high Killip score 3-4, high O2 requirement and elevated CK enzyme, ALT and LDH levels (Figure 4, 5).

Figure 4. 28-Day Mortality in the Background of LOS, GCS and ALT

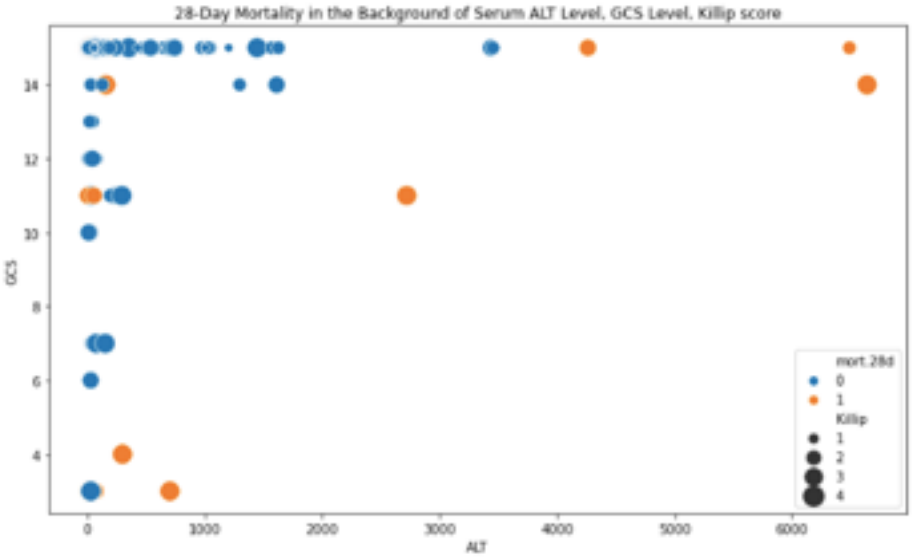


Figure 5. 28-Day Mortality in the Background of ALT, GCS and Killip score

Based on Variables previously identified for Predictive Scoring

There was a trend of increased mortality with male gender, high NYHA level 3-4, low systolic BP and elevated serum creatinine.

There was no associated increased mortality with differing age, diabetes and COPD status.

Based on Other Variables Relevant to Clinical Practice

There was a trend of increased mortality with elevated BNP levels. Mortality occurred more commonly on the high-normal LVEDD, but not the markedly distended ones

Mortalities tended to occur within the 1st week of admission.

Forecasting

An increasing LVEDD is associated with mild increase in MAP and heart rate, but marked increase in BNP levels. There is no correlation between LVEDD and D-dimer values

Short-term mortality (28-day) can be modelled using 5 variables on admission: GCS, Killip score, acute renal failure (ARF), ALT and FiO2 requirement (Figures 4-7). These were developed using OLS, Feature Importances and Logistic Regression, with p <0..5, R squared 0.23 and predictive accuracy of 99%.

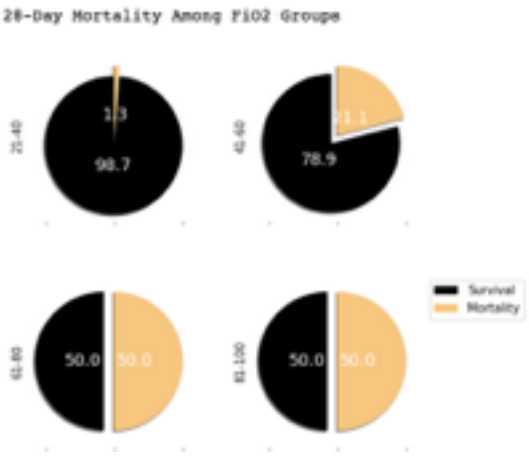


Figure 6. 28-Day Mortality Among FiO2 groups

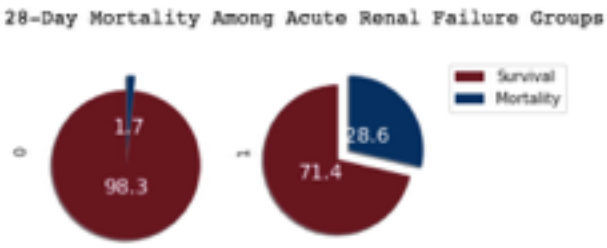


Figure 7. 28-Day Mortality Among ARF groups

Discussion

The 2.84% 6-month mortality rate of this cohort is low (by intrapolation) compared to the commonly recognized 1-year mortality of 22%.[2] However, since both the mortality rate and readmission rates increase with time, and if it grows logarithmically, it will reach the expected mortality rate at 1 year. Likewise, hospital discharges that were against medical advice was high at 5%. This could be accounted for by cultural beliefs towards death and uncertainty towards western medical approaches. It is possible that surveillance of these untoward hospital discharges would show early out-of-hospital mortalities.

Clinicians often resort to risk calculators for guidance to the prognostic approach to patients. One of the heart failure risk calculators is the Meta-analysis Global Group in Chronic Heart Failure (MAGGIC).[6] The 13 independent predictors identified include (in order of predictive strength): age, lower EF, NYHA class, serum creatinine, diabetes, not prescribed beta-blocker,

lower systolic BP, lower body mass, time since diagnosis, current smoker, COPD, male gender, not prescribed ACE-inhibitor or ARB.

Of the 13 identified predictors in MAGGIC, 8 variables were available for analysis in this present study. (Medications were available in the Physionet site, but was not included in this analysis). Our results supported the findings in MAGGIC for 5 variables: high NYHA, elevated serum creatinine, low systolic BP and male gender.

Clinical practice is often guided by a heart failure patient's LVEDD size. While we noted a slight association with increased BP and heart rate, this study did not show that increasing LVEDD size led to increased risk for mortality.

The forecasting method used in this study identified several variables that were not included in the MAGGIC risk calculator: GCS, Killip score, ARF, ALT level and FiO2 requirement.

The higher propensity for mortality in patients arriving at the hospital with very low GCS at 3-4 is understandable. The very low neurological status is reflective of the advanced stage of multiple organ deterioration, where heart failure was the presumed underlying cause in this study.

Killip score is most commonly used in describing the status of heart failure among patients who are suffering from AMI, from Class I with no heart failure symptoms to Class IV for cardiogenic shock. The original data collectors, however, chose to include it in the data for the patients as a general hear failure classifier, regardless of AMI diagnosis. Used as a marker for severity of heart failure, the Killip score proved to be a predictor for early mortality.

Acute renal failure could be a sign of decompensated heart failure. Thus while the percentage of patients who suffered from ARF was low in the cohort, those that did succumb to ARF had a very high risk for early mortality. HF management frequently involve multiple drugs, thus, injury due to renal toxic drugs should also be considered.

The ALT is one of the panel for liver function tests. Elevated levels could indicate left- and/or right-sided heart failure.[7] While the cohort values were not particularly elevated, those that suffered mortality had markedly elevated values that could indicate shock liver from both malperfusion and congestion.

Congestion leading to respiratory compromise was present in almost all patients in this cohort. While the majority needed only mild-moderate oxygen supplementation, those that had high requirements, indicating the severity of the congestion, had a higher incidence of early death.

The variables that were predictive for early mortality were from various other organ systems of the human body, but which are invariably linked to the health of the cardiovascular system. Heart failure is not an isolated body disease. It entails subsequent injury to other systems either because of malperfusion from a weak forward flow of blood or congestion from high-pressure back-filling, leading to multiple organ failure and death.

This study gives a glimpse as to the expanse of electronic medical records, and as to how data can be used to characterize a patient population, to guide local practitioners in managing their patients.

Some of the insights that can be provided by this study are:

1) Early mortality were mostly due to the patients' severe condition during the admission. Heath authorities could advocate for early detection of warning signs, either through surveillance or education, so that patients seek medical help while there is still a good hope of survival.
2) The institution's protocol on Discharges against advice might benefit from a review. Auditing the ultimate reasons for the decision of leaving the hospital, as well as outcomes of patients discharged against advice might identify measures that can be improved.
3) The institution's echocardiography program would benefit from a review. Most of the echo data in the database were not available. This is possibly because physicians preferred to rely on clinical examination, and did not feel the need for imaging studies. However, modern clinical practice and study results have shown that the echo results are a important features of heart failure management. Thus, improved echo capability and availability might greatly benefit this specific patient population.
4) The practice on out-patient surveillance should be reviewed and revitalized, with the hopes of decreasing the incidence of hospital readmissions. This could be in the form of improving out-patient clinic scheduling, staffing, and utilizing patient and family educational materials. Technological advances in communication present in the specific district could also be used.
5) Heart failure management remains tricky and complex. Despite new medications and techonology, the prognosis of heart failure has not improved much.[8] Unsupervised ML techniques could identify unexpected features that might provide a better picture of subpopulations of heart failure.

Conclusion

Of the numerous variables available to predict a patient's outcome, the most important ones can be selected using ML techniques. Early (28-day) mortality for this specific cohort can be modelled using the Glasgow Coma Score, Killip score, presence of acute renal failure, ALT levels, and FiO2 requirement during admission. The model predictive parameters were good, with p <0..5, R squared 0.23 and predictive accuracy of 99%.

Limitations and Recommendations

The author was not involved in the planning and collection of the dataset. There were limitations in the documentation of the data, as previously mentioned in the methodology.

The model can provide a general overview in predicting mortality for heart failure patients, however, a more robust dataset and analysis will be needed before it can be advocated for clinical use. Important variables specific to HF diagnosis and treatment should be incorporated. The model should be reviewed frequently due to the fast development of medical therapy and technology that revise the clinical trajectories of HF patients.

Disclosure

The author has nothing to disclose.

Correspondence: *yrodriguezmd@gmail.com*

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Appendix A. Classifications

New York Heart Association (NYHA) Heart Failure Classification

Class	Symptoms
I	No limitation of physical activity.
II	Comfortable at rest. Ordinary activity results in fatigue, palpitation, shortness of breath.
III	Comfortable at rest. Less than ordinary activity causes fatigue, palpitation, shortness of breath.
IV	Symptomatic at rest.

Killip Classification of Acute Myocardial Infarction

Class	Signs of heart failure
I	None
II	rales < 1/2 up the posterior lung fields, (+) S3 gallop, jugular venous distension
III	overt pulmonary edema
IV	cardiogenic shock

Appendix B. Results of Univariate Analyses on Blood (Serum) Laboratory Findings

Laboratory	**Abbreviation used**	**Result** *mean +/- SD (range), unit or median, unit*
while blood cell count	WBC	6-10/L
monocyte count	mono.ct	0.5 +/- 0.24 (range 0.01 - 2.3L) (*10^9/L)
monocyte ratio	mono.ratio	0.07
neutrophil count	neut.ct	5.6 +/- 3.2 (range 0.74 - 30) (*10^9/L)
neutrophil ratio	neut.ratio	0.8
lymphocyte count	lymph.ct	1 +/- 0.6 (range 0.08 - 6.7) (*10^9/L)
basophil count	baso.ct	0.3 +/- 0.3 (range 0 - 0.73) (*10^9/L)
basophil ratio	baso.ratio	0.005
eosinophil count	eo.ct	0.12 +/- 0.2, with a wide range of 0 - 6.6 (*10^9/L)
eosinophil ratio	eo.ratio	0.02
red blood cell count	RBC	3.9 +/- 0.8 (range 0.9 - 7)(*10^12/L)
hemoglobin	Hb	115 +/- 24 (range 29-200 g/L)
hematocrit	Hct	0.35 +/- 0.07 (range 0.09 - 0.6)
coefficient of variation of RBC distribution width	CV.RBC.DW	15 +/- 2 (range 12-30%)
standard deviation of RBC distribution width	SD.RBC.DW	49 +/- 6 (range 32-98 fL)
mean corpuscular volume	MCV	92 +/- 8 (range 57-135 fL)
mean hemoglobin volume	MHV	30 +/- 3 (range 16-45 pg)
mean hemoglobin concentration	MHC	325 +/- 14 (range 252- 363 g/L)
platelet count	Plt	145 +/- 64 (range 5-646) (*10^9/L)
mean platelet volume	MPV	12 +/- 1.6 (range 8-18 fL)
platelet distribution width	P.DW	16 +/- 1.5 (range 10-25 fL)
platelet:hematocrit	Plt.hct	0.17 +/- 0.07 (range 0.01 - 0.7%)

international normalized ratio	INR	1.3 +/- 0.7 (range 0.8 - 17)
activated partial thromboplastin time	APTT	35 +/- 8 (range 20-181 s)
thrombin time	TT	17 +/- 6 (range 10-209 s)
prothrombin activity	PT.act	66 +/- 18 (range 3-141)
prothrombin time ratio	PT.ratio	1.4 +/- 0.7 (range 0.8 - 15)
fibrinogen	fibrinogen	3.2 +/- 1 (range 0.5-8 g/L)
D-dimer	Ddimer	1.17 mg/L
creatine kinase	CK	131 +/- 268 (range 17-5920 IU/L)
creatine kinase isoenzyme	CK.enz	19 +/- 19 (range 1 - 424 IU/L)
CK isoenzyme: CK ratio	CK.enz.CK	0.21 +/- 0.14 (range 0.01 - 1)
glomerular filtration rate	GFR	68 +/- 36 (range 3 - 281 mL/min/1.73 m2)
creatinine	crea	86 umol/L
urea	urea	10 +/- 6 (range 2-46 mmol/L)
uric acid	uric.acid	482 +/- 169 (range 62-1409 umol/L)
cystatin	cystatin	1.8 +/- 1 (range 0.2 - 10 mg/L)
CO2 binding capacity	CO2.BC	24 +/- 5 (range 2-47 mmol/L)
sodium	Na	138 +/- 5 (range 107-159 mmol/L)
potassium	K	4 +/- 0.7 (range 1.7-11 mmol/L)
chloride	Cl	101 +/- 6 (range 70-125 mmol/L)
calcium	Ca	2.3 +/- 0.2 (range 1.4 - 3.4 mmol/L)
hydroxybutyrate dehydrogenase: lactate dehydrogenase ratio	HBD.LDH	0.8 +/- 0.1 (range 0.4-1.2)
hydroxybuterate dehydrogenase	HBD	184 U/L
Aspartate transaminase or Glutamic oxaloacetic transaminase	AST	25 IU/L
lactate dehydrogenase	LDH	268 +/- 237 (range 107-6279 IU/L)
brain natriuretic peptide	BNP	744 pg/mL

nucleotidase	nucleotidase	4 +/- 3 (range 0.3-31 U/L)
fucosidase	fucosidase	19 +/- 5 (range 4-59 U/L)
albumin	albumin	36 +/- 5 (range 12-52 g/L)
globulin	globulin	29 +/- 6 (range 14-88 g/L)
white globulin ratio	w.glob.ratio	1.3 +/- 0.3 (range 0.1-2.6)
glutamyltranspeptidase	GTP	42 U/L
alanine transaminase or glutamic pyruvic transaminase	ALT	20 U/L
direct bilirubin	DB	6.4 umol/L
indirect bilirubin	IB	14 +/- 9 (range 1-128)
total bilirubin	TB	18.3 umol/L
alkaline phosphatase	AP	79 U/L
bile	bile	5 umol/L
total protein	TP	65 +/- 7 range (41-100 g/L)
total cholesterol	cholesterol	4 +/- 1 (range 1-10 mmol/L)
light density lipoprotein	LDL	2 +/- 0.7 (range 0.4 -6 mmol/L)
high density lipoprotein	HDL	1 +/- 0.3 (range 0.02 -2.7 mmol/L)
triglyceride	triglyceride	1.2 +/- 1 (range 0.2 - 24 mmol/L)