Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Statistical learning and prediction of diseases associated with the occurrence of death in the emergency department: An observational study on administrative data from Saint Joseph Hospital in Kinshasa-DRC

Richard Ingwe Chuy

ringwe2019@gmail.com

Health knowledge center in DR. Congo

Didier Chuy Kalombola

Health knowledge center in DR. Congo

Julien Neze-Sebakunzi

Community of Sant'Egidio, DREAM Program DRC

Joël Ekofo Yombo

Health knowledge center in DR. Congo

Chrispin Kabanga Mbala

Health knowledge center in DR. Congo

Faustin Chenge Mukalenge

Health knowledge center in DR. Congo

Research Article

Keywords: Statistical learning, disease prediction and death

Posted Date: August 10th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9463379/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Abstract

Objective

The determinants, timing and predictive tools of mortality in emergency departments for specific diseases have already been evaluated in several studies. The diseases that are most likely to cause death in emergency departments have been studied in limited numbers. This study aimed to identify the diseases which are possibly predictive of the occurrence of death by using statistical learning methods.

Methods

Administrative data of patients admitted to the emergency departments of Saint Joseph Hospital in Kinshasa between January 1st 2018 and December 31st 2019 were reviewed retrospectively. The occurrence of death, defined as a patient who had a "deceased" outcome reported in the emergency registers, was predicted. Nineteen predictive conditions were modalities of the 'diagnosis' variable and were adjusted for age, gender and number of diagnoses. Six models were run on this data set, 70%. The AUC and its confidence interval were used to evaluate the performance of each model on the test data set, 30%.

Results

A total of five thousand one hundred and seventy-two (5172) subjects were incorporated into the analyses. The average age of the complete dataset was 47.9 ± 20.0 years. In the training and test datasets, the mean ages were 48.0 ± 20.2 and 47.4 ± 20.4 years, respectively. The training dataset comprised 50% male patients, while the test dataset included 48.8% male patients. Among these individuals, 7.5% in the training group and 7.4% in the test group did not survive. For each model, the area under the curve (AUC) values were as follows: ElasticNet 0.746 [0.689–0.784], logistic regression 0.735 [0.687–0.783], neural networks 0.735 [0.687–0.783], xGboost 0.734 [0.687–0.783], decision trees 0.50 [0.50–0.50], and random forest 0.428 [0.391–0.464]. The six primary predictors of mortality, listed in descending order, were shock states, sepsis, tuberculosis or pneumonia, coma, meningoencephalitis, and cancer.

Conclusions

Four of the six models used, performed well. ElasticNet was a network model that maximized the area under the ROC curve. Statistical learning methods applied to the twelve potential diseases in the prediction of the occurrence of death could help policy makers and health professionals to approach optimal decisions in the management of patients.

Introduction

Emergency departments are seen as a hub in the provision of hospital-based healthcare. Emergency departments in industrialized countries act as an interface between community medicine and hospitals, routine care and advanced interventions, medical action and social management (1).

Emergency departments act as important gateway to care, accounting for 40–60% of hospital admissions (2). Patients are admitted to these services for a variety of conditions, ranging from a sprained ankle to cardiac arrest (1). The question of mortality and its determinants in emergency departments has been addressed by several researchers. These researchers can be grouped into three groups according to their objectives. The first group is composed of researchers interested in studying the ability of disease-specific mortality prediction tools. This is the case of quick Sequential Organ Failure Assessment (qSoFA) in predicting mortality from sepsis or infection (3–6). The older people at risk tool compared to the risk triage tool for predicting mortality in older people (7). The validation of a simple prognostic score to predict mortality at one year of disease progression (8) and the Korean Triage and Acuity Scale where the researchers sought to understand its association with mortality among the four objectives they were pursuing (9). The second group of researchers also focused on defining factors associated with mortality for specific pathologies, namely predictors of mortality in patients with chest pain without cardiac emergencies (10). The factors associated with mortality in elderly people (11), the outcome of non-critical factors associated with mortality in elderly people (11), the outcome of non-critical septic hypotension (12), the mean lactate threshold, National Early Warning Score (NEWS) and NEWS-lactate (NEWS-L) as a predictor of mortality in elderly patients (13), predictors of mortality in cancer patients (14,15), mortality related to cardiovascular pathologies (16–18) and, traumatic pathologies and mortality in the emergency department (19,20). The third group examined the time to initiation of health interventions in patients admitted to the emergency department and/or their referral to the intensive care unit and mortality in the emergency department (21–24).

There are few studies assessing the diseases that predict mortality in emergency department admissions worldwide. The few studies found that emergency department mortality after 72 hours of admission at 1.9% with a significant contribution from cranial trauma (21.5%) and sepsis (18.8%) (25, 26) and mortality during the last 12 months of follow-up at 8% with a predominance of cardiac diseases (35%) and cancer (30%) (26).

However, few studies have sought to identify the diseases that predict the occurrence of death in emergency departments.

In the Democratic Republic of Congo (DRC), the patients admitted to emergency departments come from three main sources: the community, referrals from first-level structures or private establishments with a low technical platform and intra-hospital transfers. There is a significant lack of studies looking for diseases that predict the occurrence of death using statistical learning methods in this context.

This study aims to predict the pathologies that may contribute to the occurrence of deaths in emergency departments in one hospital in the city of Kinshasa using statistical learning. The use of these methods to model and predict certain health events in hospitals would be beneficial compared to human deduction. These techniques have the advantage of providing information that is often unexpected and that even traditional logistic regression has not found an association. They consist of programming algorithms to predict an explained variable (occurrence of death) from a set of predictors. Identifying these pathologies could help providers to expedite and optimize care whenever they encounter the relevant cases.

This research contributes to the initiative aimed at enhancing the adequacy and promptness of responses from emergency care providers in developing nations, particularly in regions like the Democratic Republic of Congo (DRC), where emergency departments are significantly lacking in resources and the presence of emergency care specialists.

Methods

Type of study

This research is a retrospective observational study that involved utilizing administrative data from paper records of all patients who were admitted to emergency departments. The protocol and the assessment report were provided to the commendatory of the study, the program aimed at strengthening the Saint Joseph Hospital, which was carried out by the Belgian Development Agency, abbreviated as enabel.

Setting and study population

The data presented were gathered from an examination of the circumstances at Saint Joseph Hospital, carried out by the Centre de Connaissances en Santé en RD. Congo, abbreviated as CCSC-ASBL, with the objective of formulating a Hospital Establishment Plan. This data pertains to the emergency departments of the hospital over a span of 24 months, specifically from January 1st, 2018 to December 31st, 2019. Saint Joseph Hospital is a Catholic institution that serves as a reference hospital for the healthcare facilities overseen by the Bureau Diocésain des Œuvres Médicales (BDOM) located in Kinshasa. The hospital's location draws in patients from Kinshasa, averaging 200 patients daily, with approximately ten visiting the emergency departments, and an annual hospitalization rate of around 50,000 patients (27). An Access entry mask was utilized to gather data from the emergency department's register. All patients included in this research had their pathology information verified and documented in the administrative records of the emergency departments. A deceased patient is defined as one who was admitted while alive, with a diagnosis and fatal outcome recorded in the emergency department register. The hospital lacks a standardized nomenclature for conditions; therefore, the descriptions provided by clinicians were accurately entered into the data mask. Depending on the severity, the names of the conditions were either retained as they were, categorized by the mechanism of occurrence or by organ, or classified under other conditions. All patients documented in the paper registers of the emergency departments were incorporated into this study.

Creation and defining of the data set

The predictors that were gathered consisted of various diseases documented in the emergency registers. The absence of a standardized disease nomenclature has resulted in over a thousand different modalities of predictors. Utilizing the fct_recorde function from the forcats package, which is designed for handling categorical variables (factors) within the tidyverse (28), these predictors have been recoded (see table 1).

Table 1. Modalities of the variable "diagnosis" after recoding

N°	Nosological entities	Diseases included
1	Surgical abdomen	Surgical abdomen, appendicitis, venting, stercoral or vesico-cutaneous fistula, ruptured ectopic pregnancy, post caesarean hemorrhage, hernias, intestinal obstruction and pelviperitonitis or peritonitis.
2	Other injuries	Work accidents, road traffic accidents without specific lesions, burns, soft tissue contusions, abrasions, sprains, fractures, hematomas, dislocations, animal bites, wounds and trauma without specific lesions, orthopedic diseases.
3	Cancers	Cervical cancer, uterus cancer, prostate cancer, stomach cancer.
4	Neurological diseases	Transient ischemic attack (TIA), stroke, cerebral atrophy, convulsion, headache, eclampsia, hypertensive encephalopathy, unspecified intracranial hypertension, neurodegenerative disease and neurological disorder.
5	Anemia or atraumatic hemorrhage	Anemia, digestive hemorrhages, hemorrhages, epistaxis
6	Renal failure or uropathy	Benign prostatic hypertrophy, acute or chronic renal failure, urethral insufficiency, lithiasis, hypertensive nephropathy, acute urinary retention, atraumatic ureteral rupture, nephrotic syndrome and urethral tumor.
7	Tuberculosis or lung diseases	Bronchial asthma, COPD, bronchopneumonia, respiratory distress, unlabeled dyspnea, acute lung edema, pleuropneumonia and tuberculosis.
8	Digestive diseases	Amoebiasis, cholera, hepatic cirrhosis, abdominal colic, hepatic cirrhosis, hepatic colic, colopathy, dilated pancreas, abdominal pain, dysentery, dysphagia, faecal impaction, gastroenteritis, pancreatitis, intestinal parasitosis and peptic ulcer.
9	Heart diseases	Cardiothyreosis, pulmonary heart, myocardial infarction, heart failure, heart disease without specific lesions.
10	Shock states	Anaphylactic, cardiogenic, hypovolemic, septic or mixed shock.
11	Sepsis	Cholecystitis and sepsis
12	Cranioencephalic trauma	Concussion, brain contusion, brain edema, traumatic brain injury
13	Infectious diseases	Abscesses, tonsillitis, Annexitis, cellulitis, cryptococcosis, dermatitis, eruptive or prolonged fever, boils, HIV infection, urogenital infection, urinary tract infection, laryngitis, lymphoedema, orchi-epididymitis, otitis, phlegmon, athlete's foot, pyothorax, salmonellosis, sinusitis, tetanus and shingles.
14	Vascular diseases	High blood pressure, embolism, thrombophlebitis, thrombosis.
15	Malaria	-

16	Diabetes	-
17	Coma	-
18	Meningoencephalitis	Meningitis or meningoencephalitis.
19	Other diseases	Adenopathies, algias, allergies, ascites, sleep apnea, nerve damage, abortions, additive driving, dehydration, various masses, epilepsy, hypoglycemia, hypotension, intoxications, pregnancy diseases, psychiatric diseases.

The data set comprised five variables, with only one being numerical - age. These variables include diagnosis, number of diagnoses, gender, age, and death. The diagnostic variable is categorical and consists of 19 modalities that will inform our future predictive diseases. The number of diagnoses among patients is treated as a categorical variable with three modalities. Modality 3+ merges modalities 3 and 4 due to an inadequate number of participants. Predictors were adjusted based on patient age, gender, and the number of diseases. Data management, descriptive statistics, and various statistical models were executed using the R software.

Data analysis

The acquired data set underwent processing prior to the implementation of the statistical learning algorithms. The dummyVars function (29) from the caret library was utilized on the complete data set across all predictors and fit variables to achieve balance, as well as to normalize the age variable. The elimination of variables exhibiting significant correlation and those with negligible or near-zero variance was not performed, given that there was only one quantitative variable, 'age', while the remaining variables were essential predictors for this research. An exploratory logistic regression employing two codings of the 'diagnosis' variable, '0/1 and -1/1 on the predictors', revealed minimal alterations in coefficient disturbance and low p-values. The data set was divided into a training dataset comprising 70% and a test dataset comprising 30%. A comparative analysis of the training and test data sets is presented in Table 2. In total, six models were executed to identify the one demonstrating optimal performance. Only the caret library (classification and regression training) was utilized (29) to execute the various models. These models include logistic regression via the 'glm' function, neural networks through the 'nnet' function, elasticnet using the 'glmnet' function, random forest with the 'rf' function, decision trees through the 'rpart' function, and Xtreme gradient boost via the 'xgbTree' function. They were applied to the training dataset and evaluated on the test dataset to assess their performance. The elasticnet model was determined to be the optimal choice for indexing the predictors. The area under the curve and its confidence interval served as the sole metric for evaluating the performance of the different models. In summary, logistic regression relies on the computation of probabilities by applying coefficients to the predictors. Neural networks function similarly to biological neurons, where input signals 'predictors' activate a subsequent action 'the classification of the subject within the modalities of the target variable'. They have been employed to categorize individuals into death-related outcomes.

Results

In total, 5250 patients were documented in the emergency department registry of Saint Joseph Hospital. Among these, 5172 patients were incorporated into the statistical analyses, 33 patients had no diagnosis noted in the paper records, 35 patients were admitted for clinical follow-up visits, and 10 patients exhibited no vital signs upon their arrival at the emergency department, as shown in Figure 1, (Figure 1).

The average age in the complete data set was 47.9 ± 20.0 years. In the training and test data sets, the average ages were 48.0 ± 20.2 years and 47.4 ± 20.4 years, respectively. Males constituted 50.3% of the full data set, while the proportions in the training and test data sets were 50.0% and 48.8%, respectively. The distribution of other variables was similar between the training and test data sets, as illustrated in Table 2. It is important to highlight that 386 admissions resulted in fatalities during their time in the emergency department, representing a death rate of 7.46%; specifically, 271 (7.5%) in the training group and 115 (7.4%) in the test group succumbed (refer to Table 2). Among all the models evaluated, elastic net achieved the highest AUC of 0.736 (95% CI: 0.689 - 0.784). Three models yielded AUC results comparable to elastic net: logistic regression at 0.735 (95% CI: 0.687 - 0.783), neural networks at 0.735 (95% CI: 0.687 - 0.783), and xGboost at 0.734 (95% CI: 0.685 - 0.782). The traditional decision trees and random forest models exhibited the lowest performance, with AUCs of 0.500 (95% CI: 0.500 - 0.500) and 0.428 (95% CI: 0.391 - 0.464), respectively (see Table 3).

Table 2. Characteristics of the training and test data sets

Characteristics	**Training data (n = 3622)**	**Test data (n = 1550)**
Gender (F (%))	1815 (50.0)	757 (48.8)
Age (mean (SD)	48.0 (20.2)	47.38 (20.4)
Number of diagnosis (%)		
1	3257 (89.9)	1370 (88.4)
2	308 (8.5)	164 (10.6)
3+	57 (1.6)	16 (1.0)
Deceased (yes (%))	271 (7.5)	115 (7.4)
Diagnosis (yes (%))		
Other infectious diseases	180 (5.0)	70 (4.5)
Surgical abdomen	82 (2.3)	44 (2.8)
Other trauma	480 (13.3)	188 (12.1)
Cancers	44 (1.2)	19 (1.2)
Neurological diseases	406 (11.2)	180 (11.6)
Anemia or atraumatic hemorrhage	148 (4.1)	56 (3.6)
Renal failure or uropathies	112 (3.1)	51 (3.3)
Tuberculosis or lung disease	165 (4.6)	76 (4.9)
Digestive diseases	222 (6.1)	85 (5.5)
Heart disease	131 (3.6)	78 (5.0)
Diabetes	295 (8.1)	104 (6.7)
Shock states	61 (1.7)	35 (2.3)
Sepsis	131 (3.6)	47 (3.0)
Coma	78 (2.2)	43 (2.8)
Cranio-encephalic injury	144 (4.0)	66 (4.3)
Meningoencephalitis	59 (1.6)	22 (1.4)
Malaria	460 (12.7)	218 (14.1)
Vascular diseases	191 (5.3)	79 (5.1)

Other diseases	233 (6.4)	89 (5.7)

Table 3. Comparison of AUC between models

Models	AUC	CI 95%
ElasticNet	0.736	[0.688 - 0.784]
Logistic regression	0.735	[0.687 - 0.783]
Neural networks	0.735	[0.687 - 0.783]
xGBoost	0.734	[0.685 - 0.782]
Decision trees	0.5	[0.500 - 0.500]
Random forest	0.428	[0.391 - 0.464]

Discussions

The application of statistical learning techniques enabled us to categorize the various predictive diseases examined in this research based on their contribution to mortality. These techniques serve as a crucial resource in health-related investigations. The methodologies employed in our research yielded favorable results, achieving an overall score of 0.7. Among these, the elastic net demonstrated the best performance by optimizing the area under the ROC curve, as show in Figure 2, (Figure 2). Prior research, including studies that forecasted hospitalization needs in pediatric asthma patients and mortality rates in sepsis patients, identified Gradient Boosting and Random Forest as models that attained optimal prediction thresholds, respectively (30,31).

Twelve predictors were identified as being more significant in forecasting the incidence of mortality at Saint Joseph's Hospital. These predictors, listed in descending order of significance, include: shock, sepsis, tuberculosis or lung disease, coma, meningoencephalitis, cancer, malaria, other forms of trauma, neurological disorders, digestive disorders, heart disease, and vascular diseases, as shown in figure 3, (Figure 3).

These methods, in addition to emphasizing the predictors that may have played a role in the incidence of mortality and that were significantly correlated with the exploratory logistic regression, also highlight that certain predictors, which were not identified among the strong predictors, exist. This is particularly evident in the case of malaria, which was positioned as the seventh predictor, despite not showing significant association in the traditional logistic regression; nonetheless, the region where the study was conducted is endemic to this disease. Furthermore, other traumas are ranked eighth, even though they were statistically insignificant in the conventional logistic regression. This observation appears plausible given the context of the hospital environment. Indeed, St Joseph's Hospital is situated on one of the

most trafficked roads leading to Kinshasa's N'Djili airport and regularly receives patients from road traffic incidents, ranging from minor abrasions to severe trauma. The six primary diseases that have most significantly contributed to mortality are those that physiopathologically induce hypoxia or anoxia in organs, resulting in multi-organ failure, even when the underlying cause is addressed.

Limits of the study

Despite the diligent efforts of the research team, this study presents four distinct limitations. Firstly, the data was sourced from a single healthcare institution, which complicates the generalization of the results. Nevertheless, the substantial sample size provides valuable insights into potential predictors of mortality. Secondly, the reliance on a paper register and manual data transcription may have contributed to the misclassification of predictors. However, this issue was significantly mitigated by the rigorous supervision of data collection, which ensured the accuracy of the information entered into the input mask. In instances where information was challenging to interpret, a consensus between two individuals was required prior to any transcription into the input mask. Thirdly, the model's performance was notably constrained, as its training on the test dataset failed to predict any cases. The model exhibited high specificity but low sensitivity, a common occurrence when the event's prevalence is low, as observed in our sample. In such scenarios, predictions tend to gravitate towards zero (29). Given the six primary potential predictors identified in this study, it is imperative to conduct a prospective study to evaluate their efficacy in forecasting mortality. Lastly, the lack of standardization in diagnoses among providers at the hospital where the study was conducted may have introduced classification bias, as identical diagnoses may be recorded differently by various physicians, leading to misclassification by the research team. Additionally, the limitations in the model's performance can be attributed to the inadequate computational power of the system utilized for training these methods.

Conclusions

Statistical learning techniques utilized in health data have enabled the indexing of pathologies that may serve as predictors for mortality in the emergency departments of Saint Joseph Hospital in Kinshasa. The application of these methods to health data is anticipated to assist policymakers and healthcare professionals in forecasting pertinent strategies for the effective management of patients admitted to emergency departments. In this research, the elastic net model was instrumental in identifying the diseases that hold significant predictive value regarding mortality. It would be highly beneficial in the future to conduct a study that includes the first twelve predictors identified in this research to further explore their predictive power concerning mortality. Such a study would provide clinicians or researchers who engage with it a novel perspective on managing patients presenting to the emergency department with one of the twelve identified predictors of death.

Abbreviations

RDC: Democratic Republic of the Congo

AUC: Area Under the Curve

ROC: Receiver-Operating Characteristic Curve

qSoFA: quick Sequential Organ Failure Assessment

NEWS-L: NEWS Lactate

CCSC-ASBL: Centre de Connaissances en Santé en RD. Congo – Association Sans But Lucratif

BDOM: Bureau Diocésain des Oeuvres Médicales

TIA: Transient Ischemic Attack

COPD: Chronic Obstructive Pulmonary Disease

EN: ElasticNet

LR: Logistic Regression

NN: Neural Networks

xGB: eXtreme Gradient Boosting

DT: Decision Trees

RF: Random Forest

Dg: diagnosis

SS: shock state

TB.LP: tuberculosis or lung diseases

ME: meningoencephalitis

OT: other traumatics

ND: neural diseases

DD: digestive diseases

HD: heart diseases

VD: vascular diseases

A.AT.HM: anemia atraumatic hemorrhages

SABD: Surgical abdomen

CEI: Cranio-encephalitic injury

Nb.dg2: Number diagnosis equally 2

Nb.dg3+: number diagnosis equally 3 or 4

RI.UD: renal insufficient or uropathies

OD: Other Diseases.

Declarations

Ethics approval and consent to participate

The study was submitted to the Ethics Committee of the University of Kinshasa and was granted a waiver of prior ethics approval under reference number ESP/CE/85/2026. It was based exclusively on a secondary analysis of pre-existing hospital administrative data stored from CCSC-DR. Congo. It involved no direct contact with participants and no intervention, procedure, or additional data collection from individuals. This study used previously anonymized data that did not allow the direct or indirect identification of patients. The data used in this study did not involve clinical responsibilities and were collected in accordance with applicable guidelines and regulations, including the Declaration of Helsinki.

Consent for publication

Not applicable

Availability of data and materials

The dataset used for the results of this study is available and can be sent to anyone who requests it.

Competing Interests

Noone

Funding

None

Authors' contributions

RIC conceived the study, wrote the analysis plan, conducted the literature review and analysis and wrote the first draft manuscript. DCK, JN, JEY, CKM and FCM reviewed the draft manuscript, and provided critical comments. RIC finalized the manuscript which was subsequently approved by all authors.

Acknowledgements

We would like to thank the “Centre de Connaissance en Santé en RD. Congo” for providing the database used in this study.

References

1. Vassy C. L'organisation des services d'urgences, entre le social et le sanitaire. Mouvements. 2004;32(2):67.
2. Peneff J. Les Malades des urgences [Internet]. Editions Métailié; 2000 [cited 2021 Aug 8]. Available from: http://www.cairn.info/les-malades-des-urgences--9782864243465.htm
3. Green SL, Smith MTD, Cairns C, Clarke DL, Bruce J, Bekker W, et al. The Combined SIRS + qSOFA (qSIRS) Score is More Accurate Than qSOFA Alone in Predicting Mortality in Patients with Surgical Sepsis in an LMIC Emergency Department. World J Surg. 2020 Jan;44(1):21–9.
4. Singer AJ, Ng J, Thode HC, Spiegel R, Weingart S. Quick SOFA Scores Predict Mortality in Adult Emergency Department Patients With and Without Suspected Infection. Ann Emerg Med. 2017 Apr;69(4):475–9.
5. Askim Å, Moser F, Gustad LT, Stene H, Gundersen M, Åsvold BO, et al. Poor performance of quick-SOFA (qSOFA) score in predicting severe sepsis and mortality - a prospective study of patients admitted with infection to the emergency department. Scand J Trauma Resusc Emerg Med. 2017 Jun 9;25(1):56.
6. Canet E, Taylor DM, Khor R, Krishnan V, Bellomo R. qSOFA as predictor of mortality and prolonged ICU admission in Emergency Department patients with suspected infection. J Crit Care. 2018 Dec;48:118–23.
7. Rizka A, Harimurti K, Pitoyo CW, Koesnoe S. Comparison between the Identification of Seniors at Risk and Triage Risk Screening Tool in predicting mortality of older adults visiting the emergency department: Results from Indonesia. Geriatr Gerontol Int. 2020 Jan;20(1):47–51.
8. Nickel CH, Kellett J, Nieves Ortega R, Lyngholm L, Hanson S, Cooksley T, et al. A simple prognostic score predicts one-year mortality of alert and calm emergency department patients: A prospective two-center observational study. Int J Clin Pract. 2020 May;74(5):e13481.
9. Kwon H, Kim YJ, Jo YH, Lee JH, Lee JH, Kim J, et al. The Korean Triage and Acuity Scale: associations with admission, disposition, mortality and length of stay in the emergency department. Int J Qual Health Care J Int Soc Qual Health Care. 2019 Jul 1;31(6):449–55.
10. Skoczyński P, Wizowska J, Pochciał P, Leśkiewicz M, Zyśko D. Predictors of mortality in emergency department patients with chest pain without cardiovascular emergencies. Adv Clin Exp Med Off Organ Wroclaw Med Univ. 2020 Jan;29(1):147–55.
11. García-Peña C, Pérez-Zepeda MU, Robles-Jiménez LV, Sánchez-García S, Ramírez-Aldana R, Tella-Vega P. Mortality and associated risk factors for older adults admitted to the emergency department: a hospital cohort. BMC Geriatr. 2018 Jun 18;18(1):144.
12. Coeckelenbergh S, Van Nuffelen M, Mélot C. Sepsis is frequent in initially non-critical hypotensive emergency department patients and is associated with increased mortality. Am J Emerg Med. 2019 Dec;37(12):2242–5.

13. Dundar ZD, Kocak S, Girisgin AS. Lactate and NEWS-L are fair predictors of mortality in critically ill geriatric emergency department patients. Am J Emerg Med. 2020 Feb;38(2):217–21.
14. El Majzoub I, Qdaisat A, Chaftari PS, Yeung S-CJ, Sawaya RD, Jizzini M, et al. Association of emergency department admission and early inpatient palliative care consultation with hospital mortality in a comprehensive cancer center. Support Care Cancer. 2019 Jul;27(7):2649–55.
15. Kligerman MP, Sethi RKV, Kozin ED, Gray ST, Shrime MG. Morbidity and mortality among patients with head and neck cancer in the emergency department: A national perspective. Head Neck. 2019 Apr;41(4):1007–15.
16. Hertz JT, Sakita FM, Kweka GL, Limkakeng AT, Galson SW, Ye JJ, et al. Acute myocardial infarction under-diagnosis and mortality in a Tanzanian emergency department: A prospective observational study. Am Heart J. 2020 Aug;226:214–21.
17. Jackson SL, Tong X, Yin X, George MG, Ritchey MD. Emergency Department, Hospital Inpatient, and Mortality Burden of Atrial Fibrillation in the United States, 2006 to 2014. Am J Cardiol. 2017 Dec 1;120(11):1966–73.
18. Mandi DG, Yaméogo RA, Sebgo C, Bamouni J, Naibé DT, Kologo KJ, et al. Hypertensive crises in sub-Saharan Africa: Clinical profile and short-term outcome in the medical emergencies department of a national referral hospital in Burkina Faso. Ann Cardiol Angeiol (Paris). 2019 Oct;68(4):269–74.
19. Omoke NI. Firearm injuries received in emergency room of a Nigerian Teaching Hospital: Aanalysis of pattern, morbidity, and mortality. Niger J Clin Pract. 2017 May;20(5):587–94.
20. Taylor CA, Bell JM, Breiding MJ, Xu L. Traumatic Brain Injury-Related Emergency Department Visits, Hospitalizations, and Deaths - United States, 2007 and 2013. Morb Mortal Wkly Rep Surveill Summ Wash DC 2002. 2017 Mar 17;66(9):1–16.
21. Boudi Z, Lauque D, Alsabri M, Östlundh L, Oneyji C, Khalemsky A, et al. Association between boarding in the emergency department and in-hospital mortality: A systematic review. PloS One. 2020;15(4):e0231253.
22. Asheim A, Nilsen SM, Carlsen F, Eide Næss-Pleym L, Uleberg O, Dale J, et al. The effect of emergency department delays on 30-day mortality in Central Norway. Eur J Emerg Med Off J Eur Soc Emerg Med. 2019 Dec;26(6):446–52.
23. Groenland CNL, Termorshuizen F, Rietdijk WJR, van den Brule J, Dongelmans DA, de Jonge E, et al. Emergency Department to ICU Time Is Associated With Hospital Mortality: A Registry Analysis of 14,788 Patients From Six University Hospitals in The Netherlands. Crit Care Med. 2019 Nov;47(11):1564–71.
24. Montes FR, Vásquez SM, Camargo-Rojas CM, Rueda MV, Góez-Mogollón L, Alvarado PA, et al. Association between emergency department length of stay and adverse perioperative outcomes in emergency surgery: a cohort study in two Colombian University hospitals. BMC Emerg Med. 2019 Apr 17;19(1):27.
25. Hunchak C, Teklu S, Meshkat N, Meaney C, Puchalski Ritchie L. Patterns and predictors of early mortality among emergency department patients in Addis Ababa, Ethiopia. BMC Res Notes. 2015

Oct 24;8:605.

26. Griffin JL, Yersin M, Baggio S, Iglesias K, Velonaki V-S, Moschetti K, et al. Characteristics and predictors of mortality among frequent users of an Emergency Department in Switzerland. Eur J Emerg Med Off J Eur Soc Emerg Med. 2018 Apr;25(2):140–6.
27. Chenge Mukalenge F, Mboko Iyeti A, Ngumbu Mabanza E, Kakudji Kyungu A, Kaboko Yeselo M, Mfuamba Kabasele F, et al. ETAT DES LIEUX DE L'HOPITAL SAINT JOSEPH – DE LIMETE/KINSHASA – RD CONGO. 2021.
28. Vincent. Comment recoder les modalités d'une variable qualitative. 2018;
29. Kuhn M. Building Predictive Models in R Using the caret Package. American Statistical Association [Internet]. Volume 28, Issue 5. 2008; Available from: https://www.jstatsoft.org/index
30. Patel SJ, Chamberlain DB, Chamberlain JM. A Machine Learning Approach to Predicting Need for Hospitalization for Pediatric Asthma Exacerbation at the Time of Emergency Department Triage. Acad Emerg Med Off J Soc Acad Emerg Med. 2018 Dec;25 (12):1463–70.
31. Taylor RA, Pare JR, Venkatesh AK, Mowafi H, Melnick ER, Fleischman W, et al. Prediction of In-hospital Mortality in Emergency Department Patients With Sepsis: A Local Big Data-Driven, Machine Learning Approach. Acad Emerg Med Off J Soc Acad Emerg Med. 2016 Mar;23(3):269–78.

Figures

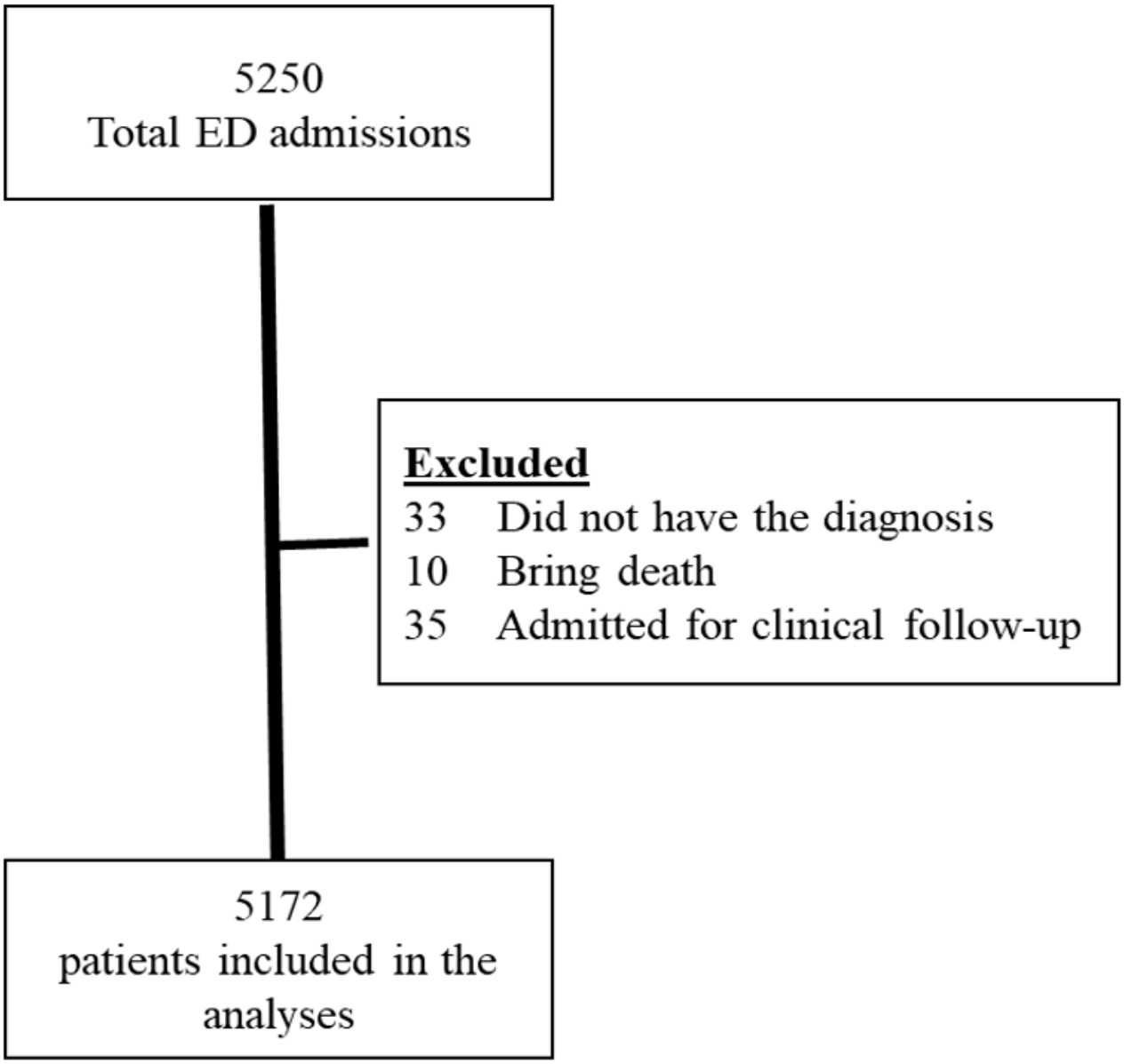


Figure 1

Flow chart of emergency department admissions included in the analysis

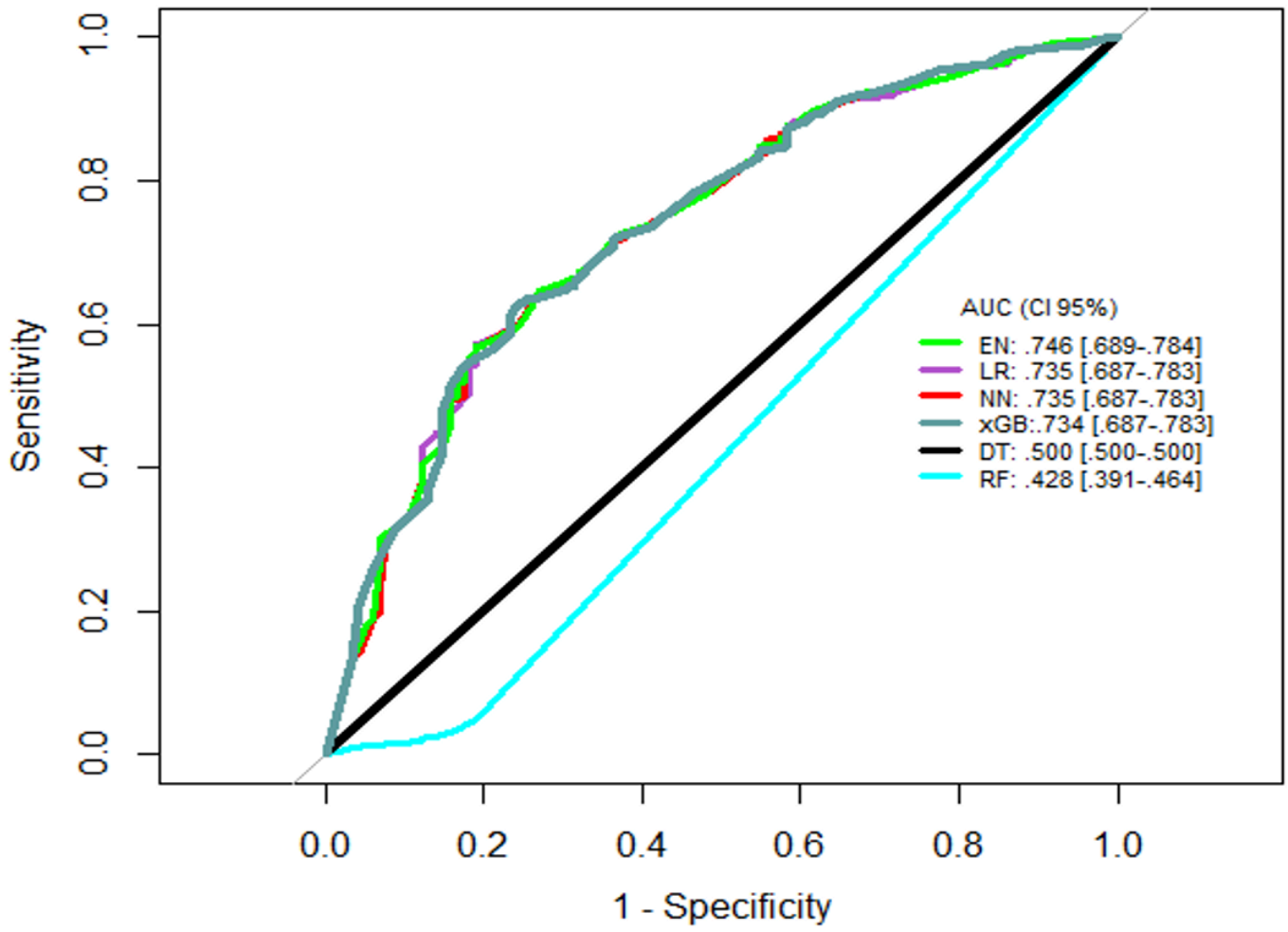


Figure 2

Plotting the ROC curves of the different models

EN: ElasticNet, LR: Logistic Regression, NN: Neural Networks, xGB: eXtreme Gradient Boosting, DT: Decision Trees, RF: Random Forest.

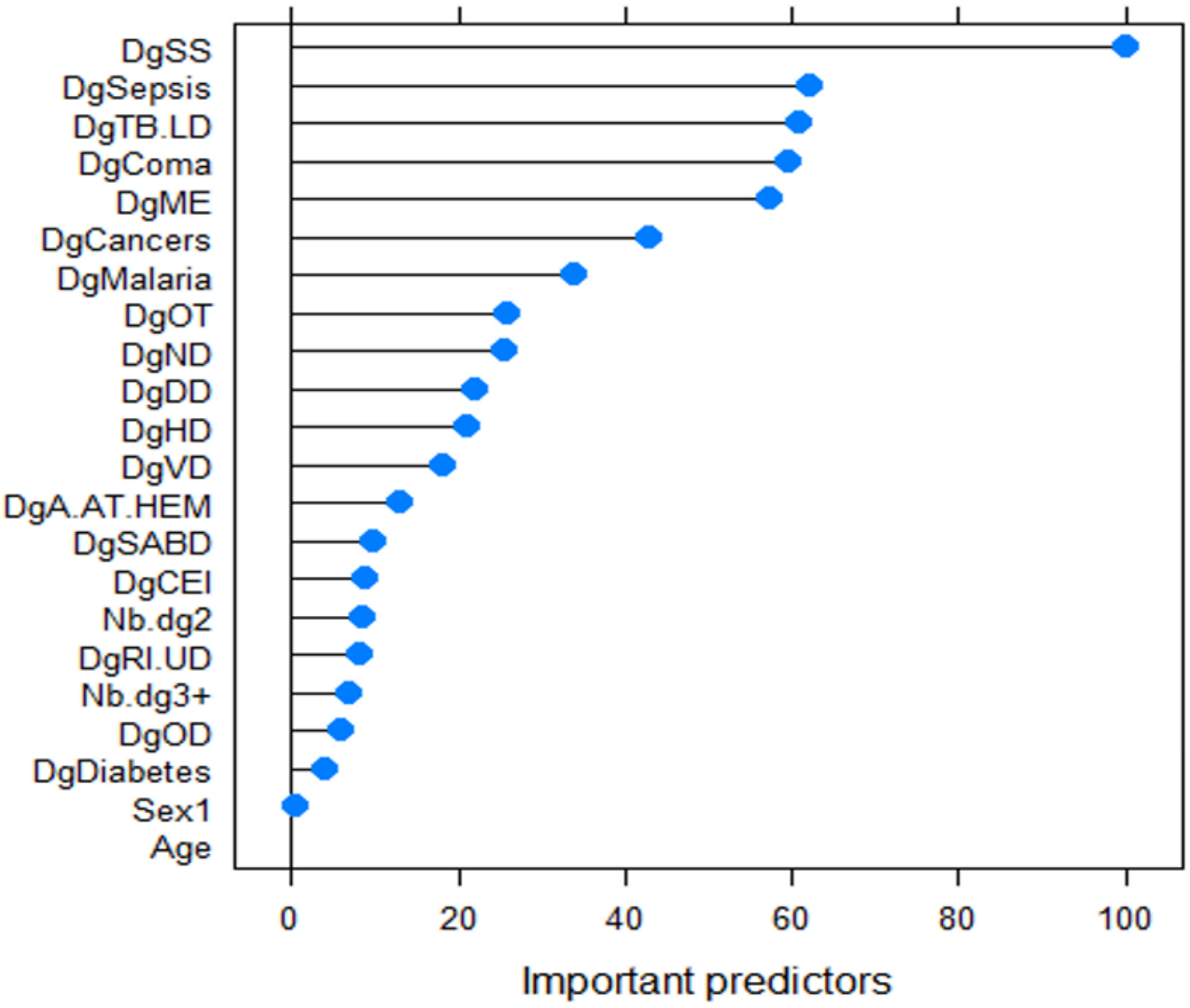


Figure 3

Diseases important in the occurrence of death

Dg: diagnosis, SS: shock state, TB.LP: tuberculosis or lung diseases, ME: meningoencephalitis, OT: other traumatics, ND: neural diseases, DD: digestive diseases, HD: heart diseases, VD: vascular diseases, A.AT.HM: anemia atraumatic hemorrhages, SABD: Surgical abdomen, CEI: Cranio-encephalitic injury, Nb.dg2: Number diagnosis equally 2, Nb.dg3+: number diagnosis equally 3 or 4, RI.UD: renal insufficient or uropathies, OD: Other Diseases.