Medical Technicians (EMT) team due to the limitation of the current ambulance service.

Conclusions

The higher odds of mortality for patients with prolonged TIT encourage the effort to improve the local STEMI network by adopting the 'Hub-and-Spoke' model.

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19.

Geo-temporal spatial visualization of outcomes using machine learning (ML) to predict the admission and mortality rate for ACS in presence of air pollution in Malaysia

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Background

The World Health Organisation estimates that outdoor air pollution causes three million fatalities annually, with 40% attributable to ischemic heart disease and stroke. In Malaysia, cardiovascular disease (CVD) is responsible for 87% of noncommunicable disease-related fatalities, and air pollution increases the risk of CVD. To date, however, Malaysian hospitals lack a system to manage and monitor CVD cases in the presence of air pollution. It has been demonstrated that machine learning (ML) algorithms can predict admission and mortality rates for cardiovascular disease (CVD) with greater precision.

Purpose

To construct an online machine learning-based prediction system for hospital admission and Acute Coronary Syndrome (ACS) mortality rates in Malaysia in the presence of air pollution, with a geospatial map for visualisation.

Methods

From 2006 to 2017, 57,694 ACS-NCVD patients and DOEM air quality data were used in this investigation. The exposure to nitrogen oxides, sulphur dioxide, ozone, and particulate matter 10 was measured at lags 00, 03, 07, and 30. To model the association between air pollution variables with hospital admission and ACS mortality rates, Support Vector Regression (SVR), Random Forest (RF), eXtreme Gradient Boosting (XGBoost), LightGBM, and Deep Learning (deepL) were utilised. The best ML algorithm was integrated into a web-based system and the model's results were visualized using a geospatial map.

Results

The results showed that XGBoost had the best performance in forecasting hospital admission rates, with an RMSE value of 1.807 when using Malaysian air quality value predictors. For estimating the ACS mortality rate in Malaysia, SVR achieved the best RMSE value of 0.284. The best ML algorithm was implemented as online web-based system with a geospatial map that depicts the projected hospital admission and ACS mortality rates.

Conclusion

Using Malaysian air quality parameters, both XGBoost and SVR algorithms are capable of predicting hospitalization and ACS mortality rates. Malaysia requires an online and mobile-friendly machine learning-based system for predicting hospital admission and cardiovascular disease mortality rates in the presence of air pollution. An online monitoring system provides policymakers and healthcare professionals with vital insights for optimising hospital resource management in the presence of air pollution.

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20.

Impact of total ischemic time (TIT) on 1-month clinical outcomes at a tertiary cardiology centre (TCC) with a limited primary percutaneous coronary intervention (LPPCI) service in the management of ST-elevation myocardial infarction (STEMI)

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Background

PPCI is the recommended treatment strategy over fibrinolytic for treatment of STEMI. However, majority of hospitals offer only a LPPCI service or fibrinolytic strategy for STEMI. TIT is associated with clinical outcomes for both treatment strategies. At a single public access tertiary cardiology centre (SPATCC) covering a large geographical area, a LPPCI service is provided.

Objectives

To establish the association between TIT with treatment strategies on 1-month clinical outcomes – defined as in-hospital, 1-month mortality and re-admission for MI, urgent re-vascularization and stroke.

Materials & methods

This was an observational, retrospective, study conducted at a SPATCC. Consecutive patients presenting to the SPATCC with an acute STEMI were enrolled between October 2020 and February 2023. Patients transferred from another healthcare facility and who were treated with PPCI or fibrinolytic therapy were excluded.

Results

Among 179 STEMI patients, 67 (37.4%) had PPCI. The TIT for patients treated with PPCI was 294.7 ($\pm$ 199.9) minutes, while those treated with fibrinolytic was 233.6 ($\pm$ 197.3) minutes. PPCI was associated with higher rates of in-hospital death (10.4% vs 5.4%, $p = 0.204$) and 30-day mortality (11.9% vs. 6.3%, $p = 0.348$). In the PPCI group, 81.8% of cases achieved guideline-recommended door-to-treatment time; whereas 41.1% in the fibrinolytic group. PPCI was associated with longer mean time for symptom onset to FMC (167.2 ($\pm$ 193.8) minutes vs 136.4 ($\pm$ 121.3) minutes, $P = 0.192$); as well as having longer door-to-treatment time and higher TIMI scores. During and after the COVID-19 pandemic, we observed a similar pattern of STEMI treatment strategies with before the pandemic. The inpatient and 30-day mortality rates between PPCI and fibrinolytic strategies remained similar, despite a 10.8% increase in the PPCI rate, shorter mean onset-FMC travel time, door-to-treatment time, TIT, and a better reperfusion time within the target window period in the post-pandemic period.

Conclusions

At a centre providing a LPPCI service, most STEMI patients were managed by fibrinolytic therapy over a PPCI strategy, with similar clinical outcomes, and with similar TIT in both treatment strategies. At a SPATCC, improvement in the early management of STEMI and improving health literacy in the population, will result in improved clinical outcomes.

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21.
Predicting failed thrombolysis at first point of encounter

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Objective

Determine factors which identify failed thrombolysis. Develop a bedside scoring system to predict failed thrombolysis in ED.

Design

Retrospective Case control, Hospital database / registry, 2015–2022, Patient number R.

Inclusion

STEMI, Thrombolysis (STK) completion.

Exclusion

Bundle branch block, Cessation of fibrinolysis.

Methods

Multivariable Logisic regression (between Failed & successful thrombolysis), Weighted score Validation of scare; Sensitivity & Specificity, PPV, NPV.

Definition of failed thrombolysis

Determination of failed fibrinolytic was using the difference in the ST segment elevation of the pre and post fibrinolytic electrocardiogram (ECG) based on ACC/AHA criteria.

Class IIa

1. **It is reasonable to monitor the pattern of ST elevation, cardiac rhythm, and clinical symptoms over the 60 to 180 minutes after initiation of fibrinolytic therapy. Noninvasive findings suggestive of reperfusion include relief of symptoms, maintenance or restoration of hemodynamic and or electrical stability, and a reduction of at least 50% of the initial ST-segment elevation injury pattern on a follow-up ECG 60 to 90 minutes after initiation of therapy. (*Level of Evidence: B*)**

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22.
Prediction of short- and long-term mortality in Asian ACS patients using stacked ensemble learning

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Introduction

The conventional risk score for predicting mortality of post-Acute Coronary Syndrome (ACS) necessitates separate scoring for STEMI and NSTEMI patients and does not accounts for Asian patients. Machine learning (ML) algorithm outperforms the conventional risk score in predicting mortality risk. The stacked ensemble learning (EL) uses several high-performing ML algorithms to improve prediction accuracy than any individual ML. However, there has been a limited study on the use of EL in the mortality prediction of Asian ACS patients. Our objective is to develop an algorithm using ML and stacked EL for the prediction and identification of factors associated with three timeframes (in-hospital, 30-days, and 1-year) mortality in Asian patients with ACS, and to compare its performance to a conventional risk score.

Report

Data from NCVD was used from 2006 to 2019 to develop an in-hospital (17,168 patients), 30-days (12,648 patients), and 1-year (12,462 patients) model. 54 variables were considered. The base learners for stacked EL model are Support Vector Machine (SVM), Random Forest (RF), eXtreme Gradient Boosting (XGB), and Naive Bayes (NB), while the meta learner is Generalized Linear Model (GLM). To identify and rank significant variables, ML variable importance with backward elimination was applied. Using a 30% validation dataset, algorithms were evaluated using area under the curve (AUC) against the TIMI risk score for STEMI and NSTEMI. The stacked EL model with SVM selected features for in-hospital (14 features), 30-days (13 features), and 1-year (13 features) outperformed TIMI risk for STEMI (AUC = 0.88, 95% CI: 0.853-0.903; vs AUC = 0.79, 95% CI: 0.765-0.822, AUC = 0.84, 95% CI: 0.806-0.871; vs AUC = 0.78, 95% CI: 0.743-0.811, AUC = 0.81, 95% CI: 0.786-0.837; vs AUC = 0.77, 95% CI: 0.740-0.793) and NSTEMI (AUC = 0.87, 95% CI: 0.822-0.912; vs AUC = 0.53, 95% CI: 0.463-0.591, AUC = 0.81, 95% CI: 0.772-0.851; vs AUC = 0.53, 95% CI: 0.478-0.590, AUC = 0.76, 95% CI: 0.727-0.791; vs AUC = 0.56, 95% CI: 0.522-0.598). Common predictors identified for short- and long-term mortality were age, heartrate, killip class, and oral hypoglycaemic agent. TIMI score was reported to underestimates patients' risk of mortality.

Conclusion

The stacked EL method uses multiple ML algorithms to more effectively classify ASIAN ACS patients than TIMI score.

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