Applications and performance of machine learning algorithms in emergency medical services: a scoping review

**Supplementary document**

**Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist**

| **SECTION** | **ITEM** | **PRISMA-ScR CHECKLIST ITEM** | **REPORTED ON PAGE #** |
| --- | --- | --- | --- |
| **TITLE** |
| Title | 1 | Identify the report as a scoping review. | 1 |
| **ABSTRACT** |
| Structured summary | 2 | Provide a structured summary that includes (as applicable): background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions that relate to the review questions and objectives. | 3 |
| **INTRODUCTION** |
| Rationale | 3 | Describe the rationale for the review in the context of what is already known. Explain why the review questions/objectives lend themselves to a scoping review approach. | 4 |
| Objectives | 4 | Provide an explicit statement of the questions and objectives being addressed with reference to their key elements (e.g., population or participants, concepts, and context) or other relevant key elements used to conceptualize the review questions and/or objectives. | 5 |
| **METHODS** |
| Protocol and registration | 5 | Indicate whether a review protocol exists; state if and where it can be accessed (e.g., a Web address); and if available, provide registration information, including the registration number. | 5 |
| Eligibility criteria | 6 | Specify characteristics of the sources of evidence used as eligibility criteria (e.g., years considered, language, and publication status), and provide a rationale. | 5-6 |
| Information sources\* | 7 | Describe all information sources in the search (e.g., databases with dates of coverage and contact with authors to identify additional sources), as well as the date the most recent search was executed. | 5 |
| Search | 8 | Present the full electronic search strategy for at least 1 database, including any limits used, such that it could be repeated. | 5 |
| Selection of sources of evidence† | 9 | State the process for selecting sources of evidence (i.e., screening and eligibility) included in the scoping review. | 6 |
| Data charting process‡ | 10 | Describe the methods of charting data from the included sources of evidence (e.g., calibrated forms or forms that have been tested by the team before their use, and whether data charting was done independently or in duplicate) and any processes for obtaining and confirming data from investigators. | 6-7 |
| Data items | 11 | List and define all variables for which data were sought and any assumptions and simplifications made. | 6-7 |
| Critical appraisal of individual sources of evidence§ | 12 | If done, provide a rationale for conducting a critical appraisal of included sources of evidence; describe the methods used and how this information was used in any data synthesis (if appropriate). | NA |
| Synthesis of results | 13 | Describe the methods of handling and summarizing the data that were charted. | 7-8 |
| **RESULTS** |
| Selection of sources of evidence | 14 | Give numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally using a flow diagram. | 8 |
| Characteristics of sources of evidence | 15 | For each source of evidence, present characteristics for which data were charted and provide the citations. | Supplement file |
| Critical appraisal within sources of evidence | 16 | If done, present data on critical appraisal of included sources of evidence (see item 12). | NA |
| Results of individual sources of evidence | 17 | For each included source of evidence, present the relevant data that were charted that relate to the review questions and objectives. | 8-11 |
| Synthesis of results | 18 | Summarize and/or present the charting results as they relate to the review questions and objectives. | 10-12 |
| **DISCUSSION** |
| Summary of evidence | 19 | Summarize the main results (including an overview of concepts, themes, and types of evidence available), link to the review questions and objectives, and consider the relevance to key groups. | 12 |
| Limitations | 20 | Discuss the limitations of the scoping review process. | 17 |
| Conclusions | 21 | Provide a general interpretation of the results with respect to the review questions and objectives, as well as potential implications and/or next steps. | 17-18 |
| **FUNDING** |
| Funding | 22 | Describe sources of funding for the included sources of evidence, as well as sources of funding for the scoping review. Describe the role of the funders of the scoping review. | 18 |

JBI = Joanna Briggs Institute; PRISMA-ScR = Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews.

\* Where *sources of evidence* (see second footnote) are compiled from, such as bibliographic databases, social media platforms, and Web sites.

† A more inclusive/heterogeneous term used to account for the different types of evidence or data sources (e.g., quantitative and/or qualitative research, expert opinion, and policy documents) that may be eligible in a scoping review as opposed to only studies. This is not to be confused with *information sources* (see first footnote).

‡ The frameworks by Arksey and O’Malley (6) and Levac and colleagues (7) and the JBI guidance (4, 5) refer to the process of data extraction in a scoping review as data charting*.*

§The process of systematically examining research evidence to assess its validity, results, and relevance before using it to inform a decision. This term is used for items 12 and 19 instead of "risk of bias" (which is more applicable to systematic reviews of interventions) to include and acknowledge the various sources of evidence that may be used in a scoping review (e.g., quantitative and/or qualitative research, expert opinion, and policy document).

*From:* Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. Ann Intern Med. 2018;169:467–473. [doi: 10.7326/M18-0850](http://annals.org/aim/fullarticle/2700389/prisma-extension-scoping-reviews-prisma-scr-checklist-explanation).

**Table S1. Results of the search strategy from the four electronic databases.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| No | Search strategy items  | **Medline complete** | **CINAHL** | **Computer and Applied Science** | **Scopus** |
| S1 | (MH "Machine Learning+") OR(MH "Artificial Intelligence+") OR (MH "Unsupervised Machine Learning")OR (MH "Supervised Machine Learning+") OR (MH "Deep Learning") OR (MH "Neural Networks, Computer+") OR (MH" Natural Language Processing" | 142,643 | 27,514 | 6,796 | -- |
| S2 | TX "Machine learning" OR "deep learning" OR "neural network?" OR "support vector machine" OR "random forest" OR "decision trees" OR "nearest neighbors" OR "k?means" OR "na#ve bayes" OR "hierarchal clustering" OR "anomaly detection" OR "component analysis" OR "apriori algorithm" OR "reinforcement learning" OR "q? learning" OR "adversarial learning" OR "policy gradient" OR "policy optimi?ation" OR "natural language processing" OR "supervised W2 learning" OR "un#supervised W2 learning" OR "artificial intelligen\*" OR perceptron OR “Dimensionality Reduction” OR “ensemble learning” OR "discriminant analysis" | 351,852 | 51,274 | 261,284 | 2,123,955 |
| S3 | (MH "Emergency Medical Services+") OR (MH "Emergency Medical Dispatch") OR (MH "Emergency Medical Service Communication Systems") OR (MH "Emergency Medical Technicians")OR (MH "Ambulances") OR (MH "Ambulance Diversion")  | 117,701 | 121,413 | 325 | -- |
| S4 | TX "emergency medical service?" OR "out?of?hospital" OR "out-of-hospital" OR prehospital OR paramedic? OR ambulance OR "emergency medical technicians" OR "field triage | 50,825 | 44,919 | 1,928 | 255,316 |
| S5 | S1 OR S2  | 338,229 | 61,741 | 261,284 | -- |
| S6 | S5 OR S6  | 146,091 | 137,920 | 1,930 | -- |
| S7 | S5 AND S5 (Total) | 2,379 | 879 | 162 | 3,241 |

**Supplemental Table S2. Included Clinical studies.**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Author year** | **Study objective** | **Medical condition** | **Task** | **Region** | **No. of MLA** | **No. of cases input features** | **Type of input features** | **Best****ML** | **Performance metrics****AUC, Acc, Se, Sp** |
| Davis 2005 1{Davis, 2005 #1}{Davis, 2005 #1} | Neural network analysis was performed to identify patients predicted to benefit from prehospital intubation. | Trauma | Tx | USA | S | 13625/ NA | Clinical | NN | 0.93, NA, 0.85, 0.864 |
| Yang 2005 2 | To predict defibrillation outcomes to ROSC or No-ROSC using pre-shock ECG time series. | OHCA | CO | Europe | S | 110/ NA | ECG | NN | NA, 0.75, 0.83, 0.67 |
| Chen 2008 3 | Present a classifier for use as a decision assist tool to identify a hypovolemic state in trauma patients during helicopter transport to a hospital, when reliable acquisition of vital-sign data may be difficult. | Trauma | Dx | USA | M | 898/ 5 | Clinical | Ensemble | 0.76, NA, 0.9, 0.4 |
| Davis 2008 4 | To use ANN, SVM, and decision trees to explore the role of air medicine in TBI | Trauma | CO | USA | M | 11961/ NA | Clinical | NN | 0.92, NA, NA, NA |
| Krizmaric 2009 5 | Intelligent analysis in predicting outcome of out-of-hospital cardiac arrest | OHCA | CO | Europe | M | 477/ 11 | ECG | DT | NA, 0.934, NA, NA |
| Scheetz 2009 6 | To use crash scene data available to emergency responders to classify adults with moderate and severe injuries. | Trauma | Dx | USA | S | 74626/ 13 | Accident data | DT | NA, NA, 0.937, 0.7753 |
| Forberg 2012 7 | To examine the ability of an artificial neural network (ANN) to safely reduce the number of ecgs transmitted by identifying patients without STEMI and patients not needing acute PCI. | CVD | Dx | Europe | S | 560/ 8 | ECG, Clinical | NN | NA, NA, 0.97, 0.68 |
| Jiang 2012 8 | To use ensembled neural networks (ENN) to model survival rate for the patients with out-of-hospital cardiac arrest | OHCA | CO | Asia-Pacific | S | 4095/ 11 | Circumstantial, EMS data, Clinical | NN | NA, 0.89, NA, NA |
| Ayala 2014 9 | Introduces a new approach to rhythm analysis during CPR that combines two strategies: a state-of-the-art CPR artifact suppression filter and a shock advice algorithm (SAA) designed to optimally classify the filtered signal. | OHCA | Dx | Europe | S | 247/ NA | ECG | SVM | NA, NA, NA, NA |
| Yunoki 2014 10 | Propose an intelligent triage support system using a Bayesian network with the aim of improving the accuracy of call triage, the core of an emergency care support system. | Other | Dx | Asia-Pacific | S | 61927/ 41 | Audio | Bayesian | NA, 0.9487, NA, NA |
| Liu 2014 11 | This study examined the utility of standard vital signs, HRV, HRC, and ML for predicting the need for lsis in trauma patients by comparing the performance of multivariate logistic regression identification versus ML technologies. | Trauma | Tx | USA | M | 104/ NA | ECG | NN | 0.99, NA, NA, NA |
| Goto 2014 12 | To develop a simple and generally applicable bedside tool for predicting outcomes in children after cardiac arrest. | OHCA | CO | Asia-Pacific | S | 5379/ 3 | Clinical | DT | 0.88, NA, 0.797, 0.952 |
| Scerbo 2014 13 | To validate the Random Forest computer model (RFM) as means of better triaging trauma patients to level 1 trauma centers. | Trauma | CO | USA | S | 1653/ 83 | Clinical | RF | NA, NA, 0.89, 0.42 |
| He 2015 14 | Investigate whether combination of multiple VF features, by differen machine learning strategies could improve the prediction capacity of defibrillation outcome using a large multicenter database of OHCA patients. | OHCA | CO | Europe | M | 3828/ 16 | ECG | NN | 0.875, NA, 0.809, 0.809 |
| Figuera 2016 15 | Detection of Shockable Rhythms in Automated External Defibrillators using machine learning | OHCA | Dx | USA | M | 29816/ 30 | ECG | SVM | NA, NA, 0.966, 0.988 |
| Rad 2016 16 | Develop a system for automatic rhythm interpretation by using signal processing and machine learning algorithms. | OHCA | Dx | Europe | M | 302/ 32 | ECG, Clinical | Gaussian Mixture Model | NA, 0.68, NA, NA |
| Shandilya 2016 17 | E hypothesize that a more complete picture of the cardiovascular system can be gained through non-linear dynamics and integration of multiple physiologic measures from biomedical signals. | OHCA | CO | USA | M | 153/ 20 | ECG | NN | 0.837, 0.774, NA, NA |
| Chicote 2016 18 | Predict defibrillation success in OHCA scenarios | OHCA | CO | Europe | S | 163/ 6 | ECG | SVM | NA, NA, 0.804, 0.769 |
| He 2016 19 | To find out whether combining VF features with additional attributesthat related to the previous shock could enhance the prediction performance for subsequentshocks | OHCA | CO | Asia-Pacific | S | 528/ 3 | ECG | NN | 0.904, NA, 0.765, 0.9 |
| Rad 2017 20 | Develop ECG-based algorithms for the retrospective and automatic classification of resuscitation cardiac rhythms. | OHCA | Dx | Europe | M | 1631/ 14 | ECG | NN | NA, 0.785, NA, NA |
| Yasuda 2017 21 | The aim is to achieve higher overall performance and clarify the method for deciding the determination thresholds while simultaneously achieving both fail-safe determination and overall accuracy. | Other | Dx | Asia-Pacific | M | 328111/ 86 | Clinical | RF | NA, 0.923, NA, NA |
| Ruiz 2018 22 | Design and evaluate a simple algorithm able to discriminate pulsatile rhythms from pulseless electrical activity during automated external defibrillator analysis intervals | OHCA | Dx | Europe | S | 302/ 6 | ECG | DT | NA, NA, 0.983, 0.984 |
| Chen 2018 23 | Develop an artificial neural network (ANN) algorithm to predict LVO using prehospital accessible data | CVD | Dx | Asia-Pacific | S | 777/ 18 | Clinical | NN | 0.833, NA, NA, NA |
| Kim 2018 24 | Developed a casualty classification model based on machine learning approaches for triage in mass casualty incidents by using a simplified consciousness score and vital signs that can be remotely monitored through wearable devices, without relying on medical practitioners. | Trauma | Dx | USA | M | 460865/ 5 | Clinical | NN | 0.89, NA, NA, NA |
| Thorpe 2018 25 | To compare the diagnostic efficacy of two such candidate metrics: Velocity Asymmetry Index (VAI) and Velocity Curvature Index (VCI). Additionally, we investigate a simple decision tree combining both metrics. | CVD | Dx | USA | S | 66/ 66 | TCD waveform | DT | 0.94, 0.91, 0.94, 0.88 |
| Spangler 2019 26 | Generating risk scores based on hospital outcomes using routinely collected prehospital data. | Other | Tx | Europe | S | 68668/ NA | Operation, Clinical | Ensemble | NA, NA, NA, NA |
| Chan 2019 27 | Demonstrate that a support vector machine (SVM) can classify agonal breathing instances in real-time within a bedroom environment. | OHCA | Dx | USA | S | 162/ NA | Clinical | SVM | 0.9993, NA, 0.9724, 0.9951 |
| Harford 2019 28 | Develop a machine learning model to predict a patient’s Cerebral Performance Category (CPC) score given a set of intervention and intermediate outcomes during a cardiac arrest event. | OHCA | CO | USA | M | 2639/ 27 | Clinical | NN | NA, NA, 0.825, NA |
| Elola 2019 29 | Develop a pulse detection algorithm based exclusively on the ECG acquired by defibrillation pads. | OHCA | Dx | USA | M | 3914/ NA | ECG | SVM | NA, NA, 0.976, 0.862 |
| Kwon 2019 30 | Develop and validate a deep-learning-based out-of-hospital cardiac arrest prognostic system (DCAPS) for predicting neurologic recovery and survival to discharge. | OHCA | CO | Asia-Pacific | M | 36190/ 10 | Clinical | NN | 0.953, NA, 0.951, 0.797 |
| Blomberg 2019 31 | Examining whether a machine learning framework could recognize out-of-hospital cardiac arrest from audio files of calls to the emergency medical dispatch center | OHCA | Dx | Europe | M | 918/ NA | Audio | Ensemble | NA, NA, 0.841, 0.973 |
| Picon 2019 32 | Introduces a deep learning architecture based on 1D-CNN layers and a Long Short-Term Memory (LSTM) network for the detection of VF. | OHCA | Dx | Europe | S | NA/ 20 | ECG | NN | NA, 0.991, 0.997, 0.989 |
| Elola 2019 33 | The detection of return of spontaneous circulation by evaluating the added value of capnography for the classification of PR/PEA during OHCA. | OHCA | Dx | USA | S | 426/ 9 | ECG, TI | RF | 0.92, NA, 0.966, 0.945 |
| Seki 2019 34 | To establish a prognostication model for OHCA with presumed cardiac aetiology using an advanced machine learning technique | OHCA | CO | Asia-Pacific | S | 16452/ 58 | Clinical | RF | 0.958, NA, NA, NA |
| Coult 2019 35 | To evaluated a comprehensive group of VF waveform measures with and without ongoing compressions to determine their performance under both conditions for predicting functionally-intact survival, the study’s primary outcome | OHCA | CO | USA | M | 1151/ 27 | ECG | SVM | 0.75, NA, NA, NA |
| Ivanović 2019 36 | Validate whether combining VF features can enhance the prediction accuracy in comparison to single feature | OHCA | CO | Europe | M | 251/ 28 | ECG | RF | 0.828, 0.828, 0.903, 0.754 |
| Johnsson 2020 37 | Detection of dependencies between Clinical variables in OHCA survivors and prediction of functional outcome | OHCA | CO | Europe | S | 932/ NA | Clinical | NN | 0.891, NA, NA, NA |
| Kang 2020 38 | Develop and validate an artificial intelligence (AI) algorithm based on deep learning to predict the need for critical care during EMS. | Trauma | Tx | Asia-Pacific | S | 8981181/ NA | Clinical | NN | 0.867, NA, NA, NA |
| Tollinton 2020 39 | Investigate whether machine learning approaches using features from such free text notes can improve prediction of unconscious patients who require conveyance. | Other | Dx | Europe | M | 87281/ 2 | Text | Ensemble | 0.64, NA, NA, NA |
| AlDury 2020 40 | To investigate the relative importance of 16 well-recognized factors in OHCA at the time point of ambulance arrival, and before any interventions or medications were given | OHCA | CO | Europe | S | 45067/ 16 | Clinical | RF | NA, NA, NA, NA |
| Krasteva 2020 41 | Optimize the hyperparameters of an end-to-end fully convolutional neural network architecture for shockable/nonshockable rhythm detection | OHCA | Dx | Europe | S | NA/ NA | ECG | NN | NA, NA, 0.996, 0.994 |
| Ivanović 2020 42 | Predicting defibrillation success in out-of-hospital cardiac arrested patients using conventional macine learning approches and proposing a novel approach in which predictive features are automatically learned. | OHCA | CO | Europe | S | 251/ NA | ECG | NN | NA, 0.936, 0.988, 0.882 |
| Jaureguibeitia 2020 43 | Proposing novel deep learning architectures for shock decision algorithms based on convolutional and residual networks. | OHCA | Dx | Europe | M | 4216/ NA | ECG | NN | NA, 0.986, 0.991, 0.985 |
| Polero 2020 44 | The aim of this study was to demonstrate the ability ofmachine learning classifiers to diagnose and predict anACS in patients who spontaneously consult the EMSwith undifferentiated chest pain, during a 30-day follow-up period. | CVD | Dx | USA | S | 161/ 20 | Clinical | RF | 0.8991, 0.8441, 0.8552, 0.8588 |
| Alonso 2020 45 | This study presents a new method for pulse detection during OHCA using the ECG and TI signals. | OHCA | Dx | USA | S | 1140/ 40 | ECG | SVM | NA, 0.926, 0.924, 0.93 |
| Duceau 2020 46 | To build a prediction algorithm to assist prehospital triage of AAS. | CVD | Dx | Europe | M | 976/ NA | Clinical | Ensemble | 0.73, NA, 0.79, 0.79 |
| Elola 2020 47 | To develop a machine learning model to predict rearrest. | OHCA | CO | USA | S | 162/ 21 | ECG | RF | 0.689, NA, 0.673, 0.673 |
| Prieto 2020 48 | To develop and test a natural language processing method that would improve identification of potential OM from paramedic documentation. | Other | Dx | USA | S | 54359/ NA | Text | LR | 0.939, NA, NA, NA |
| Qiu 2020 49 | To establish a computational algorithm to predict the injury severity, so as to improve the timeliness, appropriateness, and efficacy of medical care provided. | Trauma | Dx | Asia-Pacific | S | 37/ 84 | Accident | NN | 0.747, NA, NA, NA |
| Jaureguibeitia 2020 50 | To determine whether an impedance-based algorithm can accurately detect ventilations during concurrent mechanical chest compressions. | OHCA | Tx | USA | S | 423/ 14 | Clinical | RF | NA, NA, 0.963, NA |
| Wang 2021 51 | To develop an NER model on paramedictext reports for Clinical audit. | Other | Tx | Asia-Pacific | M | 44211/ 17 | Text | NN | NA, NA, 0.976, NA |
| Stemerman 2021 52 | To develope automated classification models to identify eligible patients for prehospital Clinical trials using EMS Clinical notes and compared model performance to manual review. | CVD | Dx | USA | M | 1209/ NA | Text | RF | NA, 0.92, 0.93, 0.96 |
| Manca 2021 53 | Aimed to improve the assessment of alcohol burden on ambulance services in Scotland present estimates on the burden of alcohol on ambulance callouts in Scotland | Other | Dx | Europe | S | 5416/ NA | Text | RF | NA, 0.987, 0.996, 0.941 |
| Elola 2021 54 | Determine circulation states during OHCA using the signals available in defibrillators. | OHCA | CO | USA | S | 210/ 37 | ECG | RF | NA, NA, 0.86, NA |
| Morris 2021 55 | Develop a novel prediction model for hospital-triage that utilizes criteria available to the EMS provider to predict NEI-6 and the need for a trauma team activation | Other | Tx | USA | M | 22069/ 19 | Clinical | Ensemble | 0.85, NA, NA, NA |
| Hirano 2021 56 | Develop and validate a machine learning-based prediction model of outcome for OHCA with an initial shockable rhythm | OHCA | CO | Asia-Pacific | M | 30049/ 19 | Clinical | NN | 0.888, 0.863, 0.919, 0.65 |
| Uchida 2021 57 | Develop prehospital stroke scale with ML | CVD | Dx | Asia-Pacific | M | 3178/ 19 | Clinical | Ensemble | NA, 0.65, 0.47, 0.89 |
| Seo 2021 58 | Developing and validated a machine learning-based system to predict good outcome in OHCA patients before ROSC. | OHCA | CO | Asia-Pacific | M | 5739/ 22 | ECG | Ensemble | 0.926, NA, 0.857, 0.865 |
| Candefjord 2021 59 | Evaluate if methods employing machine learning and variables that can be assessed on the scene of accident has potential to amend field triage | Trauma | Dx | USA | M | 21589/ 6 | Accident | LR | 0.86, NA, NA, NA |
| Oka 2021 60 | Our objectives were to determine the following. (1) which meteorological variable(among various meteorological variables) is the most important causative factor of heatstroke ? (2)how accurately can the observations be predicted when only meteorological variables are considered? | CVD | Dx | Asia-Pacific | S | NA/ NA | Clinical | RF | NA, NA, NA, NA |
| H 2021 61 | Proposes a novel methodology based on ma- chine learning (ML) techniques to predict both the victims’ mortality and their need for transportation to health facil- ities using data gathered from the start of the emergency call until the Departmental Fire and Rescue Service of the Doubs (SDIS25) is notified. | OHCA | CO | Europe | S | 177883/ 7 | Clinical, EMS | LR | 0.79, NA, NA, NA |
| Lee 2021 62 | Proposes a spatio-temporal demand model that incorporates batch arrivals of EMS calls. | OHCA | CO | Asia-Pacific | M | 105215/ NA | Spatiotemporal | NA | NA, NA, NA, NA |
| Urteaga 2021 63 | The aim of this study was to develop a machine learning model to differentiatePEA with unfavorable (unpea) and favorable (fapea) evolution to ROSC. | OHCA | Dx | USA | S | 1921/ 17 | ECG | RF | 0.857, NA, 0.801, 0.767 |
| Byrsell 2021 64 | To (1) examine whether a machine learning framework (ML) can increase the proportion of calls recognizing OHCA within the first minute compared with dispatchers, (2) present the performance of ML with different false positive rate (FPR) settings, (3) examine call characteristics influencing OHCA recognition. | OHCA | Dx | Europe | S | 851/ NA | Audio | Ensemble | NA, NA, 0.86, NA |
| Frigerio 2021 65 | To assess the prediction accuracy when combined, and to clarify if they are correlated in out of hospital cardiac arrest' victims. | OHCA | CO | Europe | S | 112/ 2 | Clinical | SVM | 0.77, NA, 0.805, 0.688 |
| Larsson 2021 66 | To assess whether, compared with logistic regression, the advanced machine learner xgboost (extreme Gradient Boosting) is associated with reduced prehospital trauma mistriage | Trauma | Dx | Europe | M | 813567/ 4 | Clinical | Ensemble | 0.725, NA, NA, NA |
| Yu 2021 67 | To assist decision making on ambulance attendance and conveyance to a hospital using machine learning | Other | Tx | Europe | M | 25500/ NA | Clinical | NN | NA, 0.801, NA, NA |
| Hayasaka 2021 68 | To create an AI model to classify intubation difficulty using deep learning (CNN), which connects the face image of a surgical patient and the actual difficulty of intubation. | Other | Tx | Asia-Pacific | S | 1043/ NA | Image | NN | 0.864, 0.805, 0.818, 0.833 |
| Isasi 2021 69 | To demonstrate the first reliable shock decision algorithm during LDB compressions. | OHCA | Tx | Europe | M | 5813/ 38 | ECG | SVM | NA, 0.96, 0.921, 0.968 |
| Sashidhar 2021 70 | To design and evaluate an ECG-based algorithm that predicts pulse presence with or without CPR | OHCA | CO | USA | M | 383/ NA | ECG | LR | 0.84, NA, NA, NA |
| Anthony 2021 71 | To determine whether ML is a feasible option in classifying emergency call transcriptions, based off of the caller’s description of the patient. | CVD | Dx | Other | M | 93/ 107 | Text | SVM | NA, 0.95, NA, NA |
| Bouzid 2021 72  | To develop a data-driven approach for ECG feature selection to build a Clinically relevant algorithm for real-time detection of culprit lesion | CVD | Dx | USA | S | 2400/ 557 | ECG | RF | 0.85, NA, 0.717, 0.847 |
| Mayampurath 2021 73 | To develop a model that utilizes natural language processing of EMS reports and machine learning to improve prehospital stroke identification. | CVD | Dx | USA | S | 965/ NA | text | SVM | 0.73, NA, NA, NA |
| Nemeth 2021 74 | To develop a phone- /tablet-based decision support system for prehospital tactical combat casualty care that collects physiologic and other Clinical data and uses machine learning to detect and differentiate shock manifestation. | Trauma | Dx | USA | M | 23744/ 70 | Clinical | LR | 0.85, NA, 0.73, 0.8 |
| Ferri 2021 75 | To develop a predictive model to aid non-Clinical dispatchers to classify emergency medical call incidents by their life-threatening level (yes/no), admissible response delay (undelayable, minutes, hours, days) and emergency system jurisdiction (emergency system/primary care) in real time. | Trauma | Dx | Europe | M | 1244624/ NA | Circumstantial, demo, Clinical, free text | NN | NA, 0.771, NA, NA |
| Chin 2021 76 | To develop an AI model for detecting a caller’s emotional state during out-of-hospital cardiac arrest calls by processing Audio recordings of dispatch communications. | OHCA | Dx | Asia-Pacific | S | 337/ NA | Audio | SVM | NA, NA, 0.3876, 0.9829 |
| Coult 2021 77 | To develop an algorithm to predict the short- and long-term outcomes of VF shock without requiring CPR interruption. The proposed algorithm could potentially provide the basis to inform patient-specific VF treatment decisions during resuscitation while supporting the best practice of high quality continuous CPR. | OHCA | CO | USA | S | 1151/ 13 | ECG | SVM | 0.75, NA, NA, NA |
| Tohira 2021 78 | To develop machine learning models using case characteristics and features gained by natural language processing of electronic free-text data from the ambulance services ehrs to identify fall cases | Trauma | Dx | Asia-Pacific | M | 9447/ NA | Text | SVM | NA, NA, 0.84, NA |
| Hayashi 2021 79 | To develope prehospital stroke prediction algorithms using a machine learning approach with high precision | CVD | Dx | Asia-Pacific | M | 1446/ 52 | Clinical | Ensemble | 0.98, 0.952, 0.986, 0.864 |
| Blomberg 2021 80 | To examine how a machine learning model trained to identify OHCA and alertdispatchers during emergency calls affected OHCA recognition and response | OHCA | Dx | Europe | S | 169049/ NA | Audio | Ensemble | NA, NA, 0.85, 0.974 |
| Cheng 2021 81 | To investigate whether a machine learning algorithm could detect complex dependencies between Clinical variables in emergency departments in OHCA survivors and perform reliable predictions of favorable neurologic outcomes | OHCA | CO | Asia-Pacific | M | 1071/ NA | Clinical | Ensemble | 0.956, NA, 0.875, 0.904 |
| Jekova 2021 82 | To optimize the architecture of a computationally efficient end-to-end CNN models for shock advisory decision during CPR using real-life AED recordings in OHCA | OHCA | Dx | Europe | S | 2720/ NA | ECG | NN | 0.938, NA, 0.89, NA |
| Tamminen 2021 83 | To show whether adding blood glucose to the National Early Warning Score (NEWS) parameters in a machine learning model predicts 30-day mortality more precisely than the standard NEWS in a prehospital setting | Other | Dx | Europe | S | 3632/ 8 | Clinical | RF | 0.758, NA, NA, NA |
| Li 2021 84 | We aimed to develop a machine learning model for trauma mortality prediction using variables easy to obtain in the prehospital setting. | Trauma | CO | Asia-Pacific | M | 1816723/ NA | Clinical | NN | 0.921, 0.578, 0.951, 0.559 |
| Ajumobi 2022 85 | Identification of non-fatal opioid overdose cases using 9-1-1 computer assisted dispatch and prehospital patient clinical record variables | Other | Dx | USA | S | NA/ NA | Clinical | RF | NA, NA, 0.759, 0.999 |
| Hasan 2022 86 | The aim of this study was to develop and improve prediction models for identifying adverse health outcomes for patients with suspected COVID-19 in a pre-hospital setting. | Other | CO | Europe | M | NA/ 26 | Clinical | NN | 0.9, NA, NA, NA |
| Takeda 2022 87 | The aim of this study was to investigate a predictive power for predicting ACS using the machine learning-based prehospital algorithm. | CVD | Dx | Asia-Pacific | M | NA/ 17 | Clinical | Ensemble | 0.861, 0.803, 0.772, 0.821 |
| Lin 2022 88 | The authors performed several tree-based algorithms and an association rules mining as data mining tools to find useful determinants for neurological outcomes in out-of-hospital cardiac arrest (OHCA) patients as well as to assess the effect of the first-aid and basic characteristics in the EMS system | OHCA | CO | Asia-Pacific | M | NA/ NA | Clinical | RF | NA, 0.9119, NA, NA |
| Harris 2022 89 | The purpose of this study was to use NLP to examine EMS clinician free-text narratives for characteristics associated with prehospital ROSC in pediatric OHCA. | OHCA | CO | USA | M | NA/ NA | Text | LR | 0.92, NA, NA, NA |
| Zhang 2022 90 | To achieve the automatic classification of prehospital emergency records. This study considers a deep learning-based prehospital emergency record classification model (dl-per). | Other | Dx | Asia-Pacific | S | NA/ NA | Text | NN | NA, NA, NA, NA |
| Lammers 2022 91 | To assess and compare multiple machine learning models for predicting patients at highest risk for massive transfusion on the battlefield | Trauma | Tx | USA | M | 22158/ 22 | Clinical, demo | RF | 0.984, 0.9598, NA, 0.949 |
| Thannhauser 2022 92 | To assess the performance of a single-variable approach to distinguish ACO from non-ACO patients, using AMSA prior to the first defibrillation attempt. | OHCA | CO | Europe | S | 100/ 1 | ECG | SVM | 0.8, NA, NA, NA |
| Chin 202293 | To build a machine learning–based model through text mining of emergency calls for the automated identification of severely injured patients after a road accident. | Trauma | Dx | Asia-Pacific | M | NA/ NA | Text | Bayesian | NA, 0.75, 0.68, 0.78 |
| Harford 2022 94 | To determine whether incorporating community variables into a ML model of OHCA can increase predictive accuracy of survival with functional neurologic outcome | OHCA | CO | USA | S | NA/ NA | Clinical, community | NN | 0.908, NA, NA, NA |
| Zhang 2022 95 | To develop a MLP model to predict SM in patients | CVD | Dx | Asia-Pacific | S | NA/ NA | Clinical | NN | 0.855, 0.9, 0.708, 0.918 |
| Abe 2022 96 | To develop a prehospital triage system to stratify patients with head trauma according to trauma severity by using several machine learning techniques and to evaluate the predictive accuracy of these techniques. | Trauma | Dx | Asia-Pacific | M | NA/ 18 | Clinical | Ensemble | 0.8, NA, 0.74, 0.749 |
| Liu 2022 97 | To develop an interpretableprehospital ROSC (P-ROSC) score for ROSC prediction based on patients with OHCA in Asia. | OHCA | CO | Asia-Pacific | M | NA/ 5 | Clinical | LR | 0.806, NA, NA, NA |
| Harford 2022 98 | To develop ML models that efectively predict hospital’s practice to perform coronary angiography (CA) in adult patients after OHCA and subsequent neurologic outcomes. | OHCA | CO | USA | M | 2398/ 47 | Clinical | NN | 0.908, NA, NA, NA |
| Paulin 2022 99 | To fnd out whether machine learning can be used in this context and to identify the predictors of subsequent events based on narrative texts of electronic patient care records (epcr). | Other | CO | Europe | S | NA/ NA | Text | NN | 0.654, NA, NA, NA |
| Chen 2022 100 | To implement an all-day online artificial intelligence (AI)-assisteddetection of ST-elevation myocardial infarction (STEMI) by prehospital12-lead electrocardiograms (ecgs) to facilitate patient triage for timelyreperfusion therapy. | CVD | Dx | Asia-Pacific | S | NA/ NA | ECG | NN | 0.997, 0.992, 0.9409, 0.994 |
| Kawai 2022 101 | To improve OHCA success rates, this study assessed the prognostic interactions resulting from simultaneously modifying two prehospital factors using a trained machine learning model. | OHCA | CO | Asia-Pacific | M | NA/ 24 | Clinical | NN | 0.9399, NA, NA, NA |
| Park 2022 102 | To train and validate the time to on-scene return of spontaneous circulation prediction models using time-to-event analysis among out-of-hospital cardiac arrest patients. | OHCA | CO | Asia-Pacific | M | 105215/ NA | Community, EMS | NN | 0.873, NA, NA, NA |
| HajebM 2022 103 | We demonstrate a novel application of a deep convolutional neural network encoder-decoder (CNNED) method to suppress CPR artifact in near real-time, using only ECG data. | OHCA | Dx | USA | S | NA/ NA | ECG | NN | NA, NA, 0.909, 0.991399 |
| Choi 2022 104 | We developed and tested predictive models for TBI that use machine learning algorithms using information that can be obtained in the prehospital stage. | Trauma | CO | Asia-Pacific | M | 1169/ NA | Clinical | NN | 0.799, NA, 0.803, 0.61 |
| Shi 2023 105 | To develop a cardiac arrest prediction model using deep learning (CAPD) algorithm and to validate the developed algorithm by evaluating the change in out-of-hospital cardiac arrest patient prognosis according to the increase in scene time interval (STI). | OHCA | CO | Asia-Pacific | M | NA/ 10 | Clinical | NN | 0.828, NA, 0.716, 0.768 |
| Bouzid 2023 106 | We sought to compare the diagnostic performance of out-of-hospital and ED ECG and evaluate the incremental gain of artificial intelligence-augmented ECG analysis. | CVD | Dx | USA | S | NA/ 179 | ECG | RF | 0.83, NA, 0.75, 0.95 |
| deKoning 2023 107 | Develop an AI model which would be able to predict ACS before patients visit the ED. | CVD | Dx | Europe | M | 7458/ 5 | Clinical | KNN | NA, NA, 0.995, 0.11 |
| Yoshida 2023 108 | To develop a scale that predicts the need for surgical intervention in stroke patients. | CVD | Dx | Asia-Pacific | M | 1143/ 23 | Clinical | Ensemble | 0.802, 0.765, 0.719, 0.774 |
| Krasteva 2023 109 | To present a novel deep learning algorithm for a sliding shock advisorydecision during cardiopulmonary resuscitation (CPR) and its performance evaluation as a function of the cumulative hands-off time. | OHCA | Dx | Europe | S | 13570/ 50 | ECG | NN | 0.9938, NA, 0.99, 1 |
| Alser 2023 110 | Develop and test an artificial intelligence algorithm to predictcritical care resource utilization. | Trauma | CO | USA | M | 41804/ NA | Clinical | NN | 0.848, NA, NA, NA |
| Yu 2023 111 | To develop and validate an interpretable field triage scoring system for predicting mortality in pre-hospital patients in Asia. | Other | CO | Asia-Pacific | M | 26294/ NA | Clinical | NA | 0.938, NA, 0.888, 0.905 |
| HellsÃ©n 2023 112 | Examine the 1-year prognosis of patients discharged from hospital after an OHCA. | OHCA | Dx | Europe | S | 5098/ 886 | Clinical | Ensemble | 0.73, NA, NA, NA |
| Bakidou 2023 113 | Evaluate if an Artificial Intelligence (AI) based Clinicaldecision support system can identify severely injured trauma patients in the prehospital setting. | Trauma | CO | Europe | M | 47357/ 21 | Clinical | SVM | 0.89, 0.871, NA, NA |
| Gong 2023 114 | To design a deep learning model to restore artifact-corrupted ECG signals during cardiopulmonary resuscitation (CPR) and provide shock/no-shock advice without needing additional reference signals. | OHCA | Dx | Asia-Pacific | S | 6113/ NA | ECG | NN | NA, 0.975, 0.959, 0.991 |
| Strum 2023 115 | Utilize ML algorithms to predict hospital admission foradult patients arriving at the ED through paramedic transport with an emergent acuitytriage score. | Other | CO | USA | M | NA/ 10 | Clinical | LR | 0.78, NA, 0.78, 0.37 |
| Spina 2023 116 | We assessed the performance of the Clinical algorithms currently used in our PSAP (ie, operator-based interview) to identify patients that will test positive on SARS-cov-2 rtpcr. | Other | Dx | Europe | M | 684481/ NA | Clinical | RF | 0.85, 0.85, 0.914, 0.442 |
| Kawai 2023 117 | Predictive model of hemostatic need using factors that can be collected during helicopter emergency medical service (HEMS) interventions | Trauma | CO | Asia-Pacific | M | 251/ NA | Clinical | Ensemble | 0.8, NA, NA, NA |
| Coult 2023 118 | We conducted a cohort study of VF out-of-hospital cardiac arrest to develop an ECG-based algorithm to predictpatients with refractory VF. | OHCA | CO | USA | M | 1376/ NA | Clinical | NA | 0.85, NA, 0.63, 0.91 |
| Xu 2023 119 | To develop machine learning models that can be adapted into primary and secondary MI triage tools and to externally validate these models using an independent population of injured patients. | Other | Dx | Europe | M | 193261/ 10 | Clinical | DT | 0.782, NA, 0.73, 0.739 |
| ValienteFernÃ¡ndez 2023 120 | Comparison of the predictive ability of various machine learning algorithms (MLA)versus traditional prediction scales (TPS) for massive hemorrhage (MH) in patients with severetraumatic injury (STI) | Trauma | CO | Europe | M | NA/ NA | Clinical | RF | 0.99, NA, 0.91, 1 |
| Wang 2023 121 | To develop a machine learning-based model for EMS ambulance dispatch triage in Singapore. | Other | Dx | Asia-Pacific | M | 361506/ NA | Clinical | RF | NA, 0.61, NA, NA |
| Kitano 2023 122 | Aimed to create a prediction model specific to prehospital trauma care and to achieve greater accuracy with techniques of machine learning. | Trauma | CO | USA | M | NA/ 10 | Clinical | RF | 0.95, 0.97, 0.92, 0.92 |
| Chang 2023 123 | Predict ROSC at the scene using prehospital input variables with time-adaptive cohort. | OHCA | CO | Asia-Pacific | M | 157654/ NA | Clinical | NA | NA, NA, NA, NA |
| Kim 2023 124 | To develop a prediction model for transferring patients to an inappropriate hospital for suspected cardiovascular emergency diseases at the pre-hospital stage, using variables obtained from an integrated nationwide dataset, and to assess the performance of this model | CVD | Tx | Asia-Pacific | S | 94256/ 98 | Clinical | NN | 0.813, 0.739, 0.739, 0.739 |
| Tateishi 2023 125 | Aimed to identify the prehospital factors that would affect favorable neurological survivalin patients with witnessed OHCA and an initial shockable rhythm using the decision tree model. | OHCA | CO | Asia-Pacific | S | 86495/ NA | Clinical | DT | 0.844, 0.855, 0.668, 0.908 |
| CVD denotes cardiovascular diseases; OHCA denotes out-of-hospital cardiac arrest; Dx denotes diagnosis; CO denotes CO; Tx denotes ‎Tx; USA denotes United States of America; No MLA denotes number of machine learning algorithm; M denotes multiple; S denotes single; NA ‎denotes not available; ECG denotes electrocardiograph; TCD denotes transcranial doppler; ML denotes machine learning; SVM; support vector machine; RF ‎denotes random forest; NN denotes neural network; DT denotes decision tree; LR denotes logistic\linear regression; HMM denotes hidden Markov model; ‎AUC denotes area under the receiving operator curve; Acc denotes accuracy; Se denotes sensitivity; Sp denotes specificity.‎ |

**Supplemental Table 3. The included operational studies.**

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| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Author year** | **Study objective** | **Task** | **Region** | **No. of MLA** | **No. of cases/ input features** | **Type of input features** | **Best ML** | **Performance metrics** |
| Setzler 2009 126 | The objective of this study was to better forecast EMS call volumes, specifically, at a finer spatial and temporal granularity using ANN. | Ambulance allocation | USA | S | 181730/ 4 | Circumstantial, EMS data | NN | NA, NA, NA, NA |
| Grekousis 2014 127 | Combine geographic information systems and neural networks for performing health emergency assessments and generating hazard maps that show areas that are potentially at high risk for emergencies | Ambulance allocation | Europe | S | 884/ NA | Spatial featues | NN | NA, NA, NA, NA |
| Chen 2015 128 | Assess the service area of EMS after a disaster | Ambulance allocation | Asia-Pacific | S | NA/ NA | EMS data, transportation data | NN | NA, NA, NA, NA |
| Chen 2016 129 | to investigate whether implementation of a coordinated digital-assisted program (CDAP) for Chinese hospitals can reduce the door-to-balloon (D2B) time for percutaneous coronary intervention (PCI) in acute chest pain patients in China | Ambulance allocation | Asia-Pacific | M | NA/ NA | EMS, temporal, GPS, metrological | NA | NA, NA, NA, NA |
| Bharsakade 2018 130 | Locate an optimal number of EMS base locations so that the ambulance can achieve a response time of 8 minutes to a victim’s call for help | Ambulance allocation | Asia-Pacific | S | NA/ NA | Unsupervised ML | unsupervised ML | NA, NA, NA, NA |
| Grekousis 2019 131 | Introducing a novel, three-level, spatial-based approach that identifies the geographical location of expected emergency events | Ambulance allocation | Asia-Pacific | S | 2851/ NA | EMS, geo, spatial feature | NN | NA, NA, NA, NA |
| Antunes 2019 132 | An active learning metamodeling methodology to address the problem of policy analysis within the context of computationally expensive simulation models tested using an Emergency Medical Service (EMS) simulator. | Ambulance allocation | Europe | S | NA/ 92 | EMS | Bayesian | NA, NA, NA, NA |
| Jovanovic 2019 133 | Developing a system for monitoring patient transport conditions with the comfort level classification, which is affected by the patient parameters | QA | Europe | M | 77/ 3 | Transportation, Clinical | SVM | NA, 0.9, NA, NA |
| Yang 2019 134 | Proposes a simulation-based optimization method for ambulance allocation. | Ambulance allocation | Asia-Pacific | S | NA/ NA | Spatiotemporal | Gaussian Mixture Model | NA, NA, NA, NA |
| Mapuwei 2020 135 | Examined the applicability of artificial neural network models in modelling univariate time series ambulance demand for short-term forecasting horizons in Zimbabwe | Ambulance allocation | Other | S | 108/ 7 | Ambulance demand | NN | NA, NA, NA, NA |
| Tran 2020 136 | Investigates how to detect emergency vehicles such as ambulances, fire engines,and police cars based on their siren sounds. | Ambulance identification | Asia-Pacific | S | 26675/ NA | Audio, image | NN | NA, 0.9824, NA, NA |
| Dolejš 2020 137 | Present a new travel time prediction model that is suitable for simple implementation using means that are currently available to EMS planners and decision makers and utilises real GPS dispatch logs data for speed training using ensemble learning methods | Ambulance allocation | Europe | S | NA/ NA | Traffic data | RF | NA, NA, NA, NA |
| Lin 2020 138 | Proposing an original and novel approach that leverages machine learning tools and extraction of features based on the multi-nature insights of ambulance demands | Ambulance allocation | Asia-Pacific | M | NA/ NA | Spatial, demo, EMS | Ensemble | NA, 0.245, NA, NA |
| Redfield 2020 139 | To link emergency medical services (EMS) electronic patient care reports (epcrs) to emergency department (ED) records. | QA | USA | S | 14032/ 6 | Clinical, text | LR | 0.99, NA, 0.994, NA |
| Martin 2021 140 | A forecasting methodology that utilizes machine learning methods is proposed for producing, daily, hourly, and spatiotemporal call volume estimations at a degree of granularity in space and time that is practical and actionable. | Ambulance allocation | USA | S | 633417/ NA | EMS, spatiotemporal | NN | NA, NA, NA, NA |
| Xiong 2021 141 | Develop and demonstrate a methodological framework of integrating transportation-sector data with health-related data to support various decision-making scenarios in transportation safety, emergency responses, and trauma-care triage. | route optimization | USA | S | 55000/ NA | Clinical, EMS, transportation, traffic | DT | 0.898, 0.884, 0.995, NA |
| Rashed 2021 142 | Investigation of the correlation between environmental factors such as ambient temperature, absolute humidity, and the daily number of emergency ambulance dispatchs | Ambulance allocation | Asia-Pacific | S | NA/ NA | EMS, Metrological | NN | NA, NA, NA, NA |
| Jin 2021 143 | Propose a bipartite graph convolutional neural network model to predict the EMS demand between hospital-region pairs. | Ambulance allocation | Asia-Pacific | S | 624062/ NA | Demo, Clinical, socioeconomic | NN | NA, 0.877, NA, NA |
| Cerna 2021144  | This paper proposes a novel two stage methodology based on machine learning (ML) models to forecast the turnaround time of each ambulance in a given time and hospital. | Ambulance deployment | Europe | M | 78777/ NA | Transportation, EMS | Ensemble | NA, 0.9702, NA, NA |
| Walker 2021 145 | To derive and internally and externally validate machine-learning models to predict emergency ambulance patient door–to–off-stretcher wait times that are applicable to a wide variety of emergency departments. | Ambulance deployment | Asia-Pacific | M | 421894/ 18 | Clinical | RF | NA, NA, NA, NA |
| Ramgopal 2021 146 | To develop and internally validate a metalearner algorithm to predict the hourly rate of emergency medical services (EMS) dispatches in an urban setting | Ambulance allocation | USA | M | 7364275/ NA | EMS, Metrological | Ensemble | NA, NA, NA, NA |
| Chu 2021 147 | To develop dispatch rules for a network of defibrillator-carrying drones. | Ambulance deployment | USA | M | 3573/ 8 | Clinical, Spatial, EMS | NN | NA, 0.879, 0.935, 0.771 |
| Kumar 2021 148 | To identify best Accedent Detection and Classification (ADC) machine learning model | Ambulance deployment | Asia-Pacific | M | NA/ NA | Accident features | Bayesian | NA, NA, 0.95, NA |
| Torres 2021 149 | To predict the difference in travel time between the ground truth travel time provided by a GPS and the approximation offered by two mapping systems, Google Maps (GM) and Open Source Routing Machine (OSRM). | route optimization | Europe | S | 42363/ 9 | Spatial | RF | NA, 0.7164, NA, NA |
| Watanabe 2021 150 | We tried to make prediction models for ambulance transports using the deep learning (DL) framework, Prediction One (Sony Network Communications Inc., Tokyo, Japan), with the meteorological and calendarial variables. | Ambulance allocation | Asia-Pacific | S | 5948/ NA | Metrological, EMS | NN | 0.972, NA, 0.937, 0.935 |
| Choi 2022 151 | To develop and validate machine learning modelsfor data entry error detection in a national out-of-hospital cardiac arrest (OHCA) prehospitalpatient care report database. | QA | Asia-Pacific | M | NA/ 19 | Clinical | LR | 0.95, NA, 0.83, 0.92 |
| Aldegheishem 2022 152 | Is to present a driving assistance system for ambulances based on low-cost sensors, which proposes a recommended route to reach a destination when two or more possible routes can be taken. | route optimization | Other | S | NA/ NA | Spatiotemporal | NN | NA, 0.97, NA, NA |
| Charef 2022 153 | Propose a hybrid approach consisting on a local approach using machine learning techniques to predict the congestion of different sections of a map from an origin to a destination, and a global approach to suggest the fastest path to ambulance drivers in real time as they move in openstreetmap. | route optimization | Other | M | NA/ NA | Traffic, spatiotemporal | KNN | NA, 0.86, NA, NA |
| Patel 2022 154 | Propose a system that detects an ambulance accurately and helps set up a makeshift emergency lane on the routes to be taken by it | Ambulance identification | Asia-Pacific | S | 2239/ NA | Audio | NN | NA, 0.972, NA, NA |
| Darwassh 2022 155 | Proposes an ambulance vehicle routing approach in smart cities aims to take transfer the patients conœdentially, accurately, and quickly | route optimization | Other | S | NA/ NA | Accident, geo | NA | NA, NA, NA, NA |
| Li 2022 156 | The primary objective of this study is to provide an AOD prediction model based on the current system status, hour of the day, and day of the week. With this information, decision-makers can be proactive with efforts to mitigate AOD. | Ambulance allocation | Asia-Pacific | M | NA/ NA | Historical, EMS | DT | NA, 0.9155, 0.9155, 0.6679 |
| Ceklic 2022 157 | To determine how well the text sent to paramedics en-route to the traffic crash scene by the emergency medical dispatcher (EMD), in combination with dispatch codes, can predict the need for a L&S ambulance response to traffic crashes. | Ambulance deployment | Asia-Pacific | M | NA/ 9224 | Text | Ensemble | NA, 0.98, 0.98, NA |
| Rathore 2022 158 | To propose a new vehicle routing and scheduling model equipped with novel features to ensure minimal response time using existing resources. | Ambulance allocation | Asia-Pacific | M | 9766/ NA | EMS, Clinical, geo, transportation | RF | NA, NA, NA, NA |
| Shimada-Sammori 2023 159 | We hypothesized that machine learning algorithms using meteorological and chronological informationcan be used to accurately predict high OHCA incidence and help clinicians identify “high-risk” days for OHCAincidence. | Ambulance allocation | Asia-Pacific | M | NA/ NA | Meteorological | Ensemble | 0.906, 0.835, 0.848, 0.833 |
| Manguri 2023 160 | To improve the performance accuracy of vehicle classification using certain preprocessing algorithms on the input images and testing various optimization methods. | Ambulance identification | Other | S | 6222/ NA | Image | NN | NA, 0.9844, NA, NA |
| Algamdi 2023 161 | We build a framework utilizing CV technology to support decision-makers during the Hajj season | Ambulance identification | Other | S | 1234/ NA | Image | NN | NA, NA, NA, NA |
| Abreu 2023 162 | To support decisions related to planning when, where and how many EMS resources are required. | Ambulance allocation | Europe | S | NA/ NA | EMS | NN | NA, 0.877, NA, NA |
| Ke 2023 163 | Developed an effective method to predict the number of daily heat-related ambulance calls. | Ambulance allocation | Asia-Pacific | S | NA/ NA | Meteorological | Ensemble | NA, NA, NA, NA |
| Nithya 2024 164 | To improve accuracy and reduce errors in vehicle sound classification. | Ambulance identification | Asia-Pacific | S | NA/ NA | Audio | NN | 0.98, 0.9866, 0.981, 0.994 |
| USA denotes United States of America; No. denotes number; MLA denotes machine learning algorithm; M denotes multiple; S denotes single; NA denotes not available; EMS denotes emergency medical services; ML denotes machine learning; SVM; support vector machine; RF denotes random forest; NN denotes neural network; DT denotes decision tree; LR denotes logistic\linear regression; HMM denotes hidden Markov model; KNN denotes K-nearest neighbour; AUC denotes area under the receiving operator curve; Acc denotes accuracy; Se denotes sensitivity; Sp denotes specificity. |

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