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Review Article

Identifying Techniques and Models for COVID-19 Prediction

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Abstract

Background: Technologies can predict various aspects of COVID-19, such as early prediction of cases and those at higher risks of severe disease. Predictions will yield numerous benefits and can result in a lower number of cases and deaths. Herein, we aimed to review the published models and techniques that predict various COVID-19 outcomes and identify their role in the management of the COVID-19.

Methods: This study was a review identifying the prediction models and techniques for management of the COVID-19. Web of Science, Scopus, and PubMed were searched from December 2019 until September 4th, 2021. In addition, Google Scholar was also searched.

Results: We have reviewed 59 studies. The authors reviewed prediction techniques in COVID-19 disease management. Studies in these articles have shown that in the section medical setting, most of the subjects were inpatients. In the purpose of the prediction section, mortality was also the most item. In the type of data/predict section, basic patient information, demographic, and laboratory values were the most cases. Also, in the type of technique section, logistic regression was the most item used. Training, internal and external validation, and cross-validation were among the issues raised in the type of validation section.

Conclusion: Artificial intelligence and machine learning methods were found to be useful in disease control and prevention. They accelerate the process of diagnosis and move toward great progress in emergency circumstances like the COVID-19 pandemic.

Keywords: COVID-19, Diagnosis, Prediction, SARS-CoV-2

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Introduction

Since coronavirus disease 2019 (COVID-19) emerged, it has caused nearly 272 million cases and 5.3 million deaths as of December 20th, 2021 (1). COVID-19 is caused by severe acute respiratory syndrome-coronavirus-2 (SARS-CoV-2) (2). This disease can invoke systemic inflammatory response that can involve various organs in the body, most notably the lungs (3-5). SARS-CoV-2 also has noticeable potentials for mutations that can cause further increase in incidence and mortality rates if not controlled properly and cause new and more dangerous variants, such as Delta and Omicron (6). Global vaccinations have been useful to contain the spreading and mortality of this disease, but still a long road is ahead to vaccinate a proper portion of people worldwide, especially in lower income countries (1,7). Overall, high incidence and deaths caused by the COVID-19 as well as its economic and social detriments attracted specific attentions, and gaining knowledge on its various aspects seems necessary (6,8).

Predicting different features of this disease have their specific benefits (9,10). Various technologies exist to predict the parameters related to this disease, such as Artificial Intelligence (AI)-based technologies (11-13). For example, predicting the cases earlier will lead to earlier diagnoses that may cause better quarantines to decrease the risk of transmission, as well as more timely management of the patients towards better outcomes (12). Furthermore, contacts of the sick patients will be notified earlier and seek measures to limit their spread to others and improve their health during the disease period (14-17). Several groups of people are also at increased risk for severe COVID-19 outcomes, e.g., older patients, those with underlying conditions, or the patients with high values of some inflammatory conditions (18,19). Prediction methods can identify those that are probably at higher risks for severe COVID-19; and therefore, offer greater preventive measures to these groups to avoid contracting the disease in the first place, and if infected, place specific emphasis on their early and correct treatment (11,20). For instance, such groups with underlying diseases may be advised to receive online chronic disease management to limit their contacts with healthcare facilities and other possible dangerous sites (13,16,21,22).

To the best of our knowledge, many studies and systematic reviews are available to this date that focus on the benefits and applications of technologies during the COVID-19 pandemic. However, the literature lacks adequate systematic reviews on prediction methods associated with the COVID-19. Therefore, the authors aimed to systematically review the published models and techniques that predict various COVID-19 outcomes and identify their role in the management of the disease.

Materials and Methods

This study was a review to study the prediction models and techniques for management of the COVID-19. Scopus, PubMed, and Web of Science were searched from December 2019 until September4th, 2021. In addition, Google Scholar was also searched.

Search strategy

Search strategy was organized by first and corresponding authors. The keywords were as the following: COVID-19, SARS-CoV-2, prediction, and system. The complete search strategy was as follows:

A: COVID-19 OR “Coronavirus” OR “Corona virus” OR SARS-CoV-2

B: Prognostic OR Prognoses OR Prognosis OR Prediction OR Diagnosis OR Prognostication OR Anticipation OR Forecast

C: Design OR Development OR Implementation OR System

D: [A] AND [B] AND [C]

Eligibility criteria

The authors included all studies retrieved from databases that report the prediction, incidence and diagnosis of COVID-19 disease. Excluded articles were at least one of the following criteria:

- Non-original studies, including position papers, case reports, case series, reviews, editorials, comments, and clinical trial protocols.
- Non-full texts articles, short communications, conference abstracts, and abstract papers.
- Any duplicated outcomes in databases.
- Non-human studies.
- Non-English language.

Data screening and selection study

EndNote X9 software was used to manage studies. Search results joined in a single EndNote library and duplicate studies of the similar reports removed. Three authors independently screened titles and abstracts of the retrieved articles to evaluate whether they meet the inclusion and exclusion criteria of the selected articles.

Data extraction

The following data were extracted from eligible studies: first author, type of study, country, population, medical setting, purpose of prediction, type of data/predict, type of technique, type of validation, classification measure, Area Under the Receiver Operating Characteristic (AUROC), and other findings. Data were extracted independently by three authors. The corresponding author resolved discrepancies in data extraction and checked the retrieved data to rule out duplication.

Quality assessment

This study was a review to study the prediction models and techniques for management of the COVID-19. Three independent and experienced authors checked the quality of the studies and the probable risk of bias. Any disagreement in judgment was resolved by the first author review and consensus.

Results

In this study, 306 articles were collected using a systematic search strategy. After the initial review of the retrieved articles, 87 items were deleted due to duplication and the titles and abstracts of the remaining 117 articles were reviewed. After reviewing the inclusion criteria, 58 articles were removed and 59 articles had inclusion criteria and were included in the final review (Figure 1).

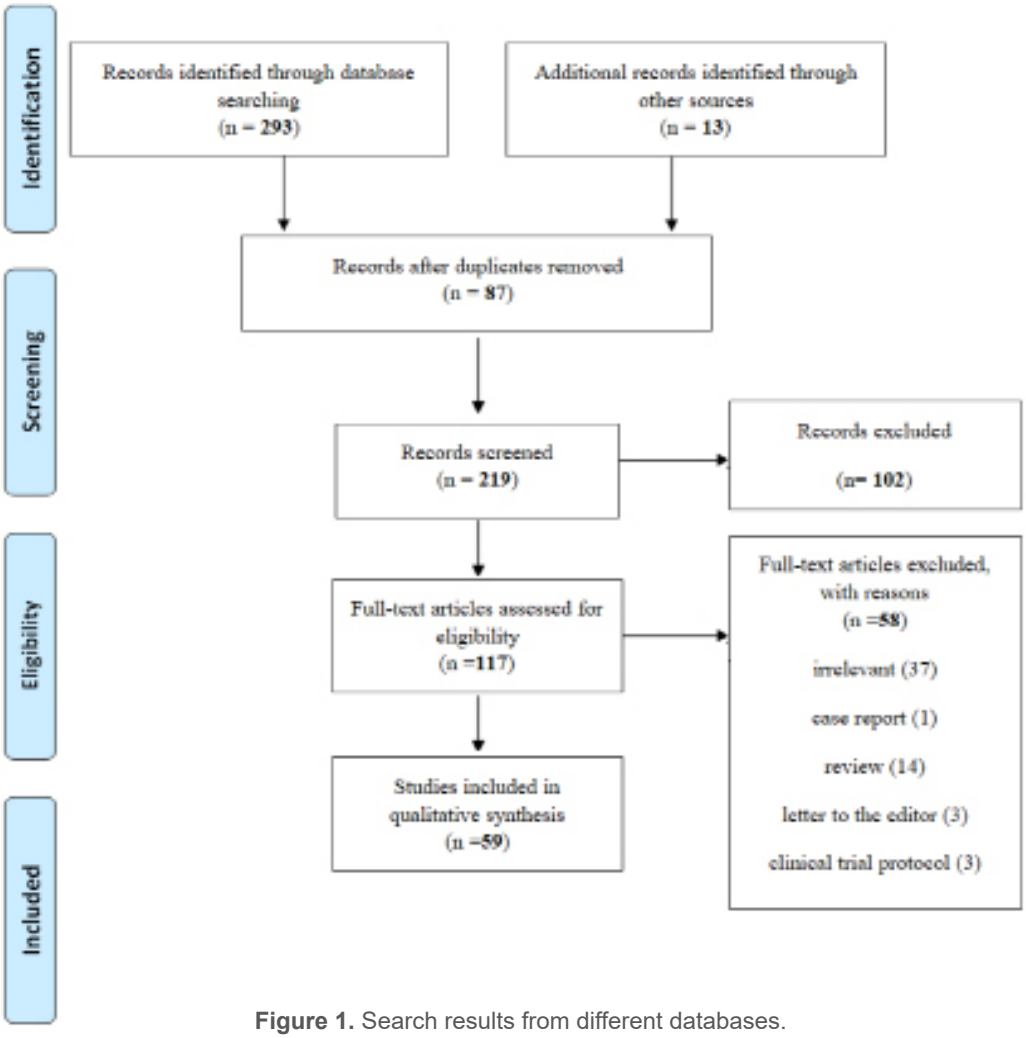

Figure 1. Search results from different databases.

In the type of data/predict section, basic patient information, demographic characteristics, and laboratory values were the most common cases. Also in the type of technique section, logistic regression was the most item. Training, internal and external validation, and cross-validation were among the issues raised in the type of validation section.

Most studies were related to China with 20 articles, the USA with 14 articles, and Italy and Spain with 4 articles. The rest of the selected articles were for South Korea with 3 articles and Philippines, UK, France, and India with 2 articles. Israel, Greece, Algeria, Mexico, Austria, Japan, Switzerland, and Turkey also had one article.

Eventually, modeling method, final model, and sample size of training were expressed in other findings (Table 1).

Studies in these articles have shown that in the section

Table 1: Prediction methods to management of COVID-19

First author (re)	Popul-ation	Medical setting	Purpose of prediction	Type of data/ predict	Type of technique	Type of validation	Classification measure		AUROC (area Under the receiver operating characteri-stics)	Other findings
							Prediction accuracy rate	Others		
Abdulaal A, *et al* (23)	398 patients with COVID-19	Inpatient	Mortality	Demographics, comorbidities, smoking history, and presenting symptoms	Neural network	k-fold cross-validation	60.87%	Patient-specific mortality= 86.25%, with a sensitivity= 87.50%, The negative predictive value= 96.49%.	The AUROC was 90.12%.	Predict mortality for that admission: Digital format, ANN. The ANN
Allenbach Y, *et al* (24)	152 patients with COVID-19	Inpatient	Being discharged alive and severe status at D14 (remaining with ventilation, or death), intensive care unit (ICU) transfer or death at day 14 (D14)	Demography and epidemiology features the clinical presentation along with the laboratory comorbidity profile. Routine blood examinations chest computed tomography (CT) scan echocardiogram data previous treatments	Logistic regression	Internal and external validation of the model: -the C-index (equivalent to AUC)= 0.80 -after correction for over-optimism by resampling= 0.78 -on the external cohort= 0.78	ICU transfer or death= 32%	A 9-point ordinal scale scoring system: -defined low (score 0–2) -moderate (score 3–5) -high (score 6–8) risk patients	N/A	A simplified scoring system: admission predicted at D14
Barda N, *et al* (25)	Patients with COVID-19	Inpatient	Mortality	Primary care, specialist care, laboratory data, in-network hospitalization data, imaging data	N/A	External validation, training–validation	88%	At a 5% risk threshold, 15% of patients are marked as high-risk, achieving a sensitivity of 88%	PSI/PORT, CURB-65 and SCAP	The baseline model: -initial training for feature selection -final training for the creation of the baseline model

Contd. table 1

Bartoletti M, *et al* (26)	1113 patients with COVID-19	Inpatient	Treatment	Age, sex, body mass index, being obese, Hypertension. Immunosuppression, solid organ transplantation, hematopoietic stem cell transplantation, corticosteroid therapy, uncontrolled human immunodeficiency virus infection	The multivariate logistic regression	Validation cohort	At a score of >3, sensitivity: 71.6% (65–79%) At a score of >3, sensitivity: 80% (73–85%)	At a score of >3, specificity, and positive and negative predictive values were: -89.1% (86–92%) -74% (67–80%) -89% (85–91%)	CURB-65, AUC	-PREDI-CO score: to allocate resources and prioritize treatments -Risk factors for SRF
Bellos I, *et al* (27)	67 patients with COVID-19	Inpatient	Treatment	Demographic, clinical and laboratory findings	Regression	Cross-validation	92.3%	Specificity: 93.3%	-CURB-65, -CRB-65 -PSI/PORT	-Selection operator (LASSO) regression model -A10-variable: to predict critical illness amongst hospitalized COVID-19 patients
Bennouar S, *et al* (28)	330 patients with COVID-19	Inpatient	Mortality	CRP and a total blood count with the calculation of the NLR ratio, blood glucose and renal function markers including blood urea nitrogen, serum creatinine, and electrolytes (sodium and potassium), albumin and total protein, hepatic enzymes: LDH, GOT and GPT, γ-GT and alkaline phosphatases (PAL)	Regression	Validation cohort	N/A	0.74 [0.66–0.82] and 0.90 [0.87–0.94], p<0.0001, respectively for severity and mortality prediction	AUC	N/A

Contd. table 1

Berenguer J, *et al* (29)	4035 patients with COVID-19	Inpatient	Mortality	Demographics, comorbidities defined as diagnoses, signs or symptoms, low age-adjusted capillary SaO2 on room air, test results, including white cell count, neutrophil-to-lymphocyte ratio, platelet count, INR, eGFR measured	Multivariable logistic regression	External validation cohort	60%	-The risk low: 0–2.1% -moderate: 4.7–6.3% -high: 10.6–19.5% -very high: 27.7–100%	N/A	SEIMC score. A simple prediction score, based on readily available clinical and laboratory data, provides a useful tool to predict 30-day mortality probability with a high degree of accuracy among hospitalized patients with COVID-19
Berry DA, *et al* (30)	3123 patients with COVID-19	Inpatient	Mortality	Demographic, clinical characteristics, treatments	Regression	N/A	N/A	N/A	N/A	Most important characteristic for survival: age
Bolourani S, *et al* (31)	11,525 patients with COVID-19	Inpatient	Predict 48-hour respiratory failure	-Demographics -comorbidities -home medications -initial vitals -laboratory values -treatments -clinical outcomes	Logistic regression	Cross-hospital validation, external validation	N/A	N/A	AUCROC, AUC	The XGBoost + SMOTEENN method (combined oversampling using SMOTE): to predict 48-*hr* respiratory failure in admitted patients with COVID-19
Booth AL, *et al* (32)	398 patients with COVID-19	Inpatient	Mortality	C-reactive protein, blood urea nitrogen, serum calcium, serum albumin, and lactic acid	Logistic regression	N/A	91%	91% specificity	AUC	-Pairwise relationship between each laboratory value -SHAP value the magnitude of other members of the five selected laboratory parameters

Contd. table 1

Cho SY, *et al* (33)	5594 patients with COVID-19	Inpatient	Survival	-Demographic characteristics -Epidemiological characteristics -hemogram parameters -maximal severity -clinical outcome obtained	Logistic regression	Validation cohort	N/A	28-day survival rates: -low-risk: 99.8% -inter-mediate-risk: 95.4% -high-risk: 82.3% -high-risk: 55.1%	N/A	-COPS: assist in making risk-adapted decisions for the allocation of medical resources -Cox proportional hazard regression model
Chow DS, *et al* (34)	3208 patients with COVID-19	Inpatient	-ICU admission -ventilation -death	-Patient comorbidities -presenting vital signs -laboratory values	Multivariable logistic regression	External validation	Critical disease= 65%	N/A	N/A	BFGS
Chung H, *et al* (35)	5601 patients with COVID-19	Inpatient	The clinical severity of COVID-19	-Basic patient information -a physical index -initial examination findings -clinical findings -comorbid diseases -general blood test results	Artificial intelligence	Cross-validation	Sensitivity= 90.2%	-Specificity= 90.4% -Accuracy= 90.4% -Balanced accuracy= 90.3%	AUC	For predicting COVID-19 severity: -AdaBoost -random forest -XGBoost -the AI model
Das AK, *et al* (36)	3524 patients with COVID-19	Inpatient	Mortality	Demographic, exposure and diagnosis confirmation features along with the outcome	Logistic regression	Cross-validation	N/A	CoVID-19 mortality risk prediction of 94.1% for a male patient aged between 80 and 89 years	AUC	-Support vector machine -random forest -gradient boosting -SMOTE
Dixit A, *et al* (37)	Covid-19 suspected cases	Outpatient	To diagnose the COVID-19 suspected individual	N/A	Artificial intelligence	Cross-validation	99.34%	N/A	N/A	Utilize chest X-rays, K-means clustering and feature extraction.
Domín-guez-Olmedo JL, *et al* (38)	1823 patients with COVID-19	Inpatient	Mortality	N/A	Logistic regression	Cross-validation	0.94 for accuracy	0.77 for the F-score, 0.93 sensitivity, and 0.91 for specificity	AUPRC, AUC	The gradient boosting method to develop a predictive model

Contd. table 1

Ebell MH, *et al* (39)	1340 patients with COVID-19	Inpatient	Mortality	Demographic, clinical, and laboratory parameters	Logistic regression	Internal validation	N/A	-The COVID-No Lab risk score: AUROCC = 0.803 -The COVID-Simple Lab score: AUROCC = 0.833	N/A	-COVID-No Lab risk -COVID-Simple Lab
Fink DL, *et al* (40)	581 individuals were admitted with suspected COVID-19	Inpatient	Diagnostic	Clinical observations and blood test results	Logistic regression	Internal validation	Sensitivity= 78.1%	-Specificity= 86.8% -COVID-19 prevalence= 10% -NPV= 96.5%.	AUC	Risk score is the first developed for COVID-19 diagnosis using the TRIPOD checklist. It may be effective as a tool to rule out COVID-19 and function at different pandemic phases of variable COVID-19 prevalence
Gao Y, *et al* (41)	2520 patients with COVID-19	Inpatient	Mortality	N/A	-Logistic regression -Support vector machine -Gradient boosted decision tree -Neural network	Internal validation	92.4%	N/A	AUC	MRPMC
Mancilla-Galindo J, *et al* (42)	83779	Inpatients and outpatients	Death	Demographic and patient history	-Multivariable cox regression model -Kaplan –Meier analysis	-Cox proportional hazards regression analysis -Validation cohort	N/A	N/A	N/A	Multivariable cox regression model
Mamidi, TKK, *et al* (43)	7,262 COVID19 patients	Inpatient	To predict an individual's risk for COVID-19 infection	-Respiratory symptoms -chronic conditions: nicotine dependence and major depressive disorder	-Cross-validation-based -logistic regression method	Stratified cross-validation (CV)	0.76	Elastic-Net models: Accuracy= 0.76 AUC=0.79 [CI: 0.76–0.83] for the all-time data	N/A	Credit scorecard modeling approach

Contd. table 1

Makridis CA, *et al* (44)	11097 patients	N/A	Mortality	Demographic and patient history, laboratory dysfunction and vital sign measures	N/A	cross-validation (CV) AUROC, F1 and mean scores of recalls	N/A	F1= 0.4 recall score= 0.76	AUROC= 0.87 AUPRC= 0.41	Final model: XGBoost model
Ma XD, *et al* (45)	305 patients	Inpatients	Mortality risk	LDH, CRP, and age	Multivariate logistic regression models	Z-score four-fold cross-validation	N/A	N/A	AUROC= 0.9521	Final model: multivariate logistic regression model Training method: Machine-learning (Random Forest and XGboost methods) Sample size of training: 75%
Ma B, *et al* (46)	330	Inpatient	An early warning system for severe symptoms	Clinical characteristics, Multiple lobe infiltrate in CT, sepsis, WBC count, smoking history, HTN, and age	Chi-square or fisher exact test	N/A	0.93	Sensitivity= 0.651 Specificity= 0.954 Accuracy= 0.93	AUROC = 0.927 (0.963-0.892)	Final model: ROC curve analysis
Liu J, *et al* (47)	COVID-19 cases aged>60 years	Inpatient	Early identification of critically ill elderly COVID-19 patients	Demographic and patient history, physical examination	Multivariable logistic regression model	Internal validation cohort external cohort	0.77	Hosmer-lemeshow goodness of fit test (p=0.393)	0.77 (95% CI: 0.71-0.83)	Final model: Nomogram model Training method: discrimination, AUC and calibration Sample size of training: 892
Li S, *et al* (48)	2924 patients	Inpatient	Mortality	Demographic, clinical, laboratory, radiological characteristics, and treatment and outcomes data	CART regression tree	Fivefold cross-validation	0.889	Sensitivity =0.899 specificity =0.889 PPV = 0.432 NPV= exceeded 97%	0.941	Final model: GBDT sample size of training: 152 Training method: gradient boosting decision tree (GBDT), logistic regression (LR) model, and simplified LR

Contd. table 1

Li L, *et al* (49)	4,086	Inpatient	Deaths caused by COVID-19 in hospitals	Age, disease severity, respiratory symptoms, cardiovascular disease, LDH, bilirubin, blood sugar, and urea	Univariate and multivariate COX proportional hazards regression analysis	Bootstrap resampling Internal validation external validation	N/A	Internal resampling (C-index) =0.97 Internal validation =0.96 External validation 0.92	N/A	Training method: nomogram modeling
Leoni, MLG, *et al* (50)	242 patients	Inpatient	Deaths from COVID-19 in critically ill patients at 4 weeks	Age, obesity, procaltitonin, SOFA score, and PaO2/FiO2	N/A	Internal validation using the bootstrap resampling technique	N/A	Discrimin-atory capacity= 0.822 (95% CI 0.770–0.873)	N/A	N/A
Lehmann J, *et al* (51)	451 patients	Residents (general population)	SARS-CoV-2 antibodies	Self-reported symptoms, gustatory/ olfactory alterations, and limb pain	Univariate analyses multivariate binary logistic regression	Univariable and multivari-able cox propor-tional hazards regression models	N/A	Sensitivity = 0.612 Specificity = 0.852	0.773 (95% CI 0.727–0.820)	Sample size of training: 451
Lasbleiz A, *et al* (52)	344 COVID-19 cases with diabetes	Outpatients	Hospitaliza-tion	Older, with more class III obesity, hypertension, insulin therapy, and lower SpO_2	Multivariate logistic regressions ROC analyses	External validation	N/A	Sensitivity =77.7%, specificity =89.2%	AUC = 0.895	Final model: multivariate logistic regression models sample size of training: 344
Kodama T, *et al* (53)	207 patients	Inpatient	Higher demand for oxygen in patients with pneumonia	CURB-65, expanded CURB-65, and A-DROP assessment tools	N/A	N/A	N/A	N/A	AUC CURB-65=0.6961 A-DROP= 0.6980 expanded CURB-65 scores= 0.8327	The strongest correlation was found for expanded CURB-65 scores (Spearman's coefficient= 0.48; p<0.0001) and was the most useful
Ji D, *et al* (54)	208 patients	N/A	Disease progression	Having comorbid conditions, being older, having a lower lymphocyte count, and having a higher LDH	N/A	N/A	N/A	Concordance indexes = 0.86 (95%CI 0.81 - 0.91) PPV= 50.7% (38.9% - 62.4%) NPV= 98.5% (94.7-99.8%)	0.91 (95% CI 0.86 to 0.94)	Final model: univariate and multivariate COX regression Kaplan-Meier analysis

Contd. table 1

Jehi L, *et al* (55)	4,536 patients	Inpatient and outpatient	The risk of hospitali-zation	Demographic comorbidities vaccination symptoms medications laboratory measures	The least absolute shrinkage and selection operator (LASSO) logistic regression algorithm	A 10-fold cross validation method	N/A	Scaled Brier score= 25.6% Sensitivity= 0.769 Specify= 0.726 PPV=0.447 0.916	0.813 (0.786-0.839)	Final model: median imputation, A sample size of training: 2852, Training method: A development cohort, multivariable logistic model, multivariate imputation by chained equations (MICE) least absolute shrinkage and selection operator (LASSO) logistic regression algorithm
Ikemura K, *et al* (56)	4313 patients	Inpatient and outpatient	Patients' chances of surviving a SARS-CoV-2 infection	Systolic and diastolic blood pressure, age, pulse oximetry level, blood urea nitrogen level, lactate dehydrogenase level, D-dimer level, troponin level, respiratory rate, and Charlson comorbidity score.	N/A	10-fold cross-validation	N/A	Sensitivity= 0.92 Specificity= 0.74 PPV= 0.513 NPV= 0.968 The maximum F2 score of MODEL-10 = 0.779 The probability threshold = 0.202.	AUPRC= 0.791	Final model: automated machine learning, A sample size of training: 80%, Training method: automated machine learning, gradient boost machine, extreme gradient boost models, deep learning model, random forest, general linear models

Contd. table 1

Heo JN, *et al* (57)	4663 patients	Inpatient	Predicting patients with COVID19 requiring intensive care	Two models: 1.Using only clinical variables 2.Added radiologic and laboratory data	Logistic regression	External validation hosmer-lemeshow test	N/A	N/A	Model 1: 0.88 [95% CI 0.85–0.92] Model 2: 0.90 [95% CI 0.86–0.93], (p=0.17)	Mean variable inflation factor = 1.08 (range 1.01–1.24) Sample size of training: 3238 Final model: Multivariate logistic regression models
Halasz G, *et al* (58)	852	Inpatient	30-day mortality	Age, MCHC, PaO2 /FiO2 ratio, T, stroke history, and sex	N/A	External validation test cohort	57%	Sensitivity = 95% Specificity = 44% NPV = 97% PPV = 37% Brier score = 0.16	AUC= 0.79 (Brier score=0.16)	Final model: Naïve Bayes classifier Sample size of training: 70%
Hajifat-halian K, *et al* (59)	N/A	Inpatient	Prediction of 7- and 14-day mortality	Age, severity of hypoxia, mean arterial pressure and renal failure at hospital presentation	Multivariable regression	External validation receiver operating charac-teristic curve hosmer-lemeshow goodness of fit (GOF) test	N/A	N/A	7 days: 0.85 (GOF p=0.340) 14 days: 0.83 (GOF p=0.471)	Multivariable regression model
Haimovich A.D, *et al* (60)	1,792 patients with COVID-19	Inpatient	Respiratory failure among emergency department patients in the early stages of hospitaliza-tion	Elixhauser comorbidity In dex,qSOFA, and CURB-65	N/A	N/A	0.76 (0.65-0.86)*	Sensitivity = 0.79 specificity= 0.78 PPV= 0.36 NPV= 0.96 LRþ= 3.55 LR- = 0.27 Brier Score= 0.25	AU-ROC= 0.76 (0.65–0.86)*	
Gude-Sampedro F, *et al* (61)	10454 patients with COVID-19	Outpatient	Disease severity (hospitaliza-tion, ICU admit and mortality)	Age, sex and comorbidities	N/A	Internal validation using the bootstrap procedure	Brier scores of Gal-COVID-19 and Charlson index = 0.150 and 0.157 (for hospitaliza-tion) = 0.025 and 0.026 (for ICU admission) = 0.043 and 0.046 (death)	N/A	AUC for: hospitaliza-tion= 0.77 admission to ICU= 0.83 death= 0.89	Final model: Logistic regression models Nagelkerke R^2 = 0.25 Nagelkerke R^2 = 0.17 Nagelkerke R^2 = 0.31 Sample size of training: 70%

Contd. table 1

Wang S, *et al* (62)	5372 patients	-	Diagnostic and prognostic	Raw chest CT image, type of disease, demographic, Comorbidity, follow up	Kaplan–Meier analysis and log-rank test	Externally validate	81%	(p=0.013 and p=0.014)	AUC: 0.87 and 0.88 sensitivity: 80.39% and 79.35% specificity: 76.61% and 81.16%,	Final model: deep learning system
Prabhaker M, *et al* (63)	1349 petient with COVID-19	Inpatient	Mortality	Demographic data such as age upon admission, gender, and clinical symptoms: fever, dry cough, sore throat, breathlessness or shortness of breath and related comorbidities	Regression	Hosmer–lemeshow goodness of fit test	81.9%	The mortality observed in the validation cohort, high (8–9), medium (5–7) and low (0–4) CSS groups was 54.80%, 28.60% and 6.5%.	AUROC curve of the model: 82.8%	Final model: scoring system (CSS)
Zhang C, *et al* (64)	80 patients with COVID-19	Inpatient	severity of COVID-19 infection	Age, white blood cell count, neutrophil, glomerular filtration rate, and myoglobin	Logistic regression	N/A	N/A	The risk of sever Covid-19 infection in high-risk group was 20.24 times than in low-risk group.	AUC of scoring system: 0.906 sensitivity of prediction is 70.8%, and the specificity is 89.3%.	Final model: scoring system
Yan L, *et al* (65)	375 patients with COVID-19	Inpatient	Mortality	Epidemiological, demographic, clinical, laboratory and mortality outcome information	Decision-trees (random forest and logistic regression)	External test	90%	100% survival prediction accuracy 81% mortality prediction accuracy	N/A	Modeling method: mathematical modelling Final model: machine learning-based model
Mei J, *et al* (66)	1364 adult patients with COVID-19	Inpatient	Mortality	Age, respiratory failure, white cell count, lymphocytes, platelets, D-dimer and lactate dehydrogenase	Univariate logistic regression	External validation	93%.	N/A	AUC statistics based on derivation cohort: 0.96 The AUC statistics based on the external validation cohort: 0.97 and 0.88 for simple model.	Prediction algorithms
Parchure P, *et al* (67)	567 patients with COVID-19	Inpatient	Mortality	Administrative data (including admission type, source of admission); data from nursing flowsheets; related laboratory results and ECG-derived variables	Time-series	RF algorithm	Accuracy of 65.5%	RF classifier yielded a sensitivity of 87.8% and specificity of 60.6%	AUROC 85.5%	Machine learning (ML) was randomly split into training (~70%) and test (~30%) sets

Contd. table 1

Mussini C, *et al* (68)	266 patients with COVID-19	Inpatient	Treatment (outcome)	Sex, PaO2/FiO2 ratio, platelets and CRP	Multivariable logistic regression	K-fold cross validation	N/A	The accuracy of the score in AUC was 0.80 and 0.70 in internal validation , test for the composite endpoint	AUC = 0.89	N/A
Schöning V, *et al* (69)	N= 657 patients tested positive for SARS-CoV-2	Inpatient & outpatient	Prognosis	Sex, C-reactive protein, sodium, hemoglobin, glomerular filtration rate, glucose, and leucocytes around the time of first positive testing	-Logistic regression -Decision tree induction (DTI) -Regression trees (CART) -Random forest	Training and prospective validation cohort	N/A	PPV = 0.90 NPV = 0.58	AUROC: (median = 0.96, interquartile range = 0.85–0.99)	Score and machine learning model
Tanboğa IH, *et al* (70)	60,980 patients with COVID-19	Inpatient	Mortality	Symptoms, biomarkers, medications, comorbidities, and clinical outcomes during index hospitalization	Multivariable logistic regression	Internal–external validation (temporal and geographic validations)	N/A	N/A	Area under the curve-receiver operating characteristic = 0.942	N/A
Rodriguez VA, *et al* (71)	N=1330 patients with COVID-19	Inpatient & outpatient	Diagnosis	Age, total white blood cell count, chest x-ray appearances and contact history as significant predictors	Multivariable logistic regression	Hosmer–Lemeshow (H–L) test and calibration plot	N/A	Sensitivity: 0.1 Specificity: 0.2 PPV:0.4 NPV:0.6	AUC = 0.880 [CI = 0.844-0.916]	N/A
Ng MY, *et al* (72)	1330 patients with and without COVID-19	Inpatient & outpatient	Diagnosis	Haematological and biochemical blood tests and CXR results	Multivariable logistic regression	Externally validated	N/A	Sensitivity: 0.1 Specificity: 0.2 PPV:0.4 NPV:0.6	The first prediction model: (AUC = 0.911 [CI = 0.880 0.941]). The second Model: (AUC = 0.880 [CI = 0.844 0.916])	N/A
Mei Q, *et al* (73)	492 patients with Covid-19	Inpatient	Mortality	Demographic characteristics, clinical information, vital signs and laboratory reports	Multivariate analysis	Validation cohorts	N/A	N/A	AUC: 0.912, 0.928, and 0.883	N/A
Wu G, *et al* (74)	725 patients with COVID-19	Inpatient	Prognostic	Clinical, laboratory and radiological variables	Logistic regression	Internal & External validation	74.4% to 87.5%	PPVs: 66.7% to 84.1%, NPVs: 73.9% to 95.7%.	AUCs: 0.84 to 0.93	Final model: Machine -Learning model

Contd. table 1

Tsui E LH (75)	1037 COVID-19 laboratory-confirmed patients	Inpatient	Prognosis	Epidemiological, clinical and laboratory	Univariate logistic regression	External validation	92.3% and 99.5%	N/A	Odds ratios (ORs) with corresponding 95% (AUC: 0.86, 95% CI: 0.82–0.91)	Final model: scoring system
Zhou J, *et al* (76)	4442 patients with COVID-19	Inpatient & outpatient	Prognosis	Age, gender, medical comorbidities, medication records, and laboratory examination results	Logistic regression	External validation & cross-validation	83% to 87%	N/A	AUC: 0.86, 95% CI: 0.82–0.91	Final model: scoring system
Vila-Corcoles A, *et al* (77)	282 laboratory-confirmed COVID-19	Inpatient & outpatient	Prognosis	Demographics, pre-existing comorbidities and early symptomatology	Logistic regression	External cohort validation	N/A	N/A	Area under ROC curve: 0.828; 95% CI: 0.774-0.882	Final model: prognostic rule
Zhang Y, *et al* (78)	Patient with COVID-19	Inpatient & outpatient	Outbreak rate	Numbers of con firmed diagnosis, recoveries and fatalities	Mathematical methods	N/A	N/A	N/A	N/A	Final model: stochastic dynamic model
Pan P, *et al* (79)	123 patients with COVID-19 in the ICU	Inpatient	Prognosis	Baseline patient information, clinical diagnosis, vital signs, laboratory test results, medical advice, and nursing care	Machine learning, Logistic regression)	5-fold cross validation	0.76	N/A	Training (AUC=0.86) verification queue (AUC=0.92)	eXtreme Gradient Boosting (XGBoost) model, 80% of these data as the training set
Peng Y, *et al* (80)	Patients with COVID-19	Inpatient & outpatient	Incidence rate	Candidate features associated to COVID-19	Random forest regression algorithm	N/A	N/A	N/A	N/A	Modeling method: techniques of features engineering, Final model: machine learning algorithm

* Se: Sensitivity, Sp: Specificity, PPV: Positive Prediction Value, NPV: Negative Prediction Value, ANN: Artificial Neural Network, CHS: Clalit Health Services, SRF: Severe Respiratory Failure, LASSO: Least Absolute Shrinkage and Selection Operator, GOT: Glutamo-Oxaloacetic Transaminase, GPT: Glutamo-Pyruvic Transaminase, γ-GT: Gamma-Glutamyl-Transpeptidase, SaO_2: Oxygen Saturation, INR: International Normalized Ratio, eGFR: estimated Glomerular Filtration Rate, CKD-EPI: Chronic Kidney Disease Epidemiology Collaboration, COPS: COVID-19 Prognosis Score, BFGS: Broyden–Fletcher–Goldfarb–Shanno, SMOTE: Synthetic Minority Oversampling Technique, NPV: Negative Predictive Value, TRIPOD: Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis, MRPMC: Mortality Risk Prediction Model for COVID-19, ICU: Intensive Care Unit.

of medical setting, most of the subjects were inpatients. In the purpose of prediction section, mortality (n=27) was also the most common item. In addition, severe status, prognosis, diagnostic, ICU transfer, treatment, survival, hospitalization, incidence rate, discharge, outbreak rate, and SARS-CoV-2 antibodies were other cases that were obtained from the articles. Figure 2 demonstrates the frequency of variables from purpose of prediction.

Discussion

The authors conducted review on the 59 included

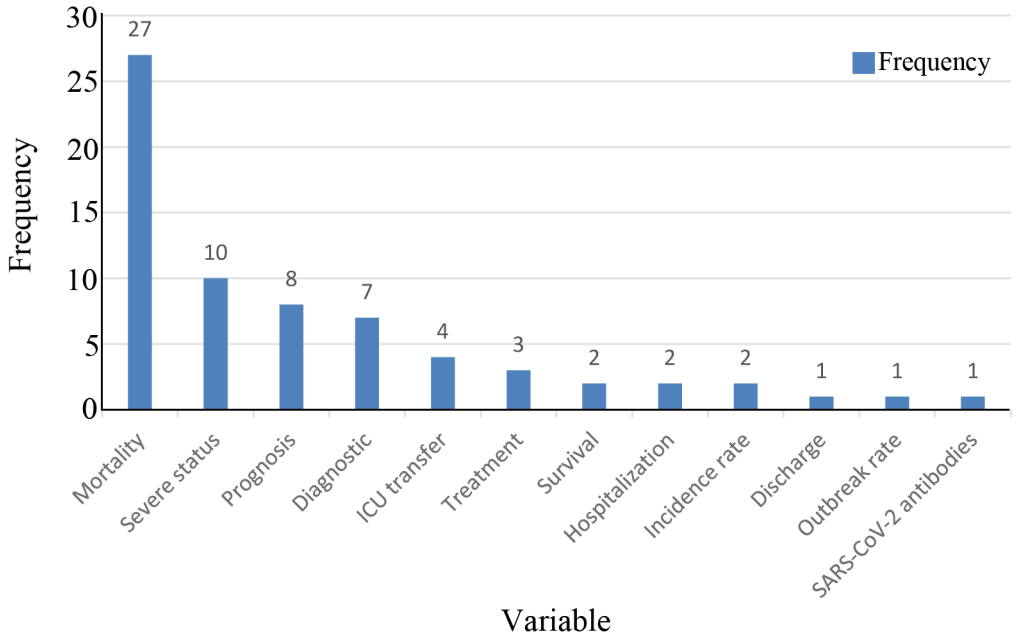

Figure 2. Frequency of the variables from purpose of the prediction.

studies from different countries like USA, China, Italy, Japan, Spain and France. The selected papers deal with different techniques used to help better management of COVID-19. Inpatient and outpatient populations were evaluated to assess the new methods' efficacy in risk prediction of COVID-19 to assist management in making decisions as soon as possible.

The majority of the studies identified in this review, used novel methodologies to predict mortality in COVID-19. These models also were used in order to detect or predict diagnosis, treatment, prognosis, early warning of severe symptoms like oxygen requirement and patients requiring intensive care (62,64,70).

Most of the studies were cohort and different modeling methods including ANN (Artificial Neural Networks), XGBoost model (eXtreme Gradient Boosting), GBDT (Gradient Boosted Decision Tree), also regression models like Multivariate logistic regression models, Univariate, and Multivariate COX regression were used (23,31,42). These prediction models utilized different types of data including demographic characteristics, laboratory tests, CT scan and imaging data (24,27,31,44).

One advantage of these models is that all these data can be prepared and collected by the physician very fast. They are time and money consuming and are available in most of the health-care centers. In the USA, Bolourani *et al* utilized XGBoost model on 11,525 patients with COVID-19. They collected patients' demographics, laboratory data, vital signs and treatment to predict 48-hour respiratory failure (31).

Tsui *et al*'s study was performed with patients demographic and laboratory data using scoring system to predict the prognosis. 1,037 COVID-19 laboratory-confirmed patients were evaluated and the prediction accuracy rate was 92.3 to 99.5% (75).

In a cohort study by Bartoletti *et al*, they collected patients' demographic data, comorbidities, laboratory tests and medical history for prediction of treatment on 1,113 patients with COVID-19. They utilized PREDI-CO score and risk factors for SRF (severe respiratory failure) (At a score of >3 specificity, positive predictive value and negative predictive value were 89.1%) (26).

Three studies also have used hematological and biochemical blood tests results included full blood count, glycemia, renal and liver function tests, creatine kinase, lactate dehydrogenase, C-reactive protein (CRP), procalcitonin, fibrinogen, D-dimer, troponin, ferritin and interleukin-6 (IL-6) as the predictors. But in these studies, other factors such as

patients' information, comorbidities, physical index, clinical observations and initial examination findings and chest X rays (CXR) findings were assessed. Therefore, the prediction rate is not specific to the blood tests (35, 40).

Vital signs of patients were mentioned as a predictor in five studies. These data source of information seemed to have less validation compared to other prediction tools (nearly 60-70% accuracy). COPS (COVID-19 Prognosis Score) and Cox proportional hazard regression model (which are based on demographic data, epidemiological characteristics, hemogram parameters at admission , maximal severity and clinical outcome) can estimate 28-day survival rates at the low-risk, intermediate-risk, high-risk and very high-risk condition (33,34).

During the COVID-19 pandemic, this system could aid in the allocation of medical resources, including intensive care, based on risk. Among demographic characteristics of patients, like gender, age, body mass index, comorbidities, *etc*., the single most important factor in surviving this viral infection has been reported to be age. Regarding the plausibility of models, and the time issue in mortality prediction, some models like admitted COVID-19 patients, XGBoost has the ability to predict 48-hour respiratory failure which is a valuable achievement (26,31).

Two studies used developed web-based tools to input patient data and to enable clinicians to view likelihood of critical disease and patients' need for critical care as a useful prognostication model (34,47). Models based on web applications have this advantage that anyone can access them. Moreover, sharing the AI models with the public has benefits in enhancing efficiency of tools and validating them. Almost all modeling methods reported good predictive performance. Most of the methods showed accuracy rates (or sensitivity) near 90% (range: 57-99.34%). Chung *et al* performed a cohort study on 5,601 patients with COVID-19 in South Korea. The XGBoost model was used to predict the COVID-19 severity via artificial intelligence. The sensitivity, specificity and balanced accuracy were all about 90% (35).

Study of Dixit *et al* also represented the 99% prediction accuracy rate of their model using artificial intelligence in interpreting chest X rays to diagnose the COVID-19 suspected patients (37). The predictive performance and validation of the studies were measured mostly by cross validation, validation cohort and C-index (50,52).

Although most of the studies were conducted in the USA and China, there were other studies from other countries like Israel, Australia, France, UK and Italy. Thus, different populations and races were included in this study and data were not limited to only one or two countries. This is an advantage of this study. Machine learning is a new technique, in which computers evaluate data. Different types of data were used in this method to evaluate and predict severity of disease, patients' mortality and treatment decision. Based on these results, machine learning methods found to be useful in predicting the future scenario of disease based on present facts and it can be used by healthcare professionals to make decisions for managing the COVID-19 accordingly. Although the sample size of the studies consists of nearly large populations from different countries, maybe further investigation should be done in order to generalize the results for all populations.

Conclusion

Artificial intelligence and deep learning are effective methods for detecting COVID-19 early and accurately. It may accelerate the diagnosis process and a step forward to automation and shortening of diagnostic evaluation. This innovation can aid in development and progression of clinical skills in diagnosis of the disease. It could help with disease control and prevention especially in emergency circumstances like COVID-19 pandemic. However, this new technique needs to be developed and refined and spread beyond clinicians to become more applicable.

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