Supplementary material

Systematic review and critical appraisal of prediction models for diagnosis and prognosis of covid-19 infection

Contents:

Search and screening

Data extraction

Supplementary Table 1. Overview of search dates, hits and inclusions

Supplementary Table 2. Overview of the primary datasets used in included studies

Supplementary Table 3. Overview of modelling techniques for diagnosis and prognosis of covid-19 infection

Supplementary material: search and screening

Search strings

arXiv: ncov or corona or Wuhan or COVID

Search strings for bioRxiv, medRxiv, PubMed, EMBASE are given on ispm.bern.github.io/covid-19/living-review/collectingdata.html

Validation

We validated the publicly available systematic review list to examine whether it is fit for purpose by comparing it to relevant hits from bioRxiv and medRxiv when combining covid-19 search terms (covid-19, sars-cov-2, novel corona, 2019-ncov) with methodological search terms (diagnostic, prognostic, prediction model, machine learning, artificial intelligence, algorithm, score, deep learning, regression) in March 2020. All relevant hits were found on the living systematic review list. We supplemented this list with hits from PubMed by searching for “covid-19” because when we performed our initial search this term was not included in the reported living systematic review search terms for PubMed.

AI for initial screening

As the amount of covid-19 literature increased exponentially over time, a new approach was needed to keep up with the literature. The results from manual screening of title and abstracts followed by full text review for final inclusion for the records retrieved up to 7 April were used to build a classification model for covid-19 prediction model studies, using the model building function within Eppi reviewer. To this end we used the final included studies within the review as relevant studies and the rest of the covid-19 retrieved studies as irrelevant documents. Eppi reviewer uses the standard SGCClassifier in Scikit-learn on word tri-grams. As output, new documents get a percentage (from the predict_proba function) where scores close to 100 indicate a high probability of belonging to the class ‘relevant document’ and scores close to 0 indicate a low probability of belonging to the class ‘relevant document’. The classifier was trained on the one set of screened articles (from searches up to March 24), and tested and retrained on a second set of screened articles (search date April 7).

Testing on the second set revealed poor positive predictive value but 100% sensitivity at a cut-off of 20%. The poor positive predictive value may be due to the broad scope of our topic (all prediction models in covid-19), poor reporting in abstracts, and small set of included documents. The model was retrained after adding the screening data of the second set, which added a considerable amount of additional documents. This led to a large increase in (apparent) positive predictive value, at the cost of a lower (apparent) sensitivity, which led us to reduce the cut-off to 10%. The largest proportion of documents had a score between 0%-9%. This set did not contain any of the relevant documents. This version of the classifier with cut-off 10% was used for the initial screening of the results from the search on May 5h, and saved around 80% of the screening burden.

Supplementary material: data extraction

Data were extracted on the following items:

- Population (China, other).

- Intended timing of model use (screening of patients, ICU admission, etc.).

- Setting (inpatients, outpatients, suspected cases).

- Participants: study design, recruitment method, number of centres, inclusion criteria, exclusion criteria, patient age (mean and standard deviation or median and interquartile range), patient sex (n males and percentage).

- Predictors: list of candidate predictors, number of candidate predictors, number of additional degrees of freedom for candidate predictors (e.g. for categorical variables with more than two categories or for modelling continuous variables non-linearly), predictors in the final model, number of predictors in the final model, number of additional degrees of freedom in the final model.

- Outcome: definition of outcome, timing of outcome.

- Analysis:

    - Total number of participants, total number of participants with the outcome.
    - Total number of participants with any missing predictor or outcome values.
    - Method for handling missing data.
    - Method for prediction model development (logistic regression, Cox regression, neural network, tree-based, etc.).
    - Method for selection of predictors during multivariable analysis and the criteria used (e.g., p-value used for selection).
    - Handling of categorical and continuous variables.
    - Method(s) for validation (e.g. apparent, internal or external) and for optimism adjustment.
    - Performance measures (calibration, discrimination, other) resulting from validation.
    - Model presentation (coefficients and confidence intervals, final model, alternative presentation formats of the model such as a web-based tool).

- Standard signalling questions and items to assess risk of bias according to PROBAST (Moons, Wolff, et al.), on four domains:
    - participants
    - predictors
    - outcome
    - analysis

If risk of bias was high in at least one of the subdomains, overall risk of bias was judged high, as per PROBAST guidance (Moons, Wolff, et al.).

Supplementary Table 1. Overview of Search dates, hits and inclusions.

search date	publication version	titles retrieved	full text screening	included papers	included models
13 March 2020	first pre-print (medRxiv) version	1916	/	/	/
24 March 2020	first published version (BMJ)	774	85	27	31
7 April 2020	first update (BMJ)	2213	114	24	35
5 May 2020	second update (BMJ)	9306	76	56	79

Supplementary Table 2. Overview of the primary datasets used in included studies.

	Authors	Description of dataset	Study design	Age mean ± se, median (IQR), or range	Sex (% male)
Hospital admission in general population					
	DeCaprio, Gartner, et al.	Medicare claims data 2015 to 2016	Administrative records	≥18	Unclear
	Update 2:				
	Jiang, Hu et al	Respiratory patients at Ruijin hospital and healthy volunteers, dates unknown	Nonnested case-control	Unclear	Unclear
Diagnosis					
	Feng, Huang, et al.	First medical centre, Chinese People's Liberation Army General Hospital, January 14 to February 9 (development) and February 10 to February 26 (validation)	Retrospective cohort	34 (IQR 29 to 42)	56%
	Lopez-Rincon, et al.	International repository of genome sequences from the China National Centre for Bioinformation (bigd.big.ac.cn/ncov), using all available samples on March 15	Unclear	Unclear	Unclear
	Meng, Wang, et al.	Various regional medical institutions in China, between December 20 to February 10	Nonnested case-control	Dev.: control: 68.5 (IQR 77 to 81), case: 46 (55 to 73); val.: control: 66 (IQR 76 to 84), case: 48 (58 to 67)	Dev.: control: 73%, case: 69%; val.: control: 69%, case: 69%
	Song, Xu, et al.	Zhijiang District of the First Affiliated Hospital of Zhejiang University School of Medicine	Unclear	38 (IQR 30 to 55)	49%
	Update 1:				
	Li, Fang, et al.	Hospital data from Zhuhai, China, January 18 to February 7	Unclear	45 ± 18	49%
	Martin, Nateqi, et al.	Simulated data based on published case reports	Unclear	Unclear	Unclear
	Sun, Koh, et al.	National Centre for Infectious Diseases (NCIP), Singapore, January 26 to February 16	Cross-sectional data	34 (median)	49%
	Wang, Weng, et al.	Second Affiliated Hospital and Yuying Children's Hospital of Wenzhou Medical University, Wenzhou, China, January 25 to March 3	Retrospective cohort	50 (IQR 37 to 58)	52%
	Wu, Zhang, et al.	Data from multiple sources, including Lanzhou Pulmonary Hospital, the First Hospital of Lanzhou University, Lanzhou University Second Hospital, the First People's Hospital of Lanzhou City, and Gansu Provincial Hospital	Unclear	Case: 47 (IQR 33 to 64) Control, pneumonia: 63 (IQR 47 to 75); Control, tuberculosis: 54 (IQR 33 to 68); Control, lung cancer: 61 (54 to 69)	Case: 48% Control, pneumonia: 48%; Control, tuberculosis: 60%; Control, lung cancer: 76%
	Update 2:				
	Batista, Miraglia et al	Hospital Israelita Albert Einstein, Sao Paolo, 17-30 March 2020	Unclear	49 ± 16	51
	Brinati, Campagner et al	IRCCS Ospedale San Raffaele Milan, end of February to mid March	Retrospective cohort	Histogram in paper	Unclear
	Chen, Tang et al	Case: 5 independent hospital from 4 cities (Huizhou, Shantou, Yongzhou, and Meizhou city), Control: Meizhou People's Hospital, 1 January to 8 February 8	Nonnested case-control	Unclear	Unclear
	Diaz-Quijano, Nunes da Silva et al	Brazilian National Surveillance information, Rio de Janeiro and Sao Paulo, 11 January to 25 March	Registry data	35 (IQR 27 to 48)	45

	Kurstjens, van der Horst et al.	Jeroen Bosch Hospital; Bernhoven Hospital; Elisabeth TweeSteden Hospital; Amphia Hospital, dates not specified	Unclear	Unclear	Case: 64, Contol: 43
	Mei, Lee et al.	18 medical centers in 13 provinces in China, 17 January and 3 March	Retrospective cohort	Case: 43, Control: 39 (mean)	Case: 50, Control: 58
	Menni, Valdes et al	Data from symptom tracker app in U.S. and U.K., 24 March to 21 April	Unclear	U.K. case: 41, U.K. control: 42, U.S. case: 45, U.S. control: 47	U.K. case: 28, U.K. control: 24
	Soares, Villavicencio et al	Albert Einstein Hospital, São Paolo, dates not mentioned	Unclear	Unclear	Unclear
	Tordjmann, Mekki et al	ED and infectious disease departments of three different hospitals (Cochin Hospital, Paris; Ambroise Paré Hospital, Boulogne; Raymond Poincaré Hospital, Garches), 15 March to 5 April 5	Retrospective cohort	57 ± 18	55
	Zhao, Wei et al	Central Hospital of Wuhan; Peking Union Medical College Hospital, 2 January to 15 (covid-19); 28 February to 3 April 3 2020 (infectious acute abdomen)	Nonnested case-control	53 (IQR 36 to 66)	47
	Diagnostic severity classification				
	Yu, Shao, et al.	Wuhan's Children's Hospital, February 1 to March 3	Retrospective cohort	0 to 15 (range)	61%
	Update 1:				
	Zhou, Yang, et al.	Hospital of Wuhan, China, January 1 to February 28	Retrospective cohort	Dev.: case: 65 ± 15, control: 49 ± 16; val.: case: 66 ± 12, control 47 ± 15	Dev.: Case: 45%, Control 66%; Val.: Case: 23%, Control: 36%
	Update 2:				
	Benchoufi, Bokobza et al	Three emergency units of Assistance Publique des Hôpitaux de Paris, 19 March to 1 April	Unclear	61 ± 17	65
	Chassagnon, Vakalopoulou, et al	Unclear, 4 March 4 to 29 March	Retrospective cohort	57 ± 17	62
	Li, Zhong et al	First Hospital of Changsha for test dataset, unknown for training, 23 January to 12 February for validation dataset, unknown to development dataset	Unclear	47 ± 15	49
	Lyu, Lui et al	The First Affiliated Hospital of Zhengzhou University, 15 January 2019 to 24 February 2020	Retrospective cohort	54 ± 17	57
	Wang, Deng et al	Jingzhou Central Hospital, 23 January to 13 February	Retrospective cohort	Unclear	51
	Zhu, Cai et al	Hwa Mei Hospital of the University of Chinese Academy of Sciences, Ningbo, Zhejiang province, China, 23 January to 20 February, 2020	Retrospective cohort	51 ± 15	35
	Diagnostic imaging				
	Barstugan, Ozkaya, et al.	Italian open data repository from the Societa Italiana di Radiologia Medica e Interventistica (sirm.org)	Unclear	Unclear	Unclear
	Chen, Wu, et al.*	Renmin Hospital of Wuhan University	Unclear	Cases: 52 (IQR 38 to 69) Controls: 48 (IQR 35 to 55)	Cases: 35% Controls: 56%
	Gozes, Frid-Adar, et al.	COVID cases: Wenzhou hospital (China), controls: chainz.cn registry, El Camino Hospital, California, LIDC registry (7 USA hospitals)	Nonnested case-control	Unclear	Unclear

	Jin, Chen, et al.	Wuhan Union Hospital, Western Campus of Wuhan Union Hospital, Jianghan Mobile Cabin Hospital Wuhan, January 11 to February 29 2020, LICD-IDRI registry from NCI, USA; ILD-HUG registry from University Hospitals of Geneva, Switzerland	Unclear	Unclear	Unclear
	Jin, Wang, et al.	Beijing Tsinghua Changgung Hospital, Wuhan No.7 Hospital, Zhongnan Hospital of Wuhan University, Tianyou Hospital Affiliated to Wuhan University of Science & Technology, Wuhan's Leishenshan Hospital, February 07 to February 20	Unclear	Unclear	Unclear
	Li, Qin, et al.	6 Chinese hospitals, August 16 2016 to February 17 2020 (covid-19 cases: December 31 2019 to February 17 2020)	Unclear	49 ± 15	55%
	Shan, Gao, et al.	Shanghai Public Health Clinical Centre and other centers in Shanghai	Unclear	Unclear	High
	Shi, Xia, et al.	Tongji Hospital of Huazhong University of Science and Technology, Shanghai Public Health Clinical Centre of Fudan University, and China-Japan Union Hospital of Jilin University	Nonnested case-control	Cases: 49 ± 14 years Controls: 56±14	Cases: 52% Controls: 46%
	Wang, Kang, et al.	Xi'an Jiaotong University First Affiliated Hospital, Nanchang University First Hospital and Xi'an No.8 Hospital of Xi'an Medical College	Unclear	Unclear	Unclear
	Xu, Jiang, et al.	First Affiliated Hospital of Zhejiang University, No. 6 People's Hospital of Wenzhou, No. 1 People's Hospital of Wenling, January 19 to February 14	Nonnested case control	Unclear	Unclear
	Ying, Zheng, et al.	Renmin Hospital of Wuhan University, Third Affiliated Hospital , Sun Yat-Sen Memorial Hospital	Unclear	Unclear	Unclear
	Zheng, Deng, et al.	Union Hospital, Tongji Medical College, Huazhong University of Science and Technology, December 13 to January 23	Retrospective cohort	Cases: 51 ± 15, control: 31 ± 10	Cases: 44%, Controls: 38%
	Update 1:				
	Abbas, Abdelsamea, et al.	Images from an international Github image repository, and controls from the Japanese Society of Radiological Technology, dates unclear.	Nonnested case-control	Unclear	Unclear
	Apostolopoulos, Mpesiana.	Images from Kaggle, including data from the Radiological Society of North America (RSNA), Radiopaedia, and the Italian Society of Medical and Interventional Radiology (SIRM), dates unclear. Controls are publically available images from China and the U.S (2013-2017).	Nonnested case-control	Unclear	Unclear
	Bukhari, Bukhari et al.	University of Montreal, Canada, and U.S.A. (locations unclear), dates unclear.	Unclear	Dev.: 63 (IQR 57 to 71); Val. 61 (IQR 56 to 64)	Dev.:51%; Val.: 53%
	Chaganti, Balachandran, et al.	Data from institutions in Europe, Canada, USA, dates unspecified.	Nonnested case-control	Unclear	Unclear
	Chowdhury, Rahman et al.	Various Italian centers, locations and dates not reported.	Other	Unclear	Unclear
	Fu, Yi et al.	Wuhan Jin Yin-Tan Hospital, Zhongshan Hospital Xiamen University, the fifth Hospital of Wuhan, January 1 2015 to February 29.	Unclear	Unclear	Unclear
	Gozes, Frid-Adar et al.	Covid-19 cases: chainz.cn registry (Chinese, January to February), a second dataset from Zhejiang Province, China with both cases and controls. Lung segmentation data from El Camino Hospital, California, and University Hospitals of Geneva (unclear whether these have covid-19 cases).	Unclear	Unclear	Unclear

	Imran, Posokhova, et al.	Cough samples of unspecified origin.	Unclear	Unclear	Unclear
	Li, Zhu et al.	The international Github image repository on covid-19, combined with controls from the Radiological Society of North America Kaggle data (2018).	Nonnested case-control	Unclear	Unclear
	Hassanien, Mahdy et al.	The international Github image repository on covid-19, combined with controls from the Montgomery County X-ray Set.	Unclear	Unclear	Unclear
	Tang, Zhao et al.	Seven hospitals with different types of CT scanners, presumably Chinese.	Unclear	45 ± 17	55%
	Wang, Zha et al.	Renmin Hospital of Wuhan University, Henan Provincial People's Hospital, the First Affiliated Hospital of Anhui Medical University, the First Hospital of China Medical University).	Retrospective cohort	Dev.: 51 ± 19 Val.: 49 ± 18; 58 ± 16	Dev.: 48% Val.: 58%; 67%
	Zhang, Xie, et al.	The international Github image repository on covid-19, combined with controls from the publically available Chestxray8 database (2017).	Nonnested case-control	Unclear	Unclear
	Zhou, Chen et al.	8 centers in China, May 2015 to Feb 2020.	Nonnested case-control	Dev.: control: 71 (IQR 60 to 81), case: 49 (38 to 57); Val.: control: 67 (IQR 60 to 79), case: 49 (35-63)	Dev.: control: 63%, case: 57%; Val.: controll: 66%, case: 54%
	Update 2:				
	Angelov, Soares	COVID-CT-Dataset (https://arxiv.org/abs/2003.13865), dates unclear	Nonnested case-control	Unclear	Unclear
	Arpan, Surya et al	covid-chestxray-dataset (github: https://github.com/ieee8023/covid-chestxray-dataset), dates unclear	Open source dataset collating X-ray images of patients with positive/suspected covid-19 or other viral pneumonias. Data collected from public sources, or indirect collection from hospitals.	Unclear	Unclear
	Bai, Wang et al.	9 hospitals in Hunan Providence, China; Rhode Island Hospital in Providence; Hospital of the University of Pennsylvania in Pennsylvania, US, 6 January to 1 April 2020 for covid-19 cases; 1 January 2017 to 30 December 2019 for pneumonia cases	Nonnested case-control	Unclear	Case:57, Control: 51
	Bassi, Attux	Taken from Chowdhurdy et al (2020): Italian Society of Medical and Interventional Radiology (SIRM) covid-19 DATABASE, Novel Corona Virus 2019 Dataset (Cohen et al. (2020)), Kaggle database Chest X-Ray images (Kermany et al. (2018), and other collected data from published articles, dates unclear	Nonnested case-control	Unclear	Unclear
	Borghesi, Maroldi	Department of Medical and Surgical Specialties, Radiological Sciences and Public Health, University of Brescia, dates unclear	Unclear	Unclear	Unclear
	Born, Brandle	Main sources of data were grepmed.com, thepocusatlas.com, butterflynetwork.com, radiopaedia.org, while individual samples were retrieved from everydayultrasound.com, and nephropocus. com amongst others. Created Github dataset from various sources	Nonnested case-control	Unclear	Unclear

		(https://github.com/ jannisborn/covid19_pocus_ultrasound), dates unclear			
	Castiglioni, Ippolito et al	Hospital San Gerardo, Monza, Italy; IRCCS Policlinico San Donato, Milan, Italy, 25 February to 19 March	Nonnested case-control	Unclear	Unclear
	Guiot, Vaidyanathan et al.	University hospitals Sart-Tilman and Notre Dame des Bruyères in Liège, Belgium, covid-19, start date unclear to 28 March 2020; Control 1 October to 24 October 2019	Nonnested case-control	Unclear	Case: 56, Control, 52
	Hu, Ruan et al	Data was assembled from 2 preprints: (1) J. Zhao, Y. Zhang, X. He, P. Xie, arXiv preprint arXiv: 2003.13865 (2020); (2) J.P. Cohen, P. Morrison, L. Dao, arXiv preprint arXiv: 2003.11597 (2020). The combined dataset is at: https://github.com/KevinHuRunWen/COVID-19, dates unclear	Nonnested case-control	Unclear	Unclear
	Islam, Fleischer	COVIDx dataset: https://github.com/lindawangg/COVID-Net, , dates unclear	Nonnested case-control	Unclear	Unclear
	Kana, Kana et al.	Development and internal validation: references: Kermany et al 2018 (http://dx.doi.org/10.17632/rscbjbr9sj.2); Cohen 2020 and additional 2585 background class images (https://github.com/ieee8023/covid-chestxraydataset/ tree/master/images), external validation: reference: Chowdhury et al 2020, dates unclear	Unclear	Unclear	Unclear
	Karim, Döhmen et al	https://github.com/ieee8023/covid-chestxraydataset; https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia; https://www.kaggle.com/c/rsna-pneumonia-detection-challenge; https://github.com/ieee8023/covid-chestxray-dataset; https://radiopaedia.org/articles/covid-19-3?lang=us; https://www.sirm.org/category/senza-categoria/covid-19/, dates unclear	Nonnested case-control	Unclear	Unclear
	Khan, Shah et al.	Two repositories: for covid-19 github by Joseph (Cohen et al. https://github.com/ieee8023/covid-chestxray-dataset. For normal, bacterial and viral pneumonia: Kaggel (Chest-X-Ray images (pneumonia) https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia), dates unclear	Unclear	Unclear	Unclear
	Kumar, Arora et al.	Shiley Eye Institute of the University of California San Diego, California Retinal Research Foundation, Medical Center Ophthalmology Associates, the Shanghai First People's Hospital, Beijing Tongren Eye Center, Guangzhou Women and Children's Medical Center, unclear center(s?) in Italy. Chest X-Ray Images (Pneumonia) on Kaggle: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia; covid-19 dataset via GooGgle Cloud: https://www.sirm.org/category/senza-categoria/covid-19/, dates unclear	Unclear	Unclear	Unclear
	Kumar, Arora et al.	Shiley Eye Institute of the University of California San Diego, California Retinal Research Foundation, Medical Center Ophthalmology Associates, the Shanghai First People's Hospital, Beijing Tongren Eye Center, Guangzhou Women and Children's Medical Center, unclear center(s?) in Italy,Chest X-Ray Images (Pneumonia) on Kaggle: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia; covid-19 dataset via GooGgle Cloud:	Unclear	Unclear	Unclear

		https://www.sirm.org/category/senza-categoria/covid-19/, dates unclear			
	Moutounet-Cartan	https://github.com/ieee8023/covid-chestxray-dataset; https://data.mendeley.com/datasets/rscbjbr9sj/2, dates unclear	Unclear	Unclear	Unclear
	Ozturk, Talo et al.	2 datasets were used: (1) J.P. Cohen, covid-19 Image Data Collection, 2020. https://github.com/ieee8023/COVID-chestxray-dataset; (2) X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, R.M. Summers, Chestx-ray8: hospital scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases, in: Proceedings of the IEEE conference on Computer Vision and Pattern Recognition, 2017, pp. 2097–2106, dates unclear	Nonnested case-control	Unclear	Unclear
	Rahimzadeh, Attar	2 datasets were used: (1) https://github.com/ieee8023/covid-chestxray-dataset (2) https://www.kaggle.com/c/rsna-pneumonia-detection-challenge, dates unclear	Nonnested case-control	Unclear	Unclear
	Rehman, Naz et al	Covid2019 chest Xray [located on Github, no link provided] Chest X-Ray Images (Pneumonia) [located on Kaggle, no link provided], dates unclear	Nonnested case-control	Unclear	Unclear
	Singh, Kumar et al	Chest CT images dataset, dates unclear	Nonnested case-control	Unclear	Unclear
	Ucar, Korkmaz	COVID chest X-ray dataset Kaggle chest X-ray pneumonia dataset, dates unclear	Nonnested case-control	Unclear reported	Unclear
	Wu, Gao, et al	COVID-CS dataset, dates unclear	Nonnested case-control	Unclear	covid-19 patients (n=400): 44%
Prognosis					
	Bai, Fang, et al.	Wuhan Pulmonary Hospital, January 3 to February 13	Retrospective cohort	53 ± 13	50%
	Caramelo, Ferreira, et al.	Simulated based on data from Wuhan, China, December 8 to February 11	Simulation	Unclear	41%
	Gong, Ou, et al:	Guangzhou Eigth People's Hospital, Zhongnan Hospital of Wuhan University, Third Affiliated Hospital of Sun Yat-sen University, January 20 to March 2	Retrospective cohort	Dev.: 49 Val.1: 52 Val.2: 42	Dev.: 47% Val.1: 44% Val.2: 50%
	Lu, Hu, et al.	Wuhan Hankou Hospital, January 21 to February 5	Retrospective cohort	Unclear	44%
	Qi, Jiang, et al.	5 hospitals from Ankang, Lishui, Zhenjiang, Lanzhou, Linxia between January 23 to February 8; date of last follow-up February 20	Prospective cohort	38 (IQR 26 to 47)	55%
	Shi, Yu, et al.	Hangzhou, Zhejiang Province, study dates unspecified, follow-up until February 17	Retrospective cohort	46 ± 19	53%
	Xie, Hungerford, et al.	Tongji Hospital and Jinyintan Hospital, admitted between January and February	Retrospective cohort	Tongji: 65 (IQR 54 to 73) Jinyintan: 56 (IQR 47 to 68)	Tongji: 52% Jinyintan: 35%
	Yan, Zhang, et al.	Tongji Hospital Wuhan, January 10 to February 18	Retrospective cohort	59 ± 16	59%
	Yuan, Yin, et al.	Hubei Public Health Clinical Centre; central Hospital of Wuhan, January 1 to January 25	Retrospective cohort	60 (IQR 47 to 69)	44%
	Update 1:				

	Huang, Cai et al.	Guangzhou 8th People's Hospital, January 20 to February 29	Retrospective cohort	45 ± 19	50%
	Pourhomayoun, Shakibi et al.	Publicly available data on Github from nCov-2019 Data Working Group with confirmed cases worldwide (76 countries) in a variety of settings.	Unclear	57 (mean)	Unclear
	Sakar, Chakrabarti	Kaggle data with cases from 22 countries in Asia, Australia, Europe, North America, January 13 to February 28.	Unclear	Unclear	Unclear
	Wang, Zha et al.	Renmin Hospital of Wuhan University, Henan Provincial People’s Hospital, Beijing Youan Hospital of Capital Medical University, Huangshi Central Hospital)	Retrospective cohort	Dev. 51 ± 19; Val. 50 ± 19, 48 ± 14	Dev. 48%; Val. 47%, 51%
	Zeng, Li et al.	Third People’s hospital of Shenzhen (Shenzhen, China) from January 11 to February 29	Retrospective cohort	Severe: 58.7 (11), non-severe: 46.1 (14.1)	Severe: 62% non-severe: 44%
	Update 2:				
	Al - Najjar, Al-Rousan	Official time series data from the Korea Centers for Disease Control and Prevention (KCDC), Unclear start date of inclusion to 9 March	Registry data	Unclear	Unclear
	Barda, Riesel et al	Data warehouse of Clalit Health Services (payer-provider), 29 January to 8 April inclusion, follow-up until 22 April (covid cases for external validation)	Retrospective cohort	41 ± 21.26	49
	Bello-Chavolla, Bahena-Lopez et al	General Directorate of Epidemiology of Mexican Ministry of Health, dates not reported	Surveillance data	47 ± 16	58
	Carr, Bendayan et al	King's College Hospital NHS Foundation Trust hospital, 1 March 1 to 5 April	Retrospective cohort	67 ± 28	55
	Chassagnon, Vakalopoulou, et al	Unclear, 4 March to 29 March	Retrospective cohort	63 ± 16	67
	Colombi, Bodini et al	“Guglielmo da Saliceto” Hospital, Piacenza, Italy, 17 February to 10 March	Retrospective cohort	Unclear	75
	Das, Mishra, et al	Data shared by Korea Centers for Disease Control and Prevention, 20 January to 7 April 7	Retrospective cohort	Unclear	44
	Guo, Liu et al.	35 hospitals in Guangdong Province and Hubei Province, 27 December 2019, to 4 March 2020	Retrospective cohort	42 (IQR 31 to 57)	48
	Hu, Liu et al	Sino-French New City Branch of Tongji Hospital (n=183; Dev) and Optical Valley Branch of Tongji Hospital (n=64; Val), 28 January 2020 to 11 March 2020 (dev)	Dev: Retrospective cohort , Val: Unclear	68 ± 10 in non-survivors; 61 ± 13 in survivors in non-survivors	58
	Hu, Yao et al	Electronic patient care reports from an emergency medical team that collected in Wuhan from 7 February 7 to 7 March	Retrospective cohort	61 ± 16	51
	Ji, Zhang et al	Fuyang Second People’s Hospital (FYSPH), Anhui; the fifth medical center of Chinese PLA general hospital (PLAGH), Beijing, Unclear; data collected from 20 January through 22 February	Retrospective cohort	44 ± 16	56
	Jiang, Coffee et al	Wenzhou Central Hospital and Cangnan People’s Hospital in Wenzhou, China, dates not reported	Prospective cohort	43 (IQR 32, 49)	62
	Levy, Richardson et al.	Northwell Health acute care hospitals (New York metropolitan area), 1 March 1 to 12 April	Retrospective cohort	Unclear	58
	Liu, Fang et al.	Wuhan Pulmonary Hospital, 28 January to 8 March	Retrospective cohort	Unclear	alive: 50, died 57
	McRae, Simmons et al.	development: Wuhan, China Hospital, external validation: Hospital in Shenzhen, China, dates unclear	Dev: Retrospective	Unclear	discharged: 44, died: 70

			cohort , Val: Unclear		
	Singh, Valley et al	Michigan Medicine, between 9 March, 2020 and 7 April, 2020	Dev: Retrospective cohort , Val: Registry data	61 (IQR 50 to 71)	58
	Vaid, Somani et al	Mount Sinai Health System, 9 March to 11 April	Unclear	62 (IQR 49 to 92)	58
	Vazquez Guillamet, Vazquez Guillamet et al.	Medical Decision Network, Charlottesville & Barnes Jewish Hospital dataset, 1 January 2015 to 30 September 2015 & 2016 to 2019	Dev: Retrospective cohort , Val: Unclear	Unclear	47
	Vazquez Guillamet, Vazquez Guillamet et al.	Medical Decision Network, Charlottesville & Barnes Jewish Hospital dataset, Jan 1, 2015 to September 30, 2015 & 2016 to 2019	Retrospective cohort	Unclear	47
	Vazquez Guillamet, Vazquez Guillamet et al.	Medical Decision Network, Charlottesville & Barnes Jewish Hospital dataset, Jan 1, 2015 to September 30, 2015 & 2016 to 2019	Retrospective cohort	Unclear	47
	Zhang, Shi et al	Wuhan Sixth Hospital ;Taikang Tongji Hopsital; King's College Hospital, 1 February to 23 February, 1 March to 8 April	Unclear	61 (IQR 50 to 68)	49

* The study also included a prospective validation cohort of 27 consecutive patients (11 with covid-19 pneumonia)

Supplementary Table 3. Overview of modelling techniques for diagnosis and prognosis of covid-19 infection.

Study	Outcome	Predictors in final model	Modelling technique
Hospital admission in general population			
Decaprio, Gartner, et al.	Hospital admission for covid-19 pneumonia (proxy events)*1	Age, sex, number of previous hospital admissions, 11 diagnostic features, interactions between age and diagnostic features	Logistic regression
Decaprio, Gartner, et al.	Hospital admission for covid-19 pneumonia (proxy events)*1	Age and 500+ features related to diagnosis history	Tree-based (XGBoost)
Decaprio, Gartner, et al.	Hospital admission for covid-19 pneumonia (proxy events)*1	500+ undisclosed features, including age, diagnostic history, social determinants of health, Charlson comorbidity index	Tree-based (XGBoost)
Update 2:			
Jiang, Hu et al.	Detection of respiratory diseases such as covid-19	Infrared/thermal video of face	Neural net (Recurrent neural network: BiGRU-AT)
Diagnosis			
Feng, Huang, et al.	Suspected covid-19 pneumonia	Age, temperature, heart rate, diastolic blood pressure, systolic blood pressure, basophil count, platelet count, mean corpuscular haemoglobin content, eosinophil count, monocyte count, fever, shiver, shortness of breath, headache, fatigue, sore throat, fever classification, interleukin-6	Logistic regression (LASSO) (vs. Logistic regression (ridge), decision tree, Adaboost)
Lopez-Rincon, et al.	covid-19 diagnosis	Specific sequences of base pairs	Neural net (deep convolutional neural network)
Meng, Wang, et al.	COVID-19 diagnosis	Age, activated partial thromboplastin time, red blood cell distribution width-CD, uric acid, triglyceride, serum potassium, albumin/globulin, 3-hydroxybutyrate, serum calcium	LASSO followed by logistic regression
Song, Xu, et al.	COVID-19 diagnosis	Fever, history of close contact, signs of pneumonia on CT, neutrophil-to-lymphocyte ratio, highest body temperature, sex, (age, meaningful respiratory syndromes)	Logistic regression
Update 1:			
Martin, Nateqi, et al.	Covid-19 diagnosis	Unknown	Unclear
Sun, Koh, et al.	Covid-19 diagnosis	Age, sex, temperature, heart rate, systolic blood pressure, diastolic blood pressure, sore throat	Logistic regression
Sun, Koh, et al.	Covid-19 diagnosis	Sex, temperature, heart rate, respiration rate, diastolic blood pressure, sore throat, sputum production, shortness of breath, gastrointestinal symptoms, lymphocytes, neutrophils, eosinophils, creatinine	Logistic regression
Sun, Koh, et al.	Covid-19 diagnosis	Sex, covid-19 case contact, travel to Wuhan, travel to China, temperature, heart rate, respiration rate, diastolic blood pressure, sore throat, sputum production, gastrointestinal symptoms, CXR/CT suggestive of pneumonia, neutrophils, eosinophils, creatinine, sodium	Logistic regression
Sun, Koh, et al.	Covid-19 diagnosis	Sex, covid-19 case contact, travel to Wuhan, travel to China, temperature, heart rate, respiration rate, diastolic blood pressure, sore throat, sputum production, gastrointestinal symptoms, CXR/CT	Logistic regression

			suggestive of pneumonia, neutrophils, eosinophils, creatinine, sodium	
	Wang, Weng, et al.	Covid-19 pneumonia	epidemiological history, wedge-shaped or fan-shaped lesion parallel to or near the pleura, bilateral lower lobes, ground glass opacities, crazy paving pattern, WBC count	Logistic regression (LASSO)
	Wu, Zhang, et al.	Covid-19 diagnosis	Lactate dehydrogenase, calcium, creatinine, total protein, total bilirubin, basophil, platelet distribution width, kalium, magnesium, creatine kinase isoenzyme, glucose	Tree-based (random forest)
	Update 2:			
	Batista, Miraglia et al.	Covid-19 diagnosis	Age, gender, haemoglobin, platelets, red blood cells, mean corpuscular hemoglobin concentration, mean corpuscular hemoglobin, red cell distribution width , mean corpuscular volume, leukocytes, lymphocytes, monocytes, basophils, eosinophils and c-reactive protein	Support vector machine
	Brinati, Campagner et al.	Covid-19 diagnosis	Age, aspartate aminotransferase, lymphocytes, lactodehydrogenase, PCR, WBC count, eosinophils, alanine transaminase, neutrophils, gamma-glutamyltransferase, monocytes, basophils, alkaline phosphatase, platelets	Tree-based (random forest)
	Brinati, Campagner et al.	Covid-19 diagnosis	Age, aspartate aminotransferase, lymphocytes, lactodehydrogenase, PCR, WBC count, eosinophils, alanine transaminase, neutrophils, gamma-glutamyltransferase, monocytes, basophils, alkaline phosphatase, platelets	Tree-based (Three-way random forest)
	Chen, Tang et al.	Covid-19 diagnosis	Total number of mixed GGO in peripheral area, Tree-in-bud, offending vessel augmentation in lesions, respiration, heart ratio, temperature, WBC count, cough, fatigue, lymphocyte count	Logistic regression
	Diaz-Quijano, Nunes da Silva et al.	Covid-19 diagnosis	Age, days after reporting first confirmed case in federal unit, fever, cough, sore throat, diarrhea, coryza, chills, pulmonary manifestation, other signs, HIV, kidney diseaes, trip outside Brazil up to 14 days before onset	Logistic regression
	Kurstjens, van der Horst et al.	Covid-19 diagnosis	Age, sex, CRP, LD, ferritin, absolute neutrophil count, absolute lymphocyte count, chest X-ray	Unclear
	Mei, Lee et al.	Covid-19 diagnosis	Age, sex, CT imaging, exposure history, symptoms (present or absent of fever, cough and/or sputum), WBC counts, neutrophil counts, percentage neutrophils, lymphocyte counts, percentage lymphocytes	Neural net (MLP jointly trained with CNN)
	Menni, Valdes et al.	Covid-19 diagnosis	age, sex, loss of smell and taste, severe or significant persistent cough, severe fatigue, skipped meals	Logistic regression
	Soares, Villavicencio et al.		Age, red blood cells, mean corpuscular volume, mean corpuscular hemoglobin concentration, mean corpuscular hemoglobin, red blood cell distribution width, leukocytes, basophils, monocytes, lymphocytes, platelets, mean platelet volume, creatinine, potassium, sodium, CRP	Support vector machine (Ensemble with SMOTEboost)
	Tordjmann, Mekki et al.	Covid-19 diagnosis	Eosinophils, lymphocytes, neutrophils, basophils	Logistic regression
	Zhao, Wei et al.	Covid-19 diagnosis	fever, chest CT, CRP, PCT, WBC	Logistic regression
	Diagnostic severity classification			
	Yu, Shao, et al.	Severe disease (yes/no) defined based on clinical symptoms	Direct Bilirubin, Alanine transaminase	Tree-based (decision tree)
	Update 1:			
	Zhou, Yang, et al.	Severe covid-19 pneumonia	Age, sex, onset-admission time, high BP, diabetes, CHD, COPD, white blood cell counts, lymphocyte, neutrophils, alanine transaminase,	Logistic regression

			aspartate aminotransferase, serum albumin, serum creatinine, blood urea nitrogen, CRP	
	Update 2:			
	Benchoufi, Bokobza et al .	Lung injury severity (pathologic vs normal)	lung ultrasound scores for 8 quadrants in a global score	Logistic regression (adding up the scores from the 8 quadrant in univariable logistic regression)
	Chassagnon, Vakalopoulou, et al.	Severe covid-19	Unclear	Support Vector Machines, Decision Trees, Random Forests, AdaBoost, and Gaussian Naive Bayes. Prediction made by winner takes all principle. (Lasso/Ridge)
	Li, Zhong et al.	Severe covid-19	Portion of infection, average infection Hounsfield unit, a measure of radio density	Logistic regression
	Lyu, Lui et al.	Severe/critical covid-19 pneumonia	Unclear	Unclear
	Lyu, Lui et al.	Critical covid-19 pneumonia	Unclear	Unclear
	Wang, Deng et al.	Severe covid-19	Neutrophil-to-lymphocyte ratio, red cell volume distribution width	Linear discriminant analysis
	Zhu, Cai et al.	Severe covid-19	peripheral blood cytokine IL-6, CRP, hypertension	Logistic regression
Diagnostic imaging				
	Barstugan, Ozkaya, et al	COVID-19 diagnosis	Not applicable	Support vector machine
	Chen, Wu, et al.	COVID-19 pneumonia	Not applicable	Neural net (Unet ++)
	Gozes, Frid-Adar, et al.	COVID-19 diagnosis	Not applicable	Neural net (deep convolutional neural network)
	Jin, Chen, et al.	COVID-19 diagnosis	Not applicable	Neural net (various segmentation and classification models)
	Jin, Wang, et al.	COVID-19 pneumonia	Not applicable	Neural net (convolutional neural network)
	Li, Qin, et al.	COVID-19 diagnosis	Not applicable	Neural net (COVNet)
	Shan, Gao, et al.	Segmentation and quantification of infection regions in lung from chest CT scans.	Not applicable	Neural net (VB-Net)
	Shi, Xia, et al.	COVID-19 pneumonia	5 categories of location features from imaging: volume, number, histogram, surface, radiomics	LASSO followed by tree-based (infection size-aware random forest (iSARF) method vs. logistic regression, support vector machine, Neural net.

	Wang, Kang, et al.	COVID-19 diagnosis	Not applicable	Neural net (convolutional neural network)
	Xu, Jiang, et al.	COVID-19 diagnosis	Not applicable	Neural net (convolutional neural network)
	Ying, Zheng, et al.	diagnosis of COVID-19 vs healthy controls	Not applicable	Neural net (DRENet vs. VGG16, DenseNet, ResNet for comparison)
	Ying, Zheng, et al.	diagnosis of COVID-19 vs bacterial pneumonia	Not applicable	Neural net (DRENet vs. VGG16, DenseNet, ResNet for comparison)
	Zheng, Deng, et al.	COVID19 diagnosis	Not applicable	Neural net (DeCovNet)
	Update 1:			
	Abbas, Abdelsamea, et al.	covid-19 diagnosis	Not applicable	Neural net (convolutional neural network, DeTraC)
	Apostolopoulos, Mpesiana.	covid-19 diagnosis	Not applicable	Neural net (extension of pretrained deep convolutional neural network MobileNetv2)
	Bukhari, Bukhari et al.	covid-19 diagnosis	Not applicable	Neural net (convolutional neural network ResNet-50)
	Chaganti, Balachandran, et al.	percentage lung opacity	Not applicable	Neural net (deep reinforcement learning followed by DI2N, DenseUNet)
	Chaganti, Balachandran, et al.	percentage high lung opacity	Not applicable	Neural net (deep reinforcement learning followed by DI2N, DenseUNet)
	Chaganti, Balachandran, et al.	Severity score	Not applicable	Neural net (deep reinforcement learning followed by DI2N, DenseUNet)
	Chaganti, Balachandran, et al.	Long opacity score	Not applicable	Neural net (deep reinforcement learning followed by DI2N, DenseUNet)
	Chowdhury, Rahman et al.	covid-19 vs ‘normal’ and viral pneumonia	Not applicable	Neural net (convolutional neural net SqueezeNet)
	Chowdhury, Rahman et al.	covid-19 vs ‘normal’ and viral pneumonia	Not applicable	Neural net (convolutional neural net SqueezeNet)
	Fu, Yi et al.	covid-19 diagnosis	Not applicable	Neural net (ResNet-50)
	Gozes, Frid-Adar et al.	covid-19 diagnosis	Not applicable	Neural net (U-net, ResNet-50)

	Imran, Posokhova, et al.	covid-19 diagnosis	Not applicable	Ensemble of three methods (Deep Learning-based Multi Class classifier, Classical Machine Learning-based Multi Class classifier, Deep Learning-based Binary Class classifier)
	Li, Fang, et al.	severe and critical covid-19 disease	Severity score based on CT scans	NA (external validation)
	Li, Zhu et al.	covid-19 disease	Not applicable	Neural net (convolutional neural network DenseNet-121)
	Hassanien, Mahdy et al.	covid-19 disease	Not applicable	Support vector machine
	Tang, Zhao et al.	covid-19 severe vs non-severe	Not applicable	Tree-based (Random forest)
	Wang, Zha et al.	covid-19 disease	Not applicable	Neural net
	Zhang, Xie, et al.	covid-19 disease	Not applicable	Neural net (extension of pretrained residual convolutional neural network)
	Zhou, Chen et al.	covid-19 diagnosis	Not applicable	Neural net (DenseNet121-FPN, COVID-19Net)
	Update 2:			
	Angelov, Soares.	Covid-19 diagnosis	Not applicable	Neural net (deep neural network)
	Arpan, Surya et al.	Covid-19 diagnosis	Not applicable	Neural net (A pre-trained CheXNet, with a 121-layer Dense Convolutional Network (DenseNet) backbone, followed by a fully connected layer. The deep neural network is a classification layer of 4 classes)
	Bai, Wang et al.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural network)
	Bassi, Attux.	Covid-19 diagnosis	Not applicable	Neural net (deep neural network)
	Borghesi, Maroldi.	Severity of COVID-19 pneumonia	Sum score for lung abnormalities based on X-ray	Sum score from various zones
	Born, Brandle.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural network)
	Castiglioni, Ippolito et al.	Covid-19 diagnosis	Not applicable	Neural net (nsemble of 10 convolutional neural networks (ResNET50) with sum vote rule)
	Guiot, Vaidyanathan et al.	Covid-19 diagnosis	30 radiomics features	Multivariable logistic regression

				with Elastic Net regularization
	Hu, Ruan et al.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural network - ShuffleNet V2)
	Islam, Fleischer.	Covid-19 diagnosis	Not applicable	Neural net (DenseNet-121 architecture)
	Kana, Kana et al.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural networks with transfer learning)
	Karim, Döhmen et al.	Covid-19 diagnosis	Not applicable	Neural net (ensemble of VGG-19, ResNet18 and DenseNet-161)
	Khan, Shah et al.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural networks with transfer learning)
	Kumar, Arora et al.	Covid-19 diagnosis	Not applicable	Tree-based (Random forest)
	Kumar, Arora et al.	Covid-19 diagnosis	Not applicable	XGBoost
	Moutounet-Cartan.	Covid-19 pneumonia	Not applicable	Neural net (Deep convolutional neural network following VGG16 architecture)
	Ozturk, Talo et al.	Covid-19 pneumonia	Not applicable	Neural net (convolutional neural network)
	Rahimzadeh, Attar.	Covid-19 pneumonia	Not applicable	Neural net (neural network combining Xception and ResNet50V2 networks)
	Rehman, Naz et al.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural networks)
	Rehman, Naz et al.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural networks)
	Rehman, Naz et al.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural networks)
	Rehman, Naz et al.	Covid-19 diagnosis	Not applicable	Neural net (Convolutional neural networks)
	Rehman, Naz et al.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural networks)
	Singh, Kumar et al.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural networks)
	Ucar, Korkmaz.	Covid-19 diagnosis	Not applicable	Neural net (convolutional neural networks Deep Bayes-SqueezeNet based)
	Wu, Gao, et al.	Covid-19 diagnosis	Not applicable	Neural net (Res2Net)
Prognosis				
	Bai, Fang, et al.	Deterioration into severe/critical disease (period unspecified)	Combination of demographics, signs and symptoms, laboratory results and features derived from CT images	Neural net (Multilayer perceptron + long

				short term memory vs. logistic regression, linear discriminant analysis, support vector machine, multilayer perceptron)
	Caramelo, Ferreira, et al.	Mortality (period unspecified) *2	Age, sex, presence of any comorbidity (hypertension, diabetes, cardiovascular disease, chronic respiratory disease, cancer) *3	Logistic regression
	Gong, Ou, et al.	Severe COVID-19 infection (minimum 15 day)	Age, serum LDH, CRP, variation of red blood cell distribution width, blood urea nitrogen, albumin, direct bilirubin	LASSO followed by logistic regression (vs. LASSO followed by decision tree, random forest or support vector machine)
	Lu, Hu, et al.	Mortality (12 day)	Age, C-reactive protein	Cox regression
	Qi, Jiang, et al	Hospital stay >10 days	6 features derived from CT images *3	Logistic regression
	Qi, Jiang, et al	Hospital stay >10 days	6 features derived from CT images *3	Tree-based (random forest)
	Shi, Yu, et al.	Death or severe COVID-19 (period unspecified)	Age (dichotomized), sex, hypertension	Multivariate model (not specified)
	Xie, Hungerford, et al.	Mortality (in hospital)	Age, LDH, lymphocyte count, SPO2	Logistic regression
	Yan, Zhang, et al.	Mortality (period unspecified)	Lactic dehydrogenase, lymphocyte count, high-sensitivity C-reactive protein	Tree-based (XGBoost)
	Yuan, Yin, et al.	Mortality (period unspecified)	Clinical scorings of CT images (zone, left/right, location, attenuation, distribution of affected parenchyma)	NA (external validation)
	Update 1:			
	Huang, Cai et al.	severe symptoms 3 days after admission	Underlying diseases, fast respiratory rate >24/min, elevated CRP-level (> 10mg/dL), elevated lactate dehydrogenase level (> 250U/L)	Logistic regression
	Pourhomayoun, Shakibi et al.	in-hospital mortality (period unspecified)	Unknown	Neural net (Neural Networks vs. Support Vector Machine (SVM), Random Forest, Decision Tree, Logistic Regression, and K-Nearest Neighbour (KNN))
	Sakar, Chakrabarti	death vs recovery (period unspecified)	Age, days from symptom onset to hospitalisation, from Wuhan, sex, visit to Wuhan	Tree-based (Random forest)
	Wang, Zha et al.	length of hospital stay	Age and CT features	Cox regression
	Zeng, Li et al.	severe disease progression (period unspecified)	CT features	LASSO followed by Fine and Gray
	Zeng, Li et al.	severe disease progression (period unspecified)	CT features and laboratory markers	LASSO followed by Fine and Gray
	Update 2:			
	Al - Najjar, Al-Rousan et al.	recovery from covid-19 (period unspecified)	birth year (age), sex, country, group, infection reason, confirmed date	Neural net (one hidden layer and gradient descent as

				an optimization algorithm)
	Al - Najjar, Al-Rousan et al.	mortality (period unspecified)	Age, sex, country, region, infection reason, confirmed date	Neural net (one hidden layer and gradient descent as an optimization algorithm)
	Barda, Riesel et al.	mortality (period unspecified)	Age, sex, pack years, COPD, number of wheezing/dyspnea diagnoses, albumin, red cell distribution width, c-reactive peptide, urea, lymphocyte, chloride, creatinine, high density lipoprotein, duration of hospitalizations, count of hospitalizations, count of ambulance rides, count of sulfonamide dispenses, count of anticholinergic dispenses, count of glucocorticoid dispenses, chronic respiratory disease, cardiovascular disease, diabetes, malignancy, hypertension	Tree-based (gradient boosted tree)
	Bello-Chavolla, Bahena-Lopez et al.	30-day mortality	Age, pregnancy, diabetes, obesity, pneumonia, CKD, COPD, immunosuppression	Cox proportional hazards regression
	Carr, Bendayan et al.	progression to severe covid-19 (period unspecified)	Age, National Early Warning Score (NEWS) 2, CRP, neutrophil, eGFR, albumin	Logistic regression
	Chassagnon, Vakalopoulou, et al.	composite, 4-day intubation or mortality	Unclear	Support Vector Machines, Decision Trees, Random Forests, AdaBoost, and Gaussian Naive Bayes. Prediction made by winner takes all principle (Lasso/Ridge)
	Colombi, Bodini et al.	ICU admission or in-hospital (period unspecified)	Age, cardiovascular comorbidities, median platelet count, CRP, visual assessment of well aerated lung %	Logistic regression
	Colombi, Bodini et al.	ICU admission or in-hospital mortality (period unspecified)	Age, cardiovascular comorbidities, median platelet count, LDH, CRP, software assessment of well aerated lung absolute volume, adipose tissue	Logistic regression
	Das, Mishra, et al.	ICU admission or in-hospital mortality (period unspecified)	Age, sex, province, date of diagnosis, place of exposure to covid-19	Gradient boosting algorithm
	Gong, Ou et al.	15-day progression to severe covid-19	Age, direct bilirubin, red cell distribution width, blood urea nitrogen, CRP, lactate dehydrogenase, albumin	Logistic regression
	Guo, Liu et al.	14-day progression to severe covid-19	Age, chronic illness, neutrophil to lymphocyte ratio, CRP, D-dimer	Cox proportional hazards regression
	Hu, Liu et al.	in-hospital mortality (period unspecified)	Age, high-sensitivity CRP, lymphocyte count, D-dimer	Logistic regression
	Hu, Yao et al.	in-hospital mortality (period unspecified)	Modified Early Warning Score (MEWS): heart rate, systolic blood pressure, respiratory rate, body temperature, consciousness	
	Hu, Yao et al.	in-hospital mortality (period unspecified)	Rapid Emergency Medicine Score (REMS): mean arterial pressure, pulse rate, respiratory rate, oxygen saturation, GCS, age	
	Ji, Zhang et al.	10-day progression to severe COVID-19	Comorbidity, age, lymphocyte count, lactate dehydrogenase	Cox proportional hazards regression
	Jiang, Coffee et al.	acute respiratory distress syndrome	Alanine aminotransferase, myalgias, hemoglobin, gender, temp, Na+, K+, lymphocyte count, creatinine, age, white blood count	Logistic regression
	Jiang, Coffee et al.	acute respiratory distress syndrome	Alanine aminotransferase, myalgias, hemoglobin, gender, temp, Na+, K+, lymphocyte count, creatinine, age, white blood count	K nearest neighbour
	Jiang, Coffee et al.	acute respiratory distress syndrome	Alanine aminotransferase, myalgias, hemoglobin, gender, temp, Na+, K+, lymphocyte count, creatinine, age, white blood count	Tree-based (decision tree (gain ratio))
	Jiang, Coffee et al.	acute respiratory distress syndrome	Alanine aminotransferase, myalgias, hemoglobin, gender, temp, Na+, K+, lymphocyte count, creatinine, age, white blood count	Tree-based (decision tree (gini index))
	Jiang, Coffee et al.	acute respiratory distress syndrome	Alanine aminotransferase, myalgias, hemoglobin, gender, temp, Na+, K+, lymphocyte count, creatinine, age, white blood count	Tree-based (random forest)

	Jiang, Coffee et al.	acute respiratory distress syndrome	Alanine aminotransferase, myalgias, hemoglobin, gender, temp, Na+, K+, lymphocyte count, creatinine, age, white blood count	Support vector machine
	Levy, Richardson et al.	in-hospital mortalitiy (period unspecified)	Age, serum blood urea nitrogen, emergency severity index, red cell distribution width, absolute neutrophil count, serum bicarbonate, glucose	Logistic regression (Lasso/Ridge)
	Levy, Richardson et al.	in-hospital mortalitiy (period unspecified)	SOFA score	
	Levy, Richardson et al.	in-hospital mortalitiy (period unspecified)	CURB-65 score	
	Levy, Richardson et al.	in-hospital mortalitiy (period unspecified)	SOFA+ score	
	Liu, Fang et al.	in-hospital mortalitiy (period unspecified)	Age, underlying disease status, helper T cells, Helper T cells and Suppressor T cells ratio	Logistic regression
	McRae, Simmons et al.	in-hospital mortalitiy (period unspecified)	Age, sex, cardiac troponin I, CRP, procalcitonin, myoglobin	Logistic regression (Lasso)
	Singh, Valley et al.	ICU-level care, mechanical ventilation or in-hospital mortality (period unspecified)	Epic Deterioration Index	
	Vaid, Somani et al.	intubation, discharge to hospice care or mortalit (period unspecified)	Sex, race, ethnicity, age, hypertension, atrial fibrillation, coronary artery disease, heart failure, stroke, chronic kidney disease, diabetes, asthma, COPD, cancer, heart rate, pulse, oximetry, respiration rate, temperature, systolic blood pressure, diastolic blood pressure, body weight, sodium, potassium, creatinine, lactate, white blood cells, lymphocyte percentage, haemoglobin, red blood cell distribution width, platelets, alanine, aminotransferase, aspartate, aminotransferase, albumin, total bilirubin, prothrombin time, partial thromboplastin time, PCO2, pH, CRP, ferritin, D-dimer, creatinine phosphokinase, lactate dehydrogenase, procalcitonin, troponin I	Tree-based (XGBoost)
	Vazquez Guillamet, Vazquez Guillamet et al.	in-hospital mortalitiy (period unspecified)	Age, immunosuppression, COPD, congestive heart failure, BMI, sex, tme to mechanical ventilation (days), length of hospital stay prior to hospital admission, PaO2 /FiO2, Glasgow coma scale, maximum Heart rate, maximum respiratory rate, minimum mean arterial blood pressure, maximum temperature, minimum albumin, minimum pH	Logistic regression
	Vazquez Guillamet, Vazquez Guillamet et al.	mechanical ventilation > 96 hours	Age, immunosuppression, COPD, congestive heart failure, BMI, sex, tme to mechanical ventilation (days), length of hospital stay prior to hospital admission, PaO2 /FiO2, Glasgow coma scale, maximum Heart rate, maximum respiratory rate, minimum mean arterial blood pressure, maximum temperature, minimum albumin, minimum pH	Logistic regression
	Vazquez Guillamet, Vazquez Guillamet et al.	mechanical ventilation > 96 hours	Age, immunosuppression, COPD, congestive heart failure, BMI, sex, tme to mechanical ventilation (days), length of hospital stay prior to hospital admission, PaO2 /FiO2, Glasgow coma scale, maximum Heart rate, maximum respiratory rate, minimum mean arterial blood pressure, maximum temperature, minimum albumin, minimum pH	Logistic regression
	Zhang, Shi et al.	in hospital mortality (period unspecified)	Age, sex, neutrophil count, lymphocyte count, platelet count, CRP, creatinine	Logistic regression (Lasso)
	Zhang, Shi et al.	ARDS, intubation or ECMO, ICU admission, in hospital mortality (period unspecified)	Age, sex, chronic lung disease, diabetes mellitus, malignancy, cough, dyspnoea, immunocompromised, hypertension, heart disease, chronic renal disease, fever, fatigue, diarrhoea	Logistic regression (Lasso)
	Zhang, Shi et al.	ARDS, intubation or ECMO, ICU admission, in hospital	Age, sex, neutrophil count, lymphocyte count, platelet count, CRP, creatinine	Logistic regression (Lasso)

		mortality (period unspecified)		

*1 Proxy events used: pneumonia (except from TB), influenza, acute bronchitis, or other specified upper respiratory infections (no covid-19 pneumonia cases in data).
*2 Outcome and predictor data were simulated.
*3 Wavelet-HLH_gldm_SmallDependenceLowGrayLevelEmphasis, wavelet-LHH_glcm_Correlation, wavelet-LHL_glszm_GrayLevelVariance, wavelet-LLH_glszm_SizeZoneNonUniformityNormalized, wavelet-LLH_glszm_SmallAreaEmphasis, wavelet-LLH_glcm_Correlation.