

The Role of Machine Learning Techniques to Tackle COVID-19 Crisis: A Systematic Review.

Hafsa Bareen Syeda¹, Mahanazuddin Syed², Kevin Sexton^{2, 3, 4},

Shorabuddin Syed², Salma Begum⁵, Farhan Syed⁶, Feliciano Yu^{2, 7}

¹Department of Neurology, University of Arkansas for Medical Sciences (UAMS),
Little Rock, AR, USA.

²Department of Biomedical Informatics, University of Arkansas for Medical
Sciences (UAMS), Little Rock, AR, USA.

³Department of Surgery, University of Arkansas for Medical Sciences (UAMS),
Little Rock, AR, USA.

⁴Department of Health Policy and Management, University of Arkansas for
Medical Sciences (UAMS), Little Rock, AR, USA.

⁵Department of Information Technology, University of Arkansas for Medical
Sciences (UAMS), Little Rock, AR, USA.

⁶Shadan Institute of Medical Sciences (SIMS), Hyderabad, Telangana, India.

⁷Department of Pediatrics, Arkansas Children's Hospital (ACH), Little Rock, AR,
USA.

Abstract

Background: The novel coronavirus responsible for COVID-19 has caused havoc with patients presenting a spectrum of complications forcing the healthcare experts around the globe to explore new technological solutions, and treatment plans. Machine learning (ML) based technologies have played a substantial role in solving complex problems, and several organizations have been swift to adopt and customize them in response to the challenges posed by the COVID-19 pandemic.

Objective: The objective of this study is to conduct a systematic literature review on the role of ML as a comprehensive and decisive technology to fight the COVID-19 crisis in the arena of epidemiology, diagnosis, and disease progression.

Methods: A systematic search in PubMed, Web of Science, and CINAHL databases was performed according to the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines to identify all potentially relevant studies published and made available between December 1, 2019, and June 27, 2020. The search syntax was built using keywords specific to COVID-19 and ML. A total of 128 qualified articles were reviewed and analyzed based on the study objectives.

Results: The 128 publications selected were classified into three themes based on ML applications employed to combat the COVID-19 crisis: Computational Epidemiology (CE), Early Detection and Diagnosis (EDD), and Disease Progression (DP). Of the 128 studies, 70 focused on predicting the outbreak, the impact of containment policies, and potential drug discoveries, which were grouped into the CE theme. For the EDD, we grouped forty studies that applied ML techniques to detect the presence of COVID-19 using the patients' radiological images or lab results. Eighteen publications that focused on predicting the disease progression,

outcomes (recovery and mortality), Length of Stay (LOS), and number of Intensive Care Unit (ICU) days for COVID-19 positive patients were classified under the DP theme.

Conclusions: In this systematic review, we assembled the current COVID-19 literature that utilized ML methods to provide insights into the COVID-19 themes, highlighting the important variables, data types, and available COVID-19 resources that can assist in facilitating clinical and translational research.

Keywords: COVID-19; Coronavirus; SARS-CoV-2; Machine Learning; Deep Learning; Systematic Review; Epidemiology; Pandemic; Neural Network

Introduction

COVID-19 is a worldwide health crisis, more than 16 million people are infected and caused over 666,000 deaths (up to 29 July 2020) across the globe [1]. The resulting impact on healthcare systems is that many countries have overstretched their resources to mitigate spread of the pandemic [2]. There is an urgent need for effective drugs and vaccines to treat and prevent the infection. Due to the lack of validated therapeutics, most of the containment measures to curtail the spread rely on social distancing, quarantine, and lockdown policies [2-4]. The transmission has been slowed but not eliminated; with ease of restriction, there is a fear of the second wave of infection [5, 6]. To restrict the second potential outbreak, advanced containment measures such as contact tracing, identifying hotspots, etc., are now needed [7, 8].

There is a high degree of variance in the COVID-19 symptoms ranging from mild flu to acute respiratory distress syndrome or fulminant pneumonia [9-11]. Machine Learning (ML) techniques have been employed on different scales ranging from prediction of disease spread trajectory to diagnostic and prognostic models development [12, 13]. A wide range of data types including social media, radiological images, omics data, drug databases, and data collected from public health agencies, etc. have been used for the prediction [1, 14-18]. Several studies focused on reviewing published articles and papers that apply Artificial Intelligence (AI) to fight and support the coronavirus response [12, 13, 19, 20]. One among them is a study by Wynants et al [13] that focused on critical appraisal of models that aimed to predict the risk of developing the disease, hospital admissions, and progression. However, a majority of epidemiological studies that aimed to model disease transmission or fatality rate, etc., were excluded.

The primary aim of this study is to conduct a systematic literature review on the role of ML as a technology to combat the COVID-19 crisis and to assess its application in the epidemiological, clinical, and molecular advancements. Specifically, we summarized the area of application, data types used, types of AI and ML methods employed and their performance, scientific findings, and challenges experienced in adopting this technology.

Methods

This systematic literature review followed the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework for preparation and reporting [21].

Eligibility Criteria

This study focused on peer-reviewed publications, as well as, preprints that applied ML techniques to analyze and address COVID-19 crisis on different scales including diagnostics, prognostics, disease spread forecast, omics, and drug development.

Data sources and search strategy

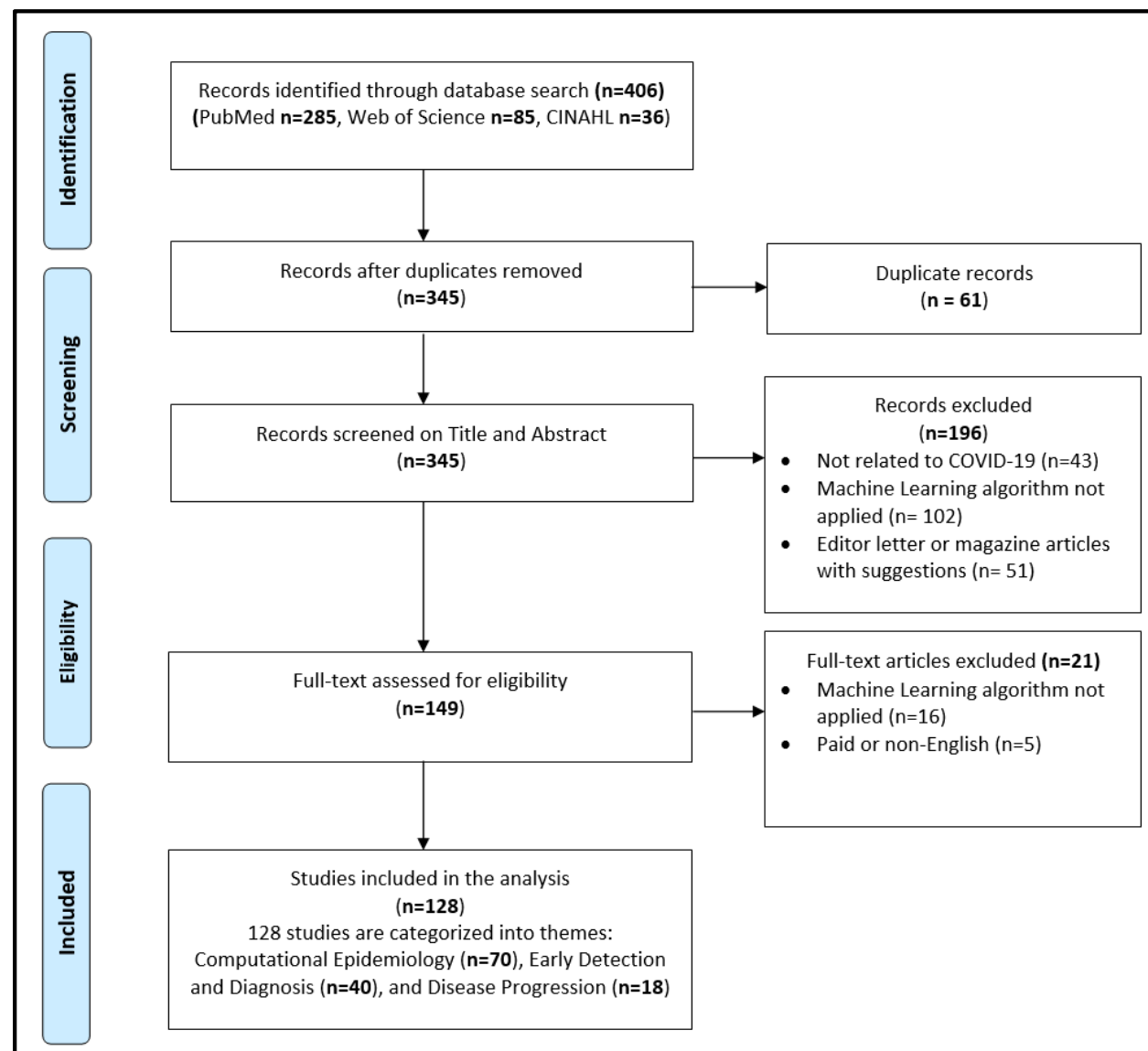
PubMed, Web of Science, and the CINAHL databases were searched, restricting the search to research articles published in English and in peer-reviewed or preprint journals or conference proceedings available from Dec 1, 2019, through June 27, 2020. The search syntax was built with the guidance of a professional librarian and included the following search terms:

"CORONAVIRUS", "COVID-19", "covid19", "cov-19", "cov19", "severe acute respiratory syndrome coronavirus 2", "Wuhan coronavirus", "Wuhan seafood market pneumonia virus", "coronavirus disease 2019 virus", "SARS-CoV-2", "SARS2", "SARS-2", "2019-nCoV", "2019 novel coronavirus", "novel corona", "Machine Learning", "Artificial Intelligence", "Deep

Learning", and "Neural Network". Refer to Multimedia Appendix 1 for search query syntax.

Figure 1 illustrates the process of identifying eligible publications.

Figure 1. PRISMA flow diagram of systematic identification, screening, eligibility, and inclusion of publications that applied ML techniques to tackle COVID-19 pandemic.



Study selection

Following the systematic search process, 406 publications were retrieved. Of that, 61 duplicate publications were removed, leaving 345 potentially relevant articles for the title and abstract screening. Two teams (HB, SS and MS, SB) screened these articles independently, leading to the removal of another 196 publications, and 149 publications were retained for a full-text assessment. These were assessed for eligibility, resulting in 128 total publications that were included in the final analysis. Disagreements were resolved by an independent review by third person (FS).

Data collection and analysis

A qualitative and quantitative descriptive analysis was performed on the qualified studies that had applied ML techniques for tackling COVID-19 pandemic. Based on the area of application, the studies were categorized into themes: 1) Computational Epidemiology (CE), 2) Early Detection and Diagnosis (EDD), and 3) Disease Progression (DP). Qualitative analysis was done on studies from the CE and quantitative descriptive analysis was done for studies that belonged to the EDD and DP themes. After the extraction and analysis, we summarized and reported the findings in tables and figures in accordance with the aim of the study.

Results

The 128 publications selected were categorized into three themes based on the ML applications employed to combat COVID-19 crisis. The three themes (CE, EDD, and DP) were identified based on ML techniques used to predict, classify, assess, track, and control the spread of the virus. Description of each theme and related publications is presented in Table 1. During the initial days of COVID-19 spread, the majority of the studies focused on predicting the outbreak and potential drug discoveries, which we identified in 70 studies, and classified them into the

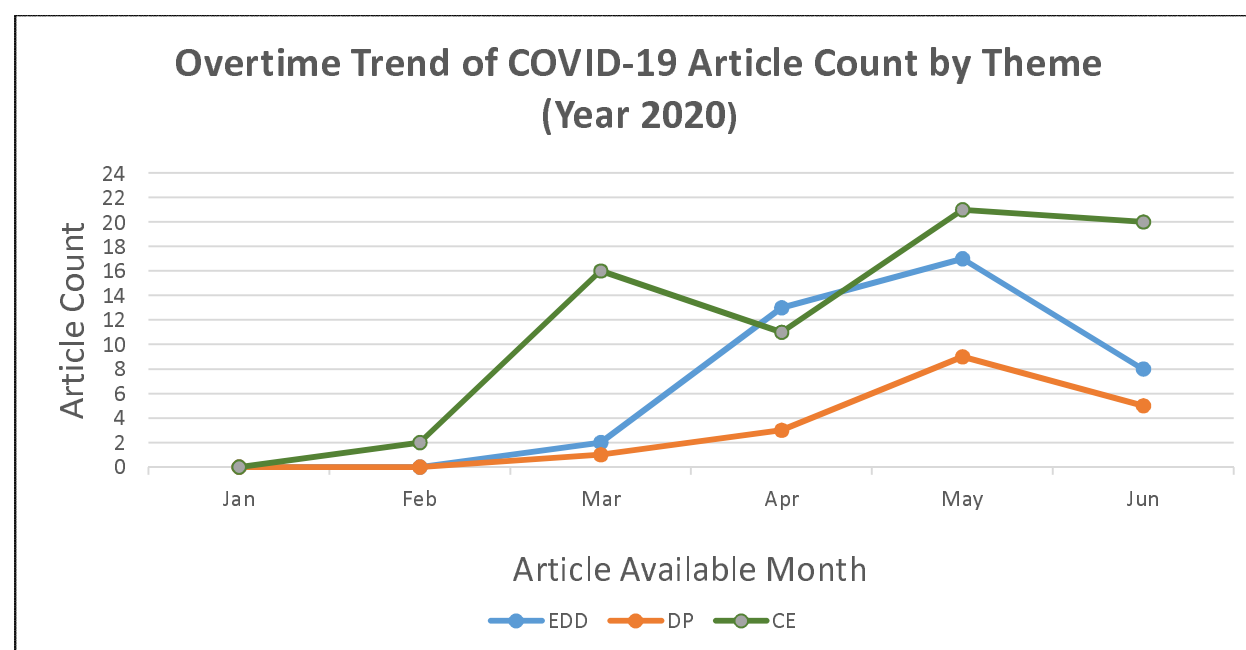
CE. Forty studies that applied ML techniques to detect COVID-19 using patients' radiological images or lab results were grouped into EDD. We identified 18 publications that focused on predicting disease progression, outcomes (recovery and mortality), Length of Stay (LOS), and the number of Intensive Care Unit (ICU) days for COVID-19 positive patients, which are grouped under DP theme. Overtime trend of COVID-19 articles by month and themes is shown in Figure 2, which depicts an initial surge of publications focusing on theme CE and then followed by EDD.

Table 1. An overview of the 128 papers analyzed in the literature, indicating the three themes and their description. The themes are listed according to the frequency of publication percentage and total count.

S.NO	Theme	Description	Publication References	Publications Count (%)
1	Computational Epidemiology (CE)	Publications focused on development and application of ML models to tackle issues central to epidemiology such as disease trends and forecast of potential outbreak, pathobiology of coronavirus infection, protein structures, potential drug discoveries, policies and social impact.	[14, 15, 17, 22-88]	70 (54.69%)
2	Early Detection and Diagnosis (EDD)	Publications focused on application of ML techniques to detect and differentiate COVID-19 positive patients from the general population.	[89-128]	40 (31.25%)
3	Disease Progression (DP)	Publications focused on ML models to predict disease progression, severity and likely outcomes in the	[16, 129-145]	18 (14.06%)

		confirmed COVID-19 population.		
--	--	--------------------------------	--	--

Figure 2. Overtime trend of COVID-19 articles that applied ML techniques made available online and categorized by the themes identified: 1) Computational Epidemiology (CE), 2) Early Detection and Diagnosis (EDD), and 3) Disease Progression (DP). For preprint articles, publication month of the latest version available as of query search date was used.



Computational Epidemiology (CE)

The 70 studies that focused on epidemiological COVID-19 concerns were further classified into three categories 1) COVID-19 Disease Trajectory (CDT), 2) Molecular Analysis-Drug Discovery (MADD), and 3) Facilitate COVID-19 Response (FCR). These classifications were based on the aims of the study such as predicting outbreak, potential drug discoveries, policies, and other measures to stop the spread as shown in Table 2. Forty studies that focused on predicting COVID-19 peaks and sizes globally, and specific to a geographical location, estimating the impact of socioeconomic factors, and environmental conditions on the spread of

the disease, and effectiveness of social distancing policies in containing the spread were grouped into the CDT. Twenty-two studies were grouped under the MADD based on the study approach in identifying existing drugs that have the potential to treat COVID-19, protein structure analysis, and predicting mutation rate in COVID-19 positive patients. The FCR includes 8 studies that emphasize on building tools to combat the ongoing pandemic such as building COVID-19 imaging repository, AI-enabled automatic cleaning and sanitizing tasks at healthcare facilities that might help clinical practitioners to provide timely services to the affected population. A majority of the studies in the CE theme used data either from social media (8 studies used data from Twitter, Weibo, or Facebook) or public data repositories such as NCBI, Drug Bank databases, and other health agencies data. Refer to Multimedia Appendix 2 for individual study details.

Table 2. Computational Epidemiology (CE) publications classified into three categories 1) COVID-19 Disease Trajectory (CDT), 2) Molecular Analysis-Drug Discovery (MADD), and 3) Facilitate COVID-19 Response (FCR).

S.NO	Category	Description	Publications Count (%)
1	COVID-19 Disease Trajectory (CDT)	Publications focused on predicting COVID-19 peaks and sizes globally (and specific to a geographical location), estimating the impact of socioeconomic factors and environmental conditions on the spread of the disease, and effectiveness of social distancing policies in containing the spread.	40 (57.14%)
2	Molecular Analysis-Drug Discovery (MADD)	Publications focused on identifying existing drugs that have the potential to treat COVID-19, analysis of protein structure, and predicting mutation rate in the COVID-19 positive patients.	22 (31.43%)
3	Facilitate COVID-19	Publications focused on building tools to combat the ongoing pandemic such as building COVID-19	8 (11.43%)

	Response (FCR)	imaging repository, AI-enabled automatic cleaning and sanitizing tasks at healthcare facilities that might help clinical practitioners to provide timely services to the affected population.	
--	----------------	---	--

Early Detection and Diagnosis (EDD)

We identified forty studies that primarily focused on diagnosing COVID-19 in patients with suspected infection mostly using chest radiological images such as Computed Tomography (CT), X-Radiation (X-Ray), and Lung Ultrasound (LUS). As shown in Table 3, twenty-three studies used X-Ray, fifteen used CT, one study used LUS, and finally, one study utilized non-imaging clinical data. Most studies used Deep Learning (DL) techniques to diagnose COVID-19 from radiological images. Nine studies employed ResNet, 4 studies used Xception, and 3 studies used VGG neural network models for either pre-training or as a diagnostic model. The study that used non-imaging clinical data to diagnose COVID-19 employed routine lab results captured in the Electronic Health Record (EHR) systems. Refer to Multimedia Appendix 3 for individual study details.

Table 3. Early Detection and Diagnosis (EDD) publications classified into four categories based on modality used for prediction: 1) X-Ray, 2) CT, 3) LUS, and 4) Non-Imaging Clinical data

S.NO	Category	Description	Publications Count (%)
1	X-Ray	Publications focused on application of ML techniques to detect and differentiate COVID-19 positive patients from the general population using X-Ray images.	23 (57.50%)
2	CT	Publications focused on application of ML techniques to detect and differentiate COVID-19 positive patients from the general population using CT images.	15 (37.50%)
3	LUS	Publication focused on application of ML techniques to detect and differentiate COVID-19 positive	1 (2.50%)

		patients from the general population using LUS images.	
4	Non-Imaging Clinical data	Publication focused on application of ML techniques to detect and differentiate COVID-19 positive patients from the general population using non-imaging clinical data.	1 (2.50%)

Disease Progression (DP)

We identified 18 studies that primarily focused on the prognosis of the disease in COVID-19 positive patients. We further classified these studies into 1) Risk Stratification: Publications focused on assessing the risk of disease progression (14 studies) and 2) Hospital Resource Management: Publications focused on predicting the need for hospital resources (4 studies) as shown in the Table 4. All studies in DP used demographic variables, 12 used comorbidities, and 11 used radiological images for analysis. Refer to Multimedia Appendix 4 for individual study details grouped under this theme.

Table 4. Disease Progression (DP) publications classified into two categories: 1) Risk Stratification and 2) Hospital Resource Management.

S.NO	Category	Description	Publications Count (%)
1	Risk Stratification	Publications focused on assessing the risk of disease progression.	14 (77.78%)
2	Hospital Resource Management	Publications focused on predicting the need for hospital resources.	4 (22.22%)

Discussion

ML techniques will continue being used for monitoring, detection, and containment of the COVID-19 pandemic [55, 93, 129]. Our systematic review focused on 128 studies that applied

ML methods and identified 3 themes: models developed to address issues central to Epidemiology; models that aid the diagnosis of patients with COVID-19; and models that help prognosis of COVID-19 patients.

Computational Epidemiology (CE)

Molecular Analysis-Drug Discovery (MADD)

On average, the conventional drug discovery process takes 10 to 15 years with very low success rates [146]. Instead, drug re-purposing attempts have been made to explore similarities between the COVID-19 and other viruses such as Severe Acute Respiratory Syndrome (SARS) and Acquired Immunodeficiency Syndrome (AIDS) [147]. With the rapid accumulation of genetic and other biomedical data in recent years, ML techniques facilitate the analysis of already available drugs and chemical compounds to find new therapeutic indications [148].

The main protease (Mpro) of COVID-19 is a key enzyme in polyprotein processing, it plays an important role in mediating viral replication and transcription [149]. Several studies have applied ML techniques to identify drug leads that target the Mpro of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), making it an attractive drug target [150, 151]. Ton et al [86] built a deep learning platform, Deep Docking (DD), which enables structure-based virtual screening of billions of purchasable molecules in a short time. DD was applied to more than 1 billion compounds available from the ZINC15 library to identify the top 1,000 potential ligands for SARS-CoV-2 Mpro protein. The proposed docking platform is a computationally cheaper and faster ML method compared to traditional docking methods, allowing faster screening of large chemical libraries, containing billions of compounds.

Beck et al [15] used a drug-target interaction ML model to identify top 10 commercially available drugs that could act on viral proteins of SARS-CoV-2. The ML model, Molecule

Transformer-Drug Target Interaction (MT-DTI) used to predict binding affinity values between marketable antiviral drugs that could target COVID-19 proteins. The author claims, MT-DTI can accurately predict binding affinity based on chemical and amino acid sequences of a target protein without their structural information. Also, the study reveals that Atazanavir was the best chemical compound with K_d of 94.94 nM followed by Remdesivir (113.13 nM), Efavirenz (199.17 nM), Ritonavir (204.05 nM), and Dolutegravir (336.91 nM) against the SARS-CoV-2 3C-like proteinase. Computational drug repositioning ML models provide a fast, and cost-effective way to identify promising repositioning opportunities, and expedited approval procedures [148, 152].

Genome sequencing of various viruses is done to identify regions of similarity that may have consequences for functional, structural, or evolutionary relationships [153]. Due to heavy computational requirements of traditional alignment-based methods, alignment-free genome comparison methods are gaining popularity [153, 154]. A case study by Randhawa et al [83] proposed a ML based alignment-free approach for an ultra-fast, inexpensive, and taxonomic classification of whole COVID-19 virus genomes and can be used for classification of COVID-19 pathogens in real time.

Facilitate COVID-19 Response (FCR)

COVID-19 lockdown and home-confinement restrictions is having adverse impact on the mental well-being of the general population and specific to high-risk groups including health care workers, children, and older adults [155]. Several studies were done to understand and respond to these public health emergencies. Li et al [62] conducted a study using ML (Support Vector Machine) model and sentiment analysis to explore the impacts of COVID-19 on people's mental health and to assist policymakers in developing actionable policies that could aid clinical

practitioners. Weibo posts were collected before and after the declaration of the pandemic to build emotional score indicators and cognitive indicators. Key findings of the study reveal that after the declaration of COVID-19 in China, there has been a significant impact on increased negative emotions including anxiety and depression, increased sensitivity to social risks, and declined happiness and life satisfaction. Raamkumar et al [17] have used the Health Belief Model (HBM) [156] to determine public perception towards physical distancing posts from multiple public health authorities. The authors used DL (a variant of recurrent neural network) text classification model to classify Facebook comments related to the posts into four HBM constructs: perceived severity, perceived susceptibility, perceived barriers, and perceived benefits. Recent developments in the field of Natural Language Processing (NLP), BERT [157], XLNet [158], and other hybrid ML models have shown promising results in the field of sentimental analysis. Future studies should focus on these advanced techniques for improved social media content analysis.

There is a growing trend of collaborations among researchers and scientists around the world to combat the COVID-19 pandemic [159]. The emergence of COVID-19 encouraged public health agencies and the scientific community including journals and publishers to promote and ensure that research findings and data relevant to this outbreak are shared rapidly and openly [13, 160]. Peng et al [65] focused on creating a repository of COVID-19 chest X-Ray and CT images. The repository, COVID-19-CT-CXR, is publicly available that contains 1,327 CT and 263 X-Ray images (as of May 9, 2020) that are weakly labeled. The authors build a pipeline to automatically extract images from biomedical literature relevant to COVID-19 using a DL model. A recent effort by National Center for Advancing Translational Sciences (NCATS) to build a centralized national data repository on COVID-19 called National COVID Cohort Collaborative (N3C) is in

progress [161]. The N3C will support collection and analysis of clinical, laboratory and diagnostic data from hospitals and health care plans. N3C along with the imaging repository such as the COVID-19-CT-CXR will accelerate clinical and translational research.

COVID-19 Disease Trajectory (CDT)

During the initial days of the COVID-19 spread, most research was focused on building mathematical models for estimating the transmission dynamics and prediction of COVID-19 developments [162, 163]. Specifically, Susceptible-Exposed-Infectious-Recovered (SEIR) and Auto-Regressive Integrated Moving Average (ARIMA) models and their extensions were widely adopted for projection of COVID-19 cases [164]. These models provided healthcare and government officials with optimal intervention strategies and control measures to combat the pandemic [164]. Yang et al [58] and Moftakhar et al [43] used ML models to fit statistical models SEIR and ARIMA respectively. Long-Short Term Memory (LSTM) model by Yang et al [58] and Artificial Neural Network (ANN) model by Moftakhar et al [43] had a good fit to the aforementioned mathematical models respectively. However, projections of both SEIR and ARIMA mathematical models had deviations less than $\pm 15\%$ range of the reported data [164]. Future studies should try to fit ML techniques on both the SEIR and ARIMA models to reduce the projection error rate and to be prepared for second wave of COVID-19.

In early days of the pandemic, majority of the studies in our review predicted potential hotspots and outbreak trends using COVID-19 data from China expecting similar epidemic growth. However, the projections were off target due to varying containment policies enforced by different countries [164, 165]. Study by Yang et al [58] used ML technique to predict the COVID-19 epidemic peaks and sizes with respect to the containment policies. The study revealed that the continual enforcement of quarantine restrictions, early detection and subsequent isolation

was most effective in the containment of the spread. Relaxing these policies would increase the spread by three-fold for a five-day delay in implementation and could cause a second peak. Such policies should be strictly enforced to prevent a second coronavirus outbreak.

Early Detection and Diagnosis (EDD)

Many countries ramped up the production of real-time reverse transcription polymerase chain reaction (RT-PCR) testing kits to diagnose COVID-19, and as of today, it remains the gold standard for confirmation [166]. However, the lab test suffers from low sensitivity as reported by several studies [166, 167]. Radiological images (CT and X-Ray) have been used by clinicians to confirm corona positive cases and it serves as an important complement to the RT-PCR test [168]. Several studies have reported that the use of chest CT for early-stage detection has proven to have a low rate of misdiagnosis and provide accurate results even in some asymptomatic cases [169].

Researchers started applying ML techniques on radiological scans to distinguish between the COVID-19 and non-COVID-19 cases, we identified 15 studies that used CT to detect COVID-19. One of the most cited studies Li et al [118], applied DL (COVNet) to differentiate COVID-19 and non-COVID-19 pneumonia CT scans. The Area Under the Receiver Operating Characteristics (AUROC) reported to identify COVID-19 on chest CT exam was 0.96 and to identify community-acquired pneumonia on chest CT exam was 0.95. The risks associated with using chest CT for diagnosis are 1) high radiation dose (7 mSv) compared to chest X-Ray (0.1 mSv) and 2) Chest CTs are more expensive compared to chest X-Ray [170, 171]. We identified 23 studies that used chest X-Ray and applied ML techniques to diagnose COVID-19 cases. A study by Apostolopoulos et al [89] applied a transfer learning strategy to train Convolutional Neural Network (CNN) models and then automated the detection of COVID-19 using chest X-

Ray images. The model (VGG19) achieved an overall accuracy of 97.82% to detect COVID-19 on a dataset of 224 COVID-19, 700 pneumonia, and 504 normal X-Ray images. A similar study was done by Khan et al [115] using transfer learning and CNN (Xception) architecture with 71 layers that were trained on the ImageNet dataset. Their model (CoroNet) achieved an average accuracy of 87% to detect COVID-19 on a dataset of 284 COVID-19, 657 pneumonia (both viral and bacterial), and 310 normal chest X-Ray images. While chest X-Rays are cost-effective and have a much lower dose when compared to chest CTs, they are less sensitive, especially in the early stages of the infection, and also in respect of mild cases [172]. We recommend newer studies to develop ML models that can detect COVID-19 from the combination of CT and X-Ray images to aid clinical practitioners.

LUS have been proven useful during the 2009 influenza epidemic (H1N1) by accurately differentiating viral and bacterial pneumonia, and were found to have higher sensitivity to detect avian influenza (H7N9) when compared to chest X-Ray [173]. Though clinicians recommend the use of LUS imaging in the emergency room for diagnosis and management of COVID-19, its role is still unclear [174]. In our review, we identified one study by Roy et al [126] who used a deep learning model on annotated LUS COVID-19 dataset to predict disease severity. The results of the study were reported to be “satisfactory”.

In general, DL techniques are employed to improve prediction accuracy by training on large volumes of data [175]. In our review, several studies applied ML techniques, either using smaller imaging datasets specific to the organization, or mid-to-large dataset from publicly available repositories. However, there is a huge amount of cost associated with developing and maintaining such repositories [176]. To overcome the data size and cost limitations, Xu et al [108] proposed a decentralized AI architecture to build a generalizable ML model that is

distributed and trained on in-house client datasets, eliminating the need for sharing sensitive clinical data. The proposed framework is in the early phase of adoption and needs technical improvements before it is widely employed by participating healthcare organizations.

An alternative to RT-PCR test, study by Joshi et al [113] proposed ML approach that utilize only Complete Blood Count (CBC) and gender to predict COVID-19 positivity. The authors build a logistic regression model on retrospective data collected from a single institute and validated on multi-institute data. Prediction of coronavirus positivity was reported to be C-statistic 78% and sensitivity 93%. The goal of the study was to develop a decision support tool that integrates readily available lab results from EHRs.

Disease Progression (DP)

Hospital Resource Management

The novel coronavirus (COVID-19) pandemic has strained global healthcare systems, especially ICUs, due to hospitalized patients having higher ICU transfer rates [133]. Identification of hospitalized patients at high-risk in advance may help healthcare providers to plan and prepare for ICU resources (beds, ventilators, and staff, etc.) [177]. A study by Cheng et al [133] developed an ML-based model to predict ICU transfers within 24 hours of hospital admission. The Random Forest model was used for prediction and was based on variables: vital signs, nursing assessment, lab results, and electrocardiograms collected during the hospitalization. The overall AUROC of the model was reported to be 79.9%. Similar work was done by Shashikumar et al [139] to predict the need for ventilation in hospitalized patients 24 hours in advance. The prediction was not only limited to COVID-19 patients but also for generally hospitalized patients. The authors used 40 clinical variables: 6 demographic and 34 dynamic variables (including lab results, vital signs, Sequential Organ Failure Assessment (SOFA), comorbidity,

and length of stay). In contrast to the traditional ML model used by Cheng et al [133], Shashikumar et al [139] resorted to a DL model (VentNet) for prediction with an Area Under the Curve (AUC) of 0.882 for the general ICU population and 0.918 for patients with COVID-19. Both the aforementioned studies relied on clinical variables for prediction whereas a study by Burian et al [130] combined clinical and imaging parameters for estimating the need for ICU treatment. The major finding of the study was, patients that needed ICU transfers had significantly increased Interleukin-6 (IL-6), C - reactive protein (CRP) and leukocyte counts and significantly decreased lymphocyte counts. All studies in this category applied ML techniques to facilitate the efficient use of clinical resources and help hospitals plan their flow of operations to fight the ongoing pandemic.

Risk Stratification

Developing a risk stratification mechanism among COVID-19 patients helps to facilitate timely assessments, allocate hospital resources, and appropriate decision making [178]. Jiang et al [136] model used demographics, vital signs, comorbidities, and lab results to predict patients that are likely to develop Acute Respiratory Distress Syndrome (ARDS). Of these variables, lab results alanine aminotransferase (ALT), the presence of myalgias, and elevated hemoglobin were the most predictive features. The overall accuracy of predicting ARDS was 80%. Moreover, using ALT alone, the model achieved an accuracy of 70%. However, the conclusion was drawn based on a limited patient (n=53) set.

Yadaw et al [144] evaluated different ML models to classify COVID-19 patients into deceased or alive classes. The classification was based on five features: age, minimum oxygen saturation during the encounter, type of patient encounter, hydroxychloroquine use, and maximum body temperature. The study revealed age and minimum oxygen saturation during encounters were the

most predictive features among different models. The author reports hydroxychloroquine as one of the top mortality predictors identified by XGBoost and Support Vector Machine (SVM) models; however, only a third of the patients in the dataset had been treated with this drug. Overall AUC was reported as 0.91. Ji et al [135] focused on early identification of COVID-19 positive patients that are likely to be at high-risk. Variables used for prediction were demographics, comorbidities, and lab results. The study identified a strong correlation between comorbidities and disease progression as supported by various other studies. The study further claims, a decrease in lymphocyte count and an increase in lactate dehydrogenase are related to disease progression. Overall AUC reported was 0.759. Both studies, Yadaw et al [144] and Ji et al [135] trained their respective ML models on the retrospective data and validated on prospective data.

Zhang et al [145] build a DL diagnostic and prognostic predictive model to detect COVID-19 and identified variables associated with risk factors for early intervention and monitoring. The study used 3,777 patients (5,468 CT scans) to differentiate coronavirus pneumonia from other pneumonia and normal controls. AUROC of the model was reported as 0.97. To improve image segmentation performance a DL model (DeepLabv3) was employed. The study further evaluated the effect of various drug treatments on lesion size and volume changes by comparing the differences between pre-treatment and post-treatment. The work claimed to provide a potential quantitative evaluation of the efficacy of drug treatment. The study employed five senior radiologists to annotate and review image segmentation, the availability of such resources is very expensive. To avoid the time-consuming annotation, Wang et al [143] used a transfer learning strategy to aid COVID-19 diagnostic and prognostic analysis. The study used a two-step transfer learning strategy, first, the model was trained on a large lung cancer CT dataset (4106 patient)

along with Epidermal Growth Factor Receptor (EGFR) gene sequencing to learn associations between chest CT image and micro-level lung functional abnormality. Later, the model was trained and validated to differentiate COVID-19 from other pneumonia (AUC 0.87-0.88) and viral pneumonia (AUC 0.86). Moreover, the model classified patients into high-risk and low-risk categories to help manage medical resources and provide early interventions. For COVID-19 disease evaluation and risk stratification, Li et al [137] built a pulmonary disease severity score using X-Rays and neural network models. The score was computed as the Euclidean distance between the patient's image and a pool of normal images using the Siamese neural network. The score predicted (AUROC 0.80) subsequent intubation or death within three days of hospital admission for patients that were initially not intubated.

This review has some inherent limitations. First, there is a possibility of studies missed due to the search methodology. Second, we removed five publications where full text was not available, and this may have introduced bias. Third, we included studies that were available as preprints. Finally, a comparison of ML model performance was not possible in the quantitative descriptive analysis as variables, sample size, and source of data was diverse across the studies. The current systematic review includes studies that were available online as of June 27th, as the pandemic progresses, we intend to write a second review on the studies published after the aforementioned date.

Conclusions

In this systematic review, we assembled the current COVID-19 literature that utilized ML methods in the area of applications ranging from tracking, containing, and treating viral infection. Our study provide insights on the prospects of ML on the identified COVID-19 themes: epidemiology, early detection, and disease progression highlighting the important

variables, data types, and available COVID-19 resources that can assist in facilitating clinical and translational research. Our study sheds light on the ML application as a potential drug discovery and risk stratification tool. The analysis of our review suggested that ML based diagnostic tools are highly accurate in detecting presence of the virus using radiological images and can be employed as a decision support tool.

Acknowledgments

This review did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflicts of Interest

None declared.

Abbreviations

AI: Artificial Intelligence

AIDS: Acquired Immunodeficiency Syndrome

ALT: alanine aminotransferase

ANN: Artificial Neural Network

ARDS: Acute Respiratory Distress Syndrome

ARIMA: Auto-Regressive Integrated Moving Average

AUC: Area Under the Curve

AUROC: Area Under the Receiver Operating Characteristics

CBC: Complete Blood Count

CDT: COVID-19 Disease Trajectory

CE: Computational Epidemiology

CNN: Convolutional Neural Network

CRP: C - reactive protein

CT: Computed Tomography

CXR: Chest X-Ray

DD: Deep Docking

DL: Deep Learning

DP: Disease Progression

EDD: Early Detection and Diagnosis

EGFR: Epidermal Growth Factor Receptor

FCR: Facilitate COVID-19 Response

HBM: Health Belief Model

EHR: Electronic Health Record

ICU: Intensive Care Unit

IL-6: Interleukin-6

LOS: Length of Stay

LSTM: Long-Short Term Memory

LUS: Lung Ultrasound

MADD: Molecular Analysis-Drug Discovery

ML: Machine Learning

Mpro: Main Protease

MT-DTI: Molecule Transformer-Drug Target Interaction

N3C: National COVID Cohort Collaborative

NCATS: National Center for Advancing Translational Sciences

NCBI: National Center for Biotechnology Information

NLP: Natural Language Processing

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-analysis

RT-PCR: Reverse Transcription Polymerase Chain Reaction

SARS: Severe Acute Respiratory Syndrome

SARS-CoV-2: Severe Acute Respiratory Syndrome Coronavirus 2

SEIR: Specifically, Susceptible-Exposed-Infectious-Recovered

SOFA: Sequential Organ Failure Assessment

SVM: Support Vector Machine

XGBoost: Extreme Gradient Boosting

X-Ray: X-Radiation

[Multimedia Appendix 1: Query syntax for study search in all 3 databases \(PubMed, CINAHL, and Web of Science\).](#)

[Multimedia Appendix 2: Details of 70 studies qualified under the Computational Epidemiology \(CE\) theme.](#)

[Multimedia Appendix 3: Details of 40 studies qualified under the Early Detection and Diagnosis \(EDD\) theme.](#)

[Multimedia Appendix 4: Details of 18 studies qualified under the Disease Progression \(DP\) theme.](#)

References

1. Dong E, Du H, Gardner L. An interactive web-based dashboard to track COVID-19 in real time. *The Lancet Infectious diseases*. 2020 May;20(5):533-4. PMID: 32087114. doi: 10.1016/s1473-3099(20)30120-1.
2. Sedik A, Iliyasu AM, Abd El-Rahiem B, Abdel Samea ME, Abdel-Raheem A, Hammad M, et al. Deploying Machine and Deep Learning Models for Efficient Data-Augmented Detection of COVID-19 Infections. 2020;12(7):769. PMID: doi:10.3390/v12070769.
3. Kakodkar P, Kaka N, Baig MN. A Comprehensive Literature Review on the Clinical Presentation, and Management of the Pandemic Coronavirus Disease 2019 (COVID-19). *Cureus*. 2020;12(4):e7560-e. PMID: 32269893. doi: 10.7759/cureus.7560.
4. Cyranoski D. 'We need to be alert': Scientists fear second coronavirus wave as China's lockdowns ease. *Nature*. 2020 Mar 30. PMID: 32231319. doi: 10.1038/d41586-020-00938-0.
5. Mahmud I, Al-Mohaimeed A. COVID-19: Utilizing local experience to suggest optimal global strategies to prevent and control the pandemic. *Int J Health Sci (Qassim)*. 2020 May-Jun;14(3):1-3. PMID: 32536840.
6. Leung K, Wu JT, Liu D, Leung GM. First-wave COVID-19 transmissibility and severity in China outside Hubei after control measures, and second-wave scenario planning: a modelling impact assessment. *Lancet*. 2020;395(10233):1382-93. PMID: 32277878. doi: 10.1016/S0140-6736(20)30746-7.
7. Ali I. COVID-19: Are We Ready for the Second Wave? *Disaster medicine and public health preparedness*. 2020:1-3. PMID: 32379015. doi: 10.1017/dmp.2020.149.
8. Xu S, Li Y. Beware of the second wave of COVID-19. *Lancet*. 2020;395(10233):1321-2. PMID: 32277876. doi: 10.1016/S0140-6736(20)30845-X.
9. Singhal T. A Review of Coronavirus Disease-2019 (COVID-19). *Indian J Pediatr*. 2020;87(4):281-6. PMID: 32166607. doi: 10.1007/s12098-020-03263-6.
10. Ozder A. A novel indicator predicts 2019 novel coronavirus infection in subjects with diabetes. *Diabetes Res Clin Pract*. 2020;166:108294-. PMID: 32623037. doi: 10.1016/j.diabres.2020.108294.
11. Soltani J, Sedighi I, Shalchi Z, Sami G, Moradveisi B, Nahidi S. Pediatric coronavirus disease 2019 (COVID-19): An insight from west of Iran. *North Clin Istanb*. 2020;7(3):284-91. PMID: 32478302. doi: 10.14744/nci.2020.90277.
12. Lalmuanawma S, Hussain J, Chhakchhuak L. Applications of machine learning and artificial intelligence for Covid-19 (SARS-CoV-2) pandemic: A review. *Chaos, solitons, and fractals*. 2020;139:110059-. PMID: PMC7315944. doi: 10.1016/j.chaos.2020.110059.
13. Wynants L, Van Calster B, Bonten MMJ, Collins GS, Debray TPA, De Vos M, et al. Prediction models for diagnosis and prognosis of covid-19 infection: systematic review and critical appraisal. *Bmj-British Medical Journal*. 2020 Apr;369. PMID: WOS:000527703000001. doi: 10.1136/bmj.m1328.
14. Sear RF, Velasquez N, Leahy R, Restrepo NJ, El Oud S, Gabriel N, et al. Quantifying COVID-19 Content in the Online Health Opinion War Using Machine Learning. *Ieee Access*. 2020;8:91886-93. PMID: WOS:000538738800019. doi: 10.1109/access.2020.2993967.
15. Beck BR, Shin B, Choi Y, Park S, Kang K. Predicting commercially available antiviral drugs that may act on the novel coronavirus (SARS-CoV-2) through a drug-target interaction deep learning model. *Computational and structural biotechnology journal*. 2020;18:784-90. PMID: 32280433. doi: 10.1016/j.csbj.2020.03.025.
16. Fu L, Li Y, Cheng A, Pang P, Shu Z. A Novel Machine Learning-derived Radiomic Signature of the Whole Lung Differentiates Stable From Progressive COVID-19 Infection: A Retrospective Cohort Study. *J Thorac Imaging*. 2020 Jun 16. PMID: 32555006. doi: 10.1097/rti.0000000000000544.

17. Sesagiri Raamkumar A, Tan SG, Wee HL. Health Belief Model-based Deep Learning Classifiers for Classifying COVID-19 Social Media Content to Examine Public Behaviors towards Physical Distancing. *JMIR public health and surveillance*. 2020 Jun 13. PMID: 32540840. doi: 10.2196/20493.
18. Syed S, Baghal A, Prior F, Zozus M, Al-Shukri S, Syeda HB, et al. Toolkit to Compute Time-Based Elixhauser Comorbidity Indices and Extension to Common Data Models. *Healthcare informatics research*. 2020 7;26(3):193-200. doi: 10.4258/hir.2020.26.3.193.
19. Shi F, Wang J, Shi J, Wu Z, Wang Q, Tang Z, et al. Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation and Diagnosis for COVID-19. *IEEE reviews in biomedical engineering*. 2020 Apr 16. PMID: 32305937. doi: 10.1109/rbme.2020.2987975.
20. Kumar A, Gupta PK, Srivastava A. A review of modern technologies for tackling COVID-19 pandemic. *Diabetes & metabolic syndrome*. 2020 May 7;14(4):569-73. PMID: 32413821. doi: 10.1016/j.dsx.2020.05.008.
21. Liberati A, Altman DG, Tetzlaff J, Mulrow C, Gøtzsche PC, Ioannidis JPA, et al. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate healthcare interventions: explanation and elaboration. *BMJ*. 2009;339:b2700. doi: 10.1136/bmj.b2700.
22. Arora P, Kumar H, Panigrahi BK. Prediction and analysis of COVID-19 positive cases using deep learning models: A descriptive case study of India. *Chaos, solitons, and fractals*. 2020 Oct;139:110017. PMID: 32572310. doi: 10.1016/j.chaos.2020.110017.
23. Ayyoubzadeh SM, Ayyoubzadeh SM, Zahedi H, Ahmadi M, S RNK. Predicting COVID-19 Incidence Through Analysis of Google Trends Data in Iran: Data Mining and Deep Learning Pilot Study. *JMIR public health and surveillance*. 2020 Apr 14;6(2):e18828. PMID: 32234709. doi: 10.2196/18828.
24. Car Z, Baressi Šegota S, Anđelić N, Lorencin I, Mrzljak V. Modeling the Spread of COVID-19 Infection Using a Multilayer Perceptron. *Computational and mathematical methods in medicine*. 2020;2020:5714714. PMID: 32565882. doi: 10.1155/2020/5714714.
25. Carrillo-Larco RM, Castillo-Cara M. Using country-level variables to classify countries according to the number of confirmed COVID-19 cases: An unsupervised machine learning approach. *Wellcome open research*. 2020;5:56. PMID: 32587900. doi: 10.12688/wellcomeopenres.15819.1.
26. Chatterjee A, Gerdes MW, Martinez SG. Statistical Explorations and Univariate Timeseries Analysis on COVID-19 Datasets to Understand the Trend of Disease Spreading and Death. *Sensors (Basel, Switzerland)*. 2020 May 29;20(11). PMID: 32486055. doi: 10.3390/s20113089.
27. Chimmula VKR, Zhang L. Time series forecasting of COVID-19 transmission in Canada using LSTM networks. *Chaos Solitons & Fractals*. 2020 Jun;135. PMID: WOS:000538179300012. doi: 10.1016/j.chaos.2020.109864.
28. Chowdhury R, Heng K, Shawon MSR, Goh G, Okonofua D, Ochoa-Rosales C, et al. Dynamic interventions to control COVID-19 pandemic: a multivariate prediction modelling study comparing 16 worldwide countries. *European journal of epidemiology*. 2020 May;35(5):389-99. PMID: 32430840. doi: 10.1007/s10654-020-00649-w.
29. Cobb JS, Seale MA. Examining the effect of social distancing on the compound growth rate of COVID-19 at the county level (United States) using statistical analyses and a random forest machine learning model. *Public health*. 2020 Apr 28;185:27-9. PMID: 32526559. doi: 10.1016/j.puhe.2020.04.016.
30. Delen D, Eryarsoy E, Davazdahemami B. No Place Like Home: Cross-National Data Analysis of the Efficacy of Social Distancing During the COVID-19 Pandemic. *JMIR public health and surveillance*. 2020 May 28;6(2):e19862. PMID: 32434145. doi: 10.2196/19862.

31. Fong SJ, Li G, Dey N, Crespo RG, Herrera-Viedma E. Finding an Accurate Early Forecasting Model from Small Dataset: A Case of 2019-nCoV Novel Coronavirus Outbreak. *International Journal of Interactive Multimedia and Artificial Intelligence*. 2020 Mar;6(1):132-40. PMID: WOS:000514841200016. doi: 10.9781/ijimai.2020.02.002.
32. Fong SJ, Li G, Dey N, Crespo RG, Herrera-Viedma E. Composite Monte Carlo decision making under high uncertainty of novel coronavirus epidemic using hybridized deep learning and fuzzy rule induction. *Applied soft computing*. 2020 Apr 9;93:106282. PMID: 32362799. doi: 10.1016/j.asoc.2020.106282.
33. Fronza R, Lusic M, Schmidt M, Lucic B. Spatial-Temporal Variations in Atmospheric Factors Contribute to SARS-CoV-2 Outbreak. *Viruses*. 2020 May 27;12(6). PMID: 32471302. doi: 10.3390/v12060588.
34. Golder S, Klein A, Magge A, O'Connor K, Cai H, Weissenbacher D. Extending A Chronological and Geographical Analysis of Personal Reports of COVID-19 on Twitter to England, UK. *medRxiv : the preprint server for health sciences*. 2020 May 8. PMID: 32511492. doi: 10.1101/2020.05.05.20083436.
35. Shaffiee Haghshenas S, Pirouz B, Shaffiee Haghshenas S, Pirouz B, Piro P, Na KS, et al. Prioritizing and Analyzing the Role of Climate and Urban Parameters in the Confirmed Cases of COVID-19 Based on Artificial Intelligence Applications. *Int J Environ Res Public Health*. 2020 May 25;17(10). PMID: 32466199. doi: 10.3390/ijerph17103730.
36. Kırbaş İ, Sözen A, Tuncer AD, Kazancıoğlu F. Comparative analysis and forecasting of COVID-19 cases in various European countries with ARIMA, NARNN and LSTM approaches. *Chaos, solitons, and fractals*. 2020 Sep;138:110015. PMID: 32565625. doi: 10.1016/j.chaos.2020.110015.
37. Klein A, Magge A, O'Connor K, Cai H, Weissenbacher D, Gonzalez-Hernandez G. A Chronological and Geographical Analysis of Personal Reports of COVID-19 on Twitter. *medRxiv : the preprint server for health sciences*. 2020 Apr 22. PMID: 32511608. doi: 10.1101/2020.04.19.20069948.
38. Liu D, Clemente L, Poirier C, Ding X, Chinazzi M, Davis JT, et al. A machine learning methodology for real-time forecasting of the 2019-2020 COVID-19 outbreak using Internet searches, news alerts, and estimates from mechanistic models. *ArXiv*. 2020 Apr 8. PMID: 32550248.
39. Liu Z, Huang S, Lu W, Su Z, Yin X, Liang H, et al. Modeling the trend of coronavirus disease 2019 and restoration of operational capability of metropolitan medical service in China: a machine learning and mathematical model-based analysis. *Global health research and policy*. 2020;5:20. PMID: 32391439. doi: 10.1186/s41256-020-00145-4.
40. Mackey T, Purushothaman V, Li J, Shah N, Nali M, Bardier C, et al. Machine Learning to Detect Self-Reporting of Symptoms, Testing Access, and Recovery Associated With COVID-19 on Twitter: Retrospective Big Data Inveillance Study. *JMIR public health and surveillance*. 2020 Jun 8;6(2):e19509. PMID: 32490846. doi: 10.2196/19509.
41. Melin P, Monica JC, Sanchez D, Castillo O. Analysis of Spatial Spread Relationships of Coronavirus (COVID-19) Pandemic in the World using Self Organizing Maps. *Chaos, solitons, and fractals*. 2020 Sep;138:109917. PMID: 32501376. doi: 10.1016/j.chaos.2020.109917.
42. Melin P, Monica JC, Sanchez D, Castillo O. Multiple Ensemble Neural Network Models with Fuzzy Response Aggregation for Predicting COVID-19 Time Series: The Case of Mexico. *Healthcare (Basel, Switzerland)*. 2020 Jun 19;8(2). PMID: 32575622. doi: 10.3390/healthcare8020181.
43. Mofattakhar L, Seif M, Safe MS. Exponentially Increasing Trend of Infected Patients with COVID-19 in Iran: A Comparison of Neural Network and ARIMA Forecasting Models. *Iranian Journal of Public Health*. 2020;49:92-100. PMID: WOS:000531776100013.

44. Mollalo A, Rivera KM, Vahedi B. Artificial Neural Network Modeling of Novel Coronavirus (COVID-19) Incidence Rates across the Continental United States. *Int J Environ Res Public Health*. 2020 Jun 12;17(12). PMID: 32545581. doi: 10.3390/ijerph17124204.
45. Pirouz B, Haghshenas SS, Haghshenas SS, Piro P. Investigating a Serious Challenge in the Sustainable Development Process: Analysis of Confirmed cases of COVID-19 (New Type of Coronavirus) Through a Binary Classification Using Artificial Intelligence and Regression Analysis. *Sustainability*. 2020 Mar;12(6). PMID: WOS:000523751400274. doi: 10.3390/su12062427.
46. Pourghasemi HR, Pouyan S, Heidari B, Farajzadeh Z, Shamsi SRF, Babaei S, et al. Spatial modelling, risk mapping, change detection, and outbreak trend analysis of coronavirus (COVID-19) in Iran (days between 19 February to 14 June 2020). *International journal of infectious diseases : IJID : official publication of the International Society for Infectious Diseases*. 2020 Jun 20. PMID: 32574693. doi: 10.1016/j.ijid.2020.06.058.
47. Qiu Y, Chen X, Shi W. Impacts of Social and Economic Factors on the Transmission of Coronavirus Disease 2019 (COVID-19) in China. *medRxiv : the preprint server for health sciences*. 2020 Mar 17. PMID: 32511444. doi: 10.1101/2020.03.13.20035238.
48. Rao JS, Zhang H, Mantero A. Contextualizing covid-19 spread: a county level analysis, urban versus rural, and implications for preparing for the next wave. *medRxiv : the preprint server for health sciences*. 2020 Apr 29. PMID: 32511653. doi: 10.1101/2020.04.24.20078204.
49. Ribeiro MHD, da Silva RG, Mariani VC, Coelho LD. Short-term forecasting COVID-19 cumulative confirmed cases: Perspectives for Brazil. *Chaos Solitons & Fractals*. 2020 Jun;135. PMID: WOS:000538179300014. doi: 10.1016/j.chaos.2020.109853.
50. Saba AI, Elsheikh AH. Forecasting the prevalence of COVID-19 outbreak in Egypt using nonlinear autoregressive artificial neural networks. *Process safety and environmental protection : transactions of the Institution of Chemical Engineers, Part B*. 2020 Sep;141:1-8. PMID: 32501368. doi: 10.1016/j.psep.2020.05.029.
51. Shen C, Chen A, Luo C, Zhang J, Feng B, Liao W. Using Reports of Symptoms and Diagnoses on Social Media to Predict COVID-19 Case Counts in Mainland China: Observational Infection Study. *Journal of Medical Internet Research*. 2020;22(5):N.PAG-N.PAG. PMID: 143524221. Language: English. Entry Date: In Process. Revision Date: 20200605. Publication Type: journal article. Journal Subset: Biomedical. doi: 10.2196/19421.
52. Simsek M, Kantarci B. Artificial Intelligence-Empowered Mobilization of Assessments in COVID-19-like Pandemics: A Case Study for Early Flattening of the Curve. *Int J Environ Res Public Health*. 2020 May 14;17(10). PMID: 32423150. doi: 10.3390/ijerph17103437.
53. Sujath R, Chatterjee JM, Hassanien AE. A machine learning forecasting model for COVID-19 pandemic in India. *Stochastic Environmental Research and Risk Assessment*. PMID: WOS:000536422000001. doi: 10.1007/s00477-020-01827-8.
54. Tiwari S, Kumar S, Guleria K. Outbreak Trends of Coronavirus Disease-2019 in India: A Prediction. *Disaster medicine and public health preparedness*. 2020 Apr 22:1-6. PMID: 32317044. doi: 10.1017/dmp.2020.115.
55. Tomar A, Gupta N. Prediction for the spread of COVID-19 in India and effectiveness of preventive measures. *The Science of the total environment*. 2020 Aug 1;728:138762. PMID: 32334157. doi: 10.1016/j.scitotenv.2020.138762.
56. Vaid S, McAdie A, Kremer R, Khanduja V, Bhandari M. Risk of a second wave of Covid-19 infections: using artificial intelligence to investigate stringency of physical distancing policies in North America. *International Orthopaedics*. PMID: WOS:000538218200001. doi: 10.1007/s00264-020-04653-3.
57. Wen A, Wang L, He H, Liu S, Fu S, Sohn S, et al. An Aberration Detection-Based Approach for Sentinel Syndromic Surveillance of COVID-19 and Other Novel Influenza-Like Illnesses. *medRxiv : the preprint server for health sciences*. 2020 Jun 9. PMID: 32577704. doi: 10.1101/2020.06.08.20124990.

58. Yang ZF, Zeng ZQ, Wang K, Wong SS, Liang WH, Zanin M, et al. Modified SEIR and AI prediction of the epidemics trend of COVID-19 in China under public health interventions. *Journal of Thoracic Disease*. 2020 Mar;12(3):165-+. PMID: WOS:000521736500010. doi: 10.21037/jtd.2020.02.64.
59. Zheng N, Du S, Wang J, Zhang H, Cui W, Kang Z, et al. Predicting COVID-19 in China Using Hybrid AI Model. *IEEE transactions on cybernetics*. 2020 Jul;50(7):2891-904. PMID: 32396126. doi: 10.1109/tcyb.2020.2990162.
60. Zhou X, Wu Z, Yu R, Cao S, Fang W, Jiang Z, et al. Modelling-based evaluation of the effect of quarantine control by the Chinese government in the coronavirus disease 2019 outbreak. *Science China Life sciences*. 2020 May 8:1-4. PMID: 32394245. doi: 10.1007/s11427-020-1717-9.
61. Zhu GK, Li J, Meng Z, Yu Y, Li YA, Tang X, et al. Learning from Large-Scale Wearable Device Data for Predicting Epidemics Trend of COVID-19. *Discrete Dynamics in Nature and Society*. 2020 May;2020. PMID: WOS:000536146200002. doi: 10.1155/2020/6152041.
62. Li SJ, Wang YL, Xue J, Zhao N, Zhu TS. The Impact of COVID-19 Epidemic Declaration on Psychological Consequences: A Study on Active Weibo Users. *International Journal of Environmental Research and Public Health*. 2020 Mar;17(6). PMID: WOS:000529342300222. doi: 10.3390/ijerph17062032.
63. Mahmoud HAH, Mengash HA. A novel technique for automated concealed face detection in surveillance videos. *Personal and Ubiquitous Computing*. PMID: WOS:000539874100001. doi: 10.1007/s00779-020-01419-x.
64. Obeid JS, Davis M, Turner M, Meystre SM, Heider PM, Lenert LA. An AI approach to COVID-19 infection risk assessment in virtual visits: a case report. *Journal of the American Medical Informatics Association : JAMIA*. 2020 May 25. PMID: 32449766. doi: 10.1093/jamia/ocaa105.
65. Peng Y, Tang YX, Lee S, Zhu Y, Summers RM, Lu Z. COVID-19-CT-CXR: a freely accessible and weakly labeled chest X-ray and CT image collection on COVID-19 from biomedical literature. *ArXiv*. 2020 Jun 11. PMID: 32550254.
66. Ramalingam B, Yin J, Rajesh Elara M, Tamilselvam YK, Mohan Rayguru M, Muthugala M, et al. A Human Support Robot for the Cleaning and Maintenance of Door Handles Using a Deep-Learning Framework. *Sensors (Basel, Switzerland)*. 2020 Jun 23;20(12). PMID: 32585864. doi: 10.3390/s20123543.
67. Wahbeh A, Nasrallah T, Al-Ramahi M, El-Gayar O. Mining Physicians' Opinions on Social Media to Obtain Insights Into COVID-19: Mixed Methods Analysis. *JMIR public health and surveillance*. 2020 Jun 18;6(2):e19276. PMID: 32421686. doi: 10.2196/19276.
68. Abdelmageed MI, Abdelmoneim AH, Mustafa MI, Elfadol NM, Murshed NS, Shantier SW, et al. Design of a Multiepitope-Based Peptide Vaccine against the E Protein of Human COVID-19: An Immunoinformatics Approach. *Biomed Research International*. 2020 May;2020. PMID: WOS:000533376900001. doi: 10.1155/2020/2683286.
69. Demirci MDS, Adan A. Computational analysis of microRNA-mediated interactions in SARS-CoV-2 infection. *Peerj*. 2020 Jun;8. PMID: WOS:000538335100008. doi: 10.7717/peerj.9369.
70. Gao K, Nguyen DD, Wang R, Wei GW. Machine intelligence design of 2019-nCoV drugs. *bioRxiv : the preprint server for biology*. 2020 Feb 4. PMID: 32511308. doi: 10.1101/2020.01.30.927889.
71. Gao K, Nguyen DD, Chen J, Wang R, Wei GW. Repositioning of 8565 Existing Drugs for COVID-19. *The journal of physical chemistry letters*. 2020 Jun 23;11:5373-82. PMID: 32543196. doi: 10.1021/acs.jpcllett.0c01579.
72. Gussow AB, Auslander N, Faure G, Wolf YI, Zhang F, Koonin EV. Genomic determinants of pathogenicity in SARS-CoV-2 and other human coronaviruses. *Proceedings of*

the National Academy of Sciences of the United States of America. 2020 Jun 10. PMID: 32522874. doi: 10.1073/pnas.2008176117.

73. Heo L, Feig M. Modeling of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) Proteins by Machine Learning and Physics-Based Refinement. *bioRxiv : the preprint server for biology*. 2020 Mar 28. PMID: 32511334. doi: 10.1101/2020.03.25.008904.

74. Ke YY, Peng TT, Yeh TK, Huang WZ, Chang SE, Wu SH, et al. Artificial intelligence approach fighting COVID-19 with repurposing drugs. *Biomedical journal*. 2020 May 15. PMID: 32426387. doi: 10.1016/j.bj.2020.05.001.

75. Kim J, Zhang J, Cha Y, Kolitz S, Funt J, Escalante Chong R, et al. Advanced bioinformatics rapidly identifies existing therapeutics for patients with coronavirus disease-2019 (COVID-19). *Journal of translational medicine*. 2020 Jun 25;18(1):257. PMID: 32586380. doi: 10.1186/s12967-020-02430-9.

76. Liu G, Carter B, Bricken T, Jain S, Viard M, Carrington M, et al. Robust computational design and evaluation of peptide vaccines for cellular immunity with application to SARS-CoV-2. *bioRxiv : the preprint server for biology*. 2020 May 17. PMID: 32511351. doi: 10.1101/2020.05.16.088989.

77. Mick E, Kamm J, Pisco AO, Ratnasiri K, Babik JM, Calfee CS, et al. Upper airway gene expression differentiates COVID-19 from other acute respiratory illnesses and reveals suppression of innate immune responses by SARS-CoV-2. *medRxiv : the preprint server for health sciences*. 2020 May 19. PMID: 32511476. doi: 10.1101/2020.05.18.20105171.

78. Mirabelli C, Wotring JW, Zhang CJ, McCarty SM, Furusmidt R, Frum T, et al. Morphological Cell Profiling of SARS-CoV-2 Infection Identifies Drug Repurposing Candidates for COVID-19. *bioRxiv : the preprint server for biology*. 2020 Jun 10. PMID: 32577649. doi: 10.1101/2020.05.27.117184.

79. Nguyen DD, Gao K, Chen J, Wang R, Wei GW. Potentially highly potent drugs for 2019-nCoV. *bioRxiv : the preprint server for biology*. 2020 Feb 13. PMID: 32511344. doi: 10.1101/2020.02.05.936013.

80. Ong E, Wong MU, Huffman A, He Y. COVID-19 coronavirus vaccine design using reverse vaccinology and machine learning. *bioRxiv : the preprint server for biology*. 2020 Mar 21. PMID: 32511333. doi: 10.1101/2020.03.20.000141.

81. Pathan RK, Biswas M, Khandaker MU. Time series prediction of COVID-19 by mutation rate analysis using recurrent neural network-based LSTM model. *Chaos, solitons, and fractals*. 2020 Sep;138:110018. PMID: 32565626. doi: 10.1016/j.chaos.2020.110018.

82. Qiang XL, Xu P, Fang G, Liu WB, Kou Z. Using the spike protein feature to predict infection risk and monitor the evolutionary dynamic of coronavirus. *Infectious Diseases of Poverty*. 2020 Mar;9(1). PMID: WOS:000529289300001. doi: 10.1186/s40249-020-00649-8.

83. Randhawa GS, Soltysiak MPM, El Roz H, de Souza CPE, Hill KA, Kari L. Machine learning using intrinsic genomic signatures for rapid classification of novel pathogens: COVID-19 case study. *Plos One*. 2020 Apr;15(4). PMID: WOS:000536647300074. doi: 10.1371/journal.pone.0232391.

84. Song Y, Song J, Wei X, Huang M, Sun M, Zhu L, et al. Discovery of Aptamers Targeting Receptor-Binding Domain of the SARS-CoV-2 Spike Glycoprotein. *Analytical chemistry*. 2020 Jun 17. PMID: 32551560. doi: 10.1021/acs.analchem.0c01394.

85. Tang B, He F, Liu D, Fang M, Wu Z, Xu D. AI-aided design of novel targeted covalent inhibitors against SARS-CoV-2. *bioRxiv : the preprint server for biology*. 2020 Mar 8. PMID: 32511346. doi: 10.1101/2020.03.03.972133.

86. Ton AT, Gentile F, Hsing M, Ban F, Cherkasov A. Rapid Identification of Potential Inhibitors of SARS-CoV-2 Main Protease by Deep Docking of 1.3 Billion Compounds. *Molecular informatics*. 2020 Mar 11. PMID: 32162456. doi: 10.1002/minf.202000028.

87. Wu K, Zou J, Chang HY. RNA-GPS Predicts SARS-CoV-2 RNA Localization to Host Mitochondria and Nucleolus. *bioRxiv : the preprint server for biology*. 2020 Apr 28. PMID: 32511373. doi: 10.1101/2020.04.28.065201.
88. Zhang HP, Saravanan KM, Yang Y, Hossain MT, Li JX, Ren XH, et al. Deep Learning Based Drug Screening for Novel Coronavirus 2019-nCoV. *Interdisciplinary Sciences-Computational Life Sciences*. PMID: WOS:000537395500001. doi: 10.1007/s12539-020-00376-6.
89. Apostolopoulos ID, Mpesiana TA. Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. *Physical and engineering sciences in medicine*. 2020 Jun;43(2):635-40. PMID: 32524445. doi: 10.1007/s13246-020-00865-4.
90. Apostolopoulos ID, Aznaouridis SI, Tzani MA. Extracting Possibly Representative COVID-19 Biomarkers from X-ray Images with Deep Learning Approach and Image Data Related to Pulmonary Diseases. *Journal of Medical and Biological Engineering*. 2020 Jun;40(3):462-9. PMID: WOS:000532877900002. doi: 10.1007/s40846-020-00529-4.
91. Ardakani AA, Kanafi AR, Acharya UR, Khadem N, Mohammadi A. Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. *Computers in biology and medicine*. 2020 Jun;121:103795. PMID: 32568676. doi: 10.1016/j.compbimed.2020.103795.
92. Bai HX, Wang R, Xiong Z, Hsieh B, Chang K, Halsey K, et al. AI Augmentation of Radiologist Performance in Distinguishing COVID-19 from Pneumonia of Other Etiology on Chest CT. *Radiology*. 2020 Apr 27:201491. PMID: 32339081. doi: 10.1148/radiol.2020201491.
93. Benbrahim H, Hachimi H, Amine A. Deep Transfer Learning with Apache Spark to Detect COVID-19 in chest X-ray Images. *Romanian Journal of Information Science and Technology*. 2020;23:S117-S29. PMID: WOS:000537095200010.
94. Chaganti S, Balachandran A, Chabin G, Cohen S, Flohr T, Georgescu B, et al. Quantification of Tomographic Patterns associated with COVID-19 from Chest CT. *ArXiv*. 2020 Apr 2. PMID: 32550252.
95. Das D, Santosh KC, Pal U. Truncated inception net: COVID-19 outbreak screening using chest X-rays. *Physical and engineering sciences in medicine*. 2020 Jun 25. PMID: 32588200. doi: 10.1007/s13246-020-00888-x.
96. El Asnaoui K, Chawki Y. Using X-ray images and deep learning for automated detection of coronavirus disease. *Journal of Biomolecular Structure & Dynamics*. PMID: WOS:000538580100001. doi: 10.1080/07391102.2020.1767212.
97. Singh KK, Siddhartha M, Singh A. Diagnosis of Coronavirus Disease (COVID-19) from Chest X-Ray images using modified XceptionNet. *Romanian Journal of Information Science and Technology*. 2020;23:S91-S105. PMID: WOS:000537095200009.
98. Song J, Wang H, Liu Y, Wu W, Dai G, Wu Z, et al. End-to-end automatic differentiation of the coronavirus disease 2019 (COVID-19) from viral pneumonia based on chest CT. *European journal of nuclear medicine and molecular imaging*. 2020 Jun 22:1-9. PMID: 32567006. doi: 10.1007/s00259-020-04929-1.
99. Toğaçar M, Ergen B, Cömert Z. COVID-19 detection using deep learning models to exploit Social Mimic Optimization and structured chest X-ray images using fuzzy color and stacking approaches. *Computers in biology and medicine*. 2020 Jun;121:103805. PMID: 32568679. doi: 10.1016/j.compbimed.2020.103805.
100. Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Rajendra Acharya U. Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Computers in biology and medicine*. 2020 Jun;121:103792. PMID: 32568675. doi: 10.1016/j.compbimed.2020.103792.
101. Tuncer T, Dogan S, Ozyurt F. An automated Residual Exemplar Local Binary Pattern and iterative ReliefF based corona detection method using lung X-ray image. *Chemometrics*

- and intelligent laboratory systems : an international journal sponsored by the Chemometrics Society. 2020 May 18;203:104054. PMID: 32427226. doi: 10.1016/j.chemolab.2020.104054.
102. Ucar F, Korkmaz D. COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images. Medical Hypotheses. 2020;140:N.PAG-N.PAG. PMID: 143703160. Language: English. Entry Date: In Process. Revision Date: 20200617. Publication Type: journal article. Journal Subset: Biomedical. doi: 10.1016/j.mehy.2020.109761.
103. Vaid S, Kalantar R, Bhandari M. Deep learning COVID-19 detection bias: accuracy through artificial intelligence. International Orthopaedics. PMID: WOS:000535872900001. doi: 10.1007/s00264-020-04609-7.
104. Waheed A, Goyal M, Gupta D, Khanna A, Al-Turjman F, Pinheiro PR. CovidGAN: Data Augmentation Using Auxiliary Classifier GAN for Improved Covid-19 Detection. IEEE Access. 2020;8:91916-23. PMID: WOS:000538738800021. doi: 10.1109/access.2020.2994762.
105. Warman A, Warman P, Sharma A, Parikh P, Warman R, Viswanadhan N, et al. Interpretable Artificial Intelligence for COVID-19 Diagnosis from Chest CT Reveals Specificity of Ground-Glass Opacities. medRxiv : the preprint server for health sciences. 2020 May 18. PMID: 32511545. doi: 10.1101/2020.05.16.20103408.
106. Wu X, Hui H, Niu M, Li L, Wang L, He B, et al. Deep learning-based multi-view fusion model for screening 2019 novel coronavirus pneumonia: A multicentre study. European Journal of Radiology. 2020;128:N.PAG-N.PAG. PMID: 143766326. Language: English. Entry Date: In Process. Revision Date: 20200618. Publication Type: journal article. Journal Subset: Biomedical. doi: 10.1016/j.ejrad.2020.109041.
107. Xie W, Jacobs C, Charbonnier JP, van Ginneken B. Relational Modeling for Robust and Efficient Pulmonary Lobe Segmentation in CT Scans. ArXiv. 2020 Apr 16. PMID: 32550251.
108. Xu Y, Ma L, Yang F, Chen Y, Ma K, Yang J, et al. A collaborative online AI engine for CT-based COVID-19 diagnosis. medRxiv : the preprint server for health sciences. 2020 May 19. PMID: 32511484. doi: 10.1101/2020.05.10.20096073.
109. Yang SY, Jiang LQ, Cao ZQ, Wang LY, Cao JW, Feng R, et al. Deep learning for detecting corona virus disease 2019 (COVID-19) on high-resolution computed tomography: a pilot study. Annals of Translational Medicine. 2020 Apr;8(7). PMID: WOS:000527389200032. doi: 10.21037/atm.2020.03.132.
110. Yi PH, Kim TK, Lin CT. Generalizability of Deep Learning Tuberculosis Classifier to COVID-19 Chest Radiographs: New Tricks for an Old Algorithm? J Thorac Imaging. 2020 Jul;35(4):W102-w4. PMID: 32427650. doi: 10.1097/rti.0000000000000532.
111. Elaziz MA, Hosny KM, Salah A, Darwish MM, Lu S, Sahlol AT. New machine learning method for image-based diagnosis of COVID-19. PLoS One. 2020;15(6):e0235187. PMID: 32589673. doi: 10.1371/journal.pone.0235187.
112. Hurt B, Kligerman S, Hsiao A. Deep Learning Localization of Pneumonia: 2019 Coronavirus (COVID-19) Outbreak. Journal of Thoracic Imaging. 2020;35(3):W87-W9. PMID: 142892562. Language: English. Entry Date: 20200504. Revision Date: 20200518. Publication Type: journal article. doi: 10.1097/RTI.0000000000000512.
113. Joshi RP, Pejaver V, Hammarlund NE, Sung H, Lee SK, Furmanchuk A, et al. A predictive tool for identification of SARS-CoV-2 PCR-negative emergency department patients using routine test results. Journal of clinical virology : the official publication of the Pan American Society for Clinical Virology. 2020 Jun 10;129:104502. PMID: 32544861. doi: 10.1016/j.jcv.2020.104502.
114. Kang H, Xia L, Yan F, Wan Z, Shi F, Yuan H, et al. Diagnosis of Coronavirus Disease 2019 (COVID-19) with Structured Latent Multi-View Representation Learning. IEEE Trans Med Imaging. 2020 May 5. PMID: 32386147. doi: 10.1109/tmi.2020.2992546.

115. Khan AI, Shah JL, Bhat MM. CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. *Computer methods and programs in biomedicine*. 2020 Jun 5;196:105581. PMID: 32534344. doi: 10.1016/j.cmpb.2020.105581.
116. Khuzani AZ, Heidari M, Shariati SA. COVID-Classfier: An automated machine learning model to assist in the diagnosis of COVID-19 infection in chest x-ray images. *medRxiv : the preprint server for health sciences*. 2020 May 18. PMID: 32511510. doi: 10.1101/2020.05.09.20096560.
117. Ko H, Chung H, Kim KW, Shin YS, Kang SJ, Lee JH, et al. COVID-19 pneumonia diagnosis using a simple 2D deep learning framework with a single chest CT image. *J Med Internet Res*. 2020 Jun 21. PMID: 32568730. doi: 10.2196/19569.
118. Li L, Qin L, Xu Z, Yin Y, Wang X, Kong B, et al. Artificial Intelligence Distinguishes COVID-19 from Community Acquired Pneumonia on Chest CT. *Radiology*. 2020 Mar 19:200905. PMID: 32191588. doi: 10.1148/radiol.2020200905.
119. Mei XY, Lee HC, Diao KY, Huang MQ, Lin B, Liu CY, et al. Artificial intelligence-enabled rapid diagnosis of patients with COVID-19. *Nature Medicine*. PMID: WOS:000534188700001. doi: 10.1038/s41591-020-0931-3.
120. Murphy K, Smits H, Knoop AJG, Korst M, Samson T, Scholten ET, et al. COVID-19 on the Chest Radiograph: A Multi-Reader Evaluation of an AI System. *Radiology*. 2020 May 8:201874. PMID: 32384019. doi: 10.1148/radiol.2020201874.
121. Oh Y, Park S, Ye JC. Deep Learning COVID-19 Features on CXR using Limited Training Data Sets. *IEEE Trans Med Imaging*. 2020 May 8. PMID: 32396075. doi: 10.1109/tmi.2020.2993291.
122. Panwar H, Gupta PK, Siddiqui MK, Morales-Menendez R, Singh V. Application of deep learning for fast detection of COVID-19 in X-Rays using nCOVnet. *Chaos, solitons, and fractals*. 2020 Sep;138:109944. PMID: 32536759. doi: 10.1016/j.chaos.2020.109944.
123. Pu J, Leader J, Bandos A, Shi J, Du P, Yu J, et al. Any unique image biomarkers associated with COVID-19? *Eur Radiol*. 2020 May 28:1-7. PMID: 32462445. doi: 10.1007/s00330-020-06956-w.
124. Rahimzadeh M, Attar A. A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2. *Informatics in medicine unlocked*. 2020;19:100360. PMID: 32501424. doi: 10.1016/j.imu.2020.100360.
125. Rajaraman S, Antani S. Training deep learning algorithms with weakly labeled pneumonia chest X-ray data for COVID-19 detection. *medRxiv : the preprint server for health sciences*. 2020 May 8. PMID: 32511448. doi: 10.1101/2020.05.04.20090803.
126. Roy S, Menapace W, Oei S, Luijten B, Fini E, Saltori C, et al. Deep learning for classification and localization of COVID-19 markers in point-of-care lung ultrasound. *IEEE Trans Med Imaging*. 2020 May 14. PMID: 32406829. doi: 10.1109/tmi.2020.2994459.
127. Saiz FA, Barandiaran I. COVID-19 Detection in Chest X-ray Images using a Deep Learning Approach. *International Journal of Interactive Multimedia and Artificial Intelligence*. 2020 Jun;6(2):11-4. PMID: WOS:000537469200003. doi: 10.9781/ijimai.2020.04.003.
128. Singh D, Kumar V, Vaishali, Kaur M. Classification of COVID-19 patients from chest CT images using multi-objective differential evolution-based convolutional neural networks. *European Journal of Clinical Microbiology & Infectious Diseases*. PMID: WOS:000529003700001. doi: 10.1007/s10096-020-03901-z.
129. Al-Najjar H, Al-Rousan N. A classifier prediction model to predict the status of Coronavirus CoVID-19 patients in South Korea. *European Review for Medical and Pharmacological Sciences*. 2020 Mar;24(6):3400-3. PMID: WOS:000525326200064.
130. Burian E, Jungmann F, Kaissis GA, Lohof FK, Spinner CD, Lahmer T, et al. Intensive Care Risk Estimation in COVID-19 Pneumonia Based on Clinical and Imaging Parameters:

Experiences from the Munich Cohort. *Journal of Clinical Medicine*. 2020 May;9(5). PMID: WOS:000540223800271. doi: 10.3390/jcm9051514.

131. Chan L, Chaudhary K, Saha A, Chauhan K, Vaid A, Baweja M, et al. Acute Kidney Injury in Hospitalized Patients with COVID-19. *medRxiv : the preprint server for health sciences*. 2020 May 8. PMID: 32511564. doi: 10.1101/2020.05.04.20090944.

132. Cheng Z, Qin L, Cao Q, Dai J, Pan A, Yang W, et al. Quantitative computed tomography of the coronavirus disease 2019 (COVID-19) pneumonia. *Radiology of infectious diseases* (Beijing, China). 2020 Apr 28. PMID: 32346594. doi: 10.1016/j.jrid.2020.04.004.

133. Cheng FY, Joshi H, Tandon P, Freeman R, Reich DL, Mazumdar M, et al. Using Machine Learning to Predict ICU Transfer in Hospitalized COVID-19 Patients. *J Clin Med*. 2020 Jun 1;9(6). PMID: 32492874. doi: 10.3390/jcm9061668.

134. Du SY, Gao S, Huang GL, Li S, Chong W, Jia ZY, et al. Chest lesion CT radiological features and quantitative analysis in RT-PCR turned negative and clinical symptoms resolved COVID-19 patients. *Quantitative Imaging in Medicine and Surgery*. 2020 Jun;10(6):1307-17. PMID: WOS:000538012700011. doi: 10.21037/qims-20-531.

135. Ji M, Yuan L, Shen W, Lv J, Li Y, Chen J, et al. A predictive model for disease progression in non-severe illness patients with Corona Virus Disease 2019. *The European respiratory journal*. 2020 May 19. PMID: 32430433. doi: 10.1183/13993003.01234-2020.

136. Jiang XG, Coffee M, Bari A, Wang JZ, Jiang XY, Huang JP, et al. Towards an Artificial Intelligence Framework for Data-Driven Prediction of Coronavirus Clinical Severity. *Cmc-Computers Materials & Continua*. 2020;63(1):537-51. PMID: WOS:000522652300033. doi: 10.32604/cmc.2020.010691.

137. Li MD, Arun NT, Gidwani M, Chang K, Deng F, Little BP, et al. Automated assessment of COVID-19 pulmonary disease severity on chest radiographs using convolutional Siamese neural networks. *medRxiv : the preprint server for health sciences*. 2020 May 26. PMID: 32511570. doi: 10.1101/2020.05.20.20108159.

138. McRae MP, Simmons GW, Christodoulides NJ, Lu Z, Kang SK, Fenyo D, et al. Clinical decision support tool and rapid point-of-care platform for determining disease severity in patients with COVID-19. *Lab on a chip*. 2020 Jun 21;20(12):2075-85. PMID: 32490853. doi: 10.1039/d0lc00373e.

139. Shashikumar SP, Wardi G, Paul P, Carlile M, Brenner LN, Hibbert KA, et al. Development and Prospective Validation of a Transparent Deep Learning Algorithm for Predicting Need for Mechanical Ventilation. *medRxiv : the preprint server for health sciences*. 2020 Jun 3. PMID: 32577682. doi: 10.1101/2020.05.30.20118109.

140. Shen B, Yi X, Sun Y, Bi X, Du J, Zhang C, et al. Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. *Cell*. 2020 May 28. PMID: 32492406. doi: 10.1016/j.cell.2020.05.032.

141. Wang Y, Chen YT, Wei Y, Li M, Zhang YW, Zhang N, et al. Quantitative analysis of chest CT imaging findings with the risk of ARDS in COVID-19 patients: a preliminary study. *Annals of Translational Medicine*. 2020 May;8(9). PMID: WOS:000533657600024. doi: 10.21037/atm-20-3554.

142. Wang YC, Luo HY, Liu SQ, Huang S, Zhou Z, Yu Q, et al. Dynamic evolution of COVID-19 on chest computed tomography: experience from Jiangsu Province of China. *Eur Radiol*. PMID: WOS:000539516400004. doi: 10.1007/s00330-020-06976-6.

143. Wang S, Zha Y, Li W, Wu Q, Li X, Niu M, et al. A Fully Automatic Deep Learning System for COVID-19 Diagnostic and Prognostic Analysis. *The European respiratory journal*. 2020 May 22. PMID: 32444412. doi: 10.1183/13993003.00775-2020.

144. Yadaw AS, Li YC, Bose S, Iyengar R, Bunyavanich S, Pandey G. Clinical predictors of COVID-19 mortality. *medRxiv : the preprint server for health sciences*. 2020 May 22. PMID: 32511520. doi: 10.1101/2020.05.19.20103036.

145. Zhang K, Liu X, Shen J, Li Z, Sang Y, Wu X, et al. Clinically Applicable AI System for Accurate Diagnosis, Quantitative Measurements, and Prognosis of COVID-19 Pneumonia Using Computed Tomography. *Cell*. 2020 Jun 11;181(6):1423-33.e11. PMID: 32416069. doi: 10.1016/j.cell.2020.04.045.
146. Mohanty S, Harun Ai Rashid M, Mridul M, Mohanty C, Swayamsiddha S. Application of Artificial Intelligence in COVID-19 drug repurposing. *Diabetes & metabolic syndrome*. 2020;14(5):1027-31. PMID: 32634717. doi: 10.1016/j.dsx.2020.06.068.
147. Pandey A, Nikam AN, Shreya AB, Mutalik SP, Gopalan D, Kulkarni S, et al. Potential therapeutic targets for combating SARS-CoV-2: Drug repurposing, clinical trials and recent advancements. *Life Sci*. 2020;256:117883-. PMID: 32497632. doi: 10.1016/j.lfs.2020.117883.
148. Réda C, Kaufmann E, Delahaye-Duriez A. Machine learning applications in drug development. *Computational and structural biotechnology journal*. 2020 2020/01/01;18:241-52. doi: <https://doi.org/10.1016/j.csbj.2019.12.006>.
149. Jin Z, Du X, Xu Y, Deng Y, Liu M, Zhao Y, et al. Structure of Mpro from SARS-CoV-2 and discovery of its inhibitors. *Nature*. 2020 2020/06/01;582(7811):289-93. doi: 10.1038/s41586-020-2223-y.
150. Li G, De Clercq E. Therapeutic options for the 2019 novel coronavirus (2019-nCoV). *Nature Publishing Group*; 2020.
151. Ullrich S, Nitsche C. The SARS-CoV-2 main protease as drug target. *Bioorg Med Chem Lett*. 2020;30(17):127377-. PMID: 32738988. doi: 10.1016/j.bmcl.2020.127377.
152. Zhao K, So H. A machine learning approach to drug repositioning based on drug expression profiles: Applications in psychiatry. 2017 06/09.
153. Zieleszinski A, Vinga S, Almeida J, Karlowski WM. Alignment-free sequence comparison: benefits, applications, and tools. *Genome Biology*. 2017 2017/10/03;18(1):186. doi: 10.1186/s13059-017-1319-7.
154. Vinga S, Almeida J. Alignment-free sequence comparison-a review. *Bioinformatics*. 2003 Mar 1;19(4):513-23. PMID: 12611807. doi: 10.1093/bioinformatics/btg005.
155. Dubey S, Biswas P, Ghosh R, Chatterjee S, Dubey MJ, Chatterjee S, et al. Psychosocial impact of COVID-19. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*. 2020 2020/09/01;14(5):779-88. doi: <https://doi.org/10.1016/j.dsx.2020.05.035>.
156. Janz NK, Becker MH. The Health Belief Model: a decade later. *Health education quarterly*. 1984 Spring;11(1):1-47. PMID: 6392204. doi: 10.1177/109019818401100101.
157. Devlin J, Chang M-W, Lee K, Toutanova K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding 2018.
158. Yang Z, Dai Z, Yang Y, Carbonell J, Salakhutdinov R, Le QV, editors. XLNet: Generalized Autoregressive Pretraining for Language Understanding. *NeurIPS*; 2019.
159. Moradian N, Ochs HD, Sedikies C, Hamblin MR, Camargo CA, Jr., Martinez JA, et al. The urgent need for integrated science to fight COVID-19 pandemic and beyond. *Journal of translational medicine*. 2020;18(1):205-. PMID: 32430070. doi: 10.1186/s12967-020-02364-2.
160. Blomberg N, Lauer KB. Connecting data, tools and people across Europe: ELIXIR's response to the COVID-19 pandemic. *European Journal of Human Genetics*. 2020 2020/06/01;28(6):719-23. doi: 10.1038/s41431-020-0637-5.
161. Melissa H, Christopher C, Kenneth G. The National COVID Cohort Collaborative (N3C): Rationale, Design, Infrastructure, and Deployment. *Journal of the American Medical Informatics Association : JAMIA*. 2020 Aug 17. PMID: 32805036. doi: 10.1093/jamia/ocaa196.
162. Ivorra B, Ferrández MR, Vela-Pérez M, Ramos AM. Mathematical modeling of the spread of the coronavirus disease 2019 (COVID-19) taking into account the undetected infections. The case of China. *Commun Nonlinear Sci Numer Simul*. 2020;88:105303-. PMID: 32355435. doi: 10.1016/j.cnsns.2020.105303.

163. Wang N, Fu Y, Zhang H, Shi H. An evaluation of mathematical models for the outbreak of COVID-19. *Precision Clinical Medicine*. 2020;3(2):85-93. doi: 10.1093/pcmedi/pbaa016 %J Precision Clinical Medicine.
164. Anirudh A. Mathematical modeling and the transmission dynamics in predicting the Covid-19 - What next in combating the pandemic. *Infect Dis Model*. 2020;5:366-74. PMID: 32666005. doi: 10.1016/j.idm.2020.06.002.
165. Jewell NP, Lewnard JA, Jewell BL. Caution Warranted: Using the Institute for Health Metrics and Evaluation Model for Predicting the Course of the COVID-19 Pandemic. *Ann Intern Med*. 2020;173(3):226-7. PMID: 32289150. doi: 10.7326/M20-1565.
166. Long C, Xu H, Shen Q, Zhang X, Fan B, Wang C, et al. Diagnosis of the Coronavirus disease (COVID-19): rRT-PCR or CT? *European journal of radiology*. 2020;126:108961-. PMID: 32229322. doi: 10.1016/j.ejrad.2020.108961.
167. Zhai P, Ding Y, Wu X, Long J, Zhong Y, Li Y. The epidemiology, diagnosis and treatment of COVID-19. *Int J Antimicrob Agents*. 2020;55(5):105955-. PMID: 32234468. doi: 10.1016/j.ijantimicag.2020.105955.
168. Ai T, Yang Z, Hou H, Zhan C, Chen C, Lv W, et al. Correlation of Chest CT and RT-PCR Testing in Coronavirus Disease 2019 (COVID-19) in China: A Report of 1014 Cases. *Radiology*. 2020 Feb 26:200642. PMID: 32101510. doi: 10.1148/radiol.2020200642.
169. Xu B, Xing Y, Peng J, Zheng Z, Tang W, Sun Y, et al. Chest CT for detecting COVID-19: a systematic review and meta-analysis of diagnostic accuracy. *Eur Radiol*. 2020:1-8. PMID: 32415585. doi: 10.1007/s00330-020-06934-2.
170. Kim YY, Shin HJ, Kim MJ, Lee M-J. Comparison of effective radiation doses from X-ray, CT, and PET/CT in pediatric patients with neuroblastoma using a dose monitoring program. *Diagnostic and interventional radiology (Ankara, Turkey)*. 2016 Jul-Aug;22(4):390-4. PMID: 27306659. doi: 10.5152/dir.2015.15221.
171. Sistrom CL, McKay NL. Costs, charges, and revenues for hospital diagnostic imaging procedures: differences by modality and hospital characteristics. *Journal of the American College of Radiology : JACR*. 2005 Jun;2(6):511-9. PMID: 17411868. doi: 10.1016/j.jacr.2004.09.013.
172. Wong MD, Thai T, Li Y, Liu H. The role of chest computed tomography in the management of COVID-19: A review of results and recommendations. 2020;245(13):1096-103. PMID: 32588660. doi: 10.1177/1535370220938315.
173. Trauer M, Matthies A, Mani N, McDermott CB, Jarman R, editors. Utility of Lung Ultrasound in COVID-19: A Systematic Scoping Review. *medRxiv : the preprint server for health sciences*; 2020.
174. Poggiali E, Dacrema A, Bastoni D, Tinelli V, Demichele E, Ramos PM, et al. *h1n12020*;295(3):E6-E. PMID: 32167853. doi: 10.1148/radiol.2020200847.
175. Chen D, Liu S, Kingsbury P, Sohn S, Storlie CB, Habermann EB, et al. Deep learning and alternative learning strategies for retrospective real-world clinical data. *NPJ digital medicine*. 2019;2:43-. PMID: 31304389. doi: 10.1038/s41746-019-0122-0.
176. Clark K, Vendt B, Smith K, Freymann J, Kirby J, Koppel P, et al. The Cancer Imaging Archive (TCIA): maintaining and operating a public information repository. *J Digit Imaging*. 2013;26(6):1045-57. PMID: 23884657. doi: 10.1007/s10278-013-9622-7.
177. Hick JL, Hanfling D, Wynia MK, Pavia AT. Duty to Plan: Health Care, Crisis Standards of Care, and Novel Coronavirus SARS-CoV-2. *NAM Perspectives*. 2020. PMID: pub.1125424535. doi: 10.31478/202003b.
178. Chen C, Wang H, Liang Z, Peng L, Zhao F, Yang L, et al. Predicting Illness Severity and Short-Term Outcomes of COVID-19: A Retrospective Cohort Study in China. *The Innovation*. 2020;1(1):100007-. PMID: PMC7237911. doi: 10.1016/j.xinn.2020.04.007.

