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A Study of Impacts of Artificial Intelligence on COVID-19 Prediction, Diagnosis, Treatment, and Prognosis

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ABSTRACT

Following the identification of Coronavirus Disease 2019 (COVID-19) in Wuhan, China in December 2019, AI researchers have teamed up with a health specialist to combat the virus. This study explores the medical and non-medical areas of COVID-19 that AI has impacted: the prevalence of the AI technologies adopted across all stages of the pandemic, the collaboration networks of global AI researchers, and the open issues. 21,219 papers from ACM Digital, Science Direct and Google Scholar were examined. Adherence to the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework and utilizing the PICO (population, intervention, comparison, and outcome) paradigm, guided the inclusion of researches in the review. Tables and graphs were utilized to display the results. Analysis revealed that AI has impacted 4 molecular, 4 clinical, and 7 societal areas of COVID-19. Deep Learning among other AI technologies was traced to all aspects of the pandemic. 2173 authors and co-authors were traced to these achievements, while 32 of the most connected 51 authors were affiliated with institutions in China, 18 to the United States, and 1 to Europe. The open issues identified had to do with the quality of datasets, AI model deployment, and privacy issues. This study demonstrates how AI may be utilized for COVID-19 diagnosis, prediction, medication and vaccine identification, prognosis, and contact person monitoring. This investigation began at the beginning of the epidemic and continued until the first batch of vaccinations received approval. The study provided collaboration opportunities for AI researchers and revealed open issues that will spike further research toward preparing the world for any future pandemic

Keywords: Artificial Intelligence, COVID-19, Diagnosis, Prognosis, Contact Tracing

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1. INTRODUCTION

In December 2019, the COVID-19 was found in Wuhan, China firstly. On March 11, 2020, the WHO called it a worldwide pandemic [104] that ushered in a worldwide health emergency concern and social and economic devastation. As of April 4, 2021, the sum of established cases of COVID-19 announced by WHO was 130,422,190 besides the 2,842,135 deaths. The United States of America (USA) was on top of the list of inveterate cases (30,304,462), then Brazil (12,910,082) and India (12,485,509). In Africa, South Africa topped the list of established cases (1,551,501), then Ethiopia (213,311) and Nigeria (163, 113).

Progressively, like other previous pandemics, COVID-19 was vigorously combated by researchers in various fields of pure and applied sciences, engineering, and social sciences in collaboration with those in medical sciences. Because the world never really prepares for a pandemic, the appropriate drugs, vaccines, and infrastructure among other desirable resources are not satisfactorily available especially at the early stages of such outbreaks just as it was not available for the COVID-19 pandemic. Outbreaks spur researchers into actively engaging emerging issues with existing capacity at the early stages [1]. Without prejudice to other approaches, evidence abounds in the literature of how Artificial Intelligence (AI) technologies contributed tremendously towards preventing and combating several previous pandemics like HIV/AIDs, Swine Flu, SARS, and EBOLA [2]. In the same vein, AI researchers have also given a lot of attention to COVID-19 by developing and deploying several AI technologies for medical and non-medical concerns of the pandemic. AI is an algorithm-based field that facilitates the simulation of human decision-making tasks by machines.

The findings of researchers in the early time of the plague were uploaded to open-access repositories like MedRXiv, ArXiv, and BioRxiv, some were published with minimal peer reviews. Therefore, considering the volume of the publications and the ‘lockdown’ condition under which most of these researches were conducted and circulated, some of the reports were concluded with cautionary notes. The warnings range from the consequences of using a small dataset for the model development to inadequate benchmarking of the process adopted, or weak peer-reviews. These limitations among others beclouded the authenticity and acceptability of some of the findings and conclusions reported within the period that spans from December 2019 through the year 2020. All the related articles of this period reflected the circumstances of the time and revealed some open issues.

Fortunately, with the discovery of the vaccine and the generality of advancement in the medical and non-medical handling of COVID-19, it is safe to affirm that research on the pandemic has matured. There is an improved understanding of the molecular structure, diagnosis procedures, and measures of control for the pandemic. This development enhances the discovery of virus mutations and the management of the various waves of the pandemic across the globe. It is therefore instructive to review the process that has led to these accomplishments and identify and discuss the open issues thereof as an agenda for the future.

This study research provides a broad review of the roles of various AI technologies across the phases of the pandemic. The scope of this research and the periods in which it is conducted provide the strength of this study over other related works. The study, therefore, seeks to provide answers to the following questions through a systematic examination of the existing studies on the application of AI to medical and non-medical strategies adopted for combating COVID-19:

a) What are the medical and non-medical areas of COVID-19 that AI has impacted?
b) What is the prevalence of the AI technologies adopted across all stages of COVID-19?
c) What is the collaboration network between global AI researchers and nations on COVID-19?
d) What are the AI open issues at the early stage of the pandemic that requires further attention from AI researchers?

1.1 Contribution of This Article

This paper dissects early publications on COVID-19 to offer a view of all the study areas. It identifies and juxtaposes earlier successes, methodologies, and challenges at the molecular, clinical, and societal stages in the application of AI to the pandemic. It ends by outlining the open issues and determining the agenda for the future. This study is of immense benefit to the AI research community, health practitioners, government, and Non-Governmental Organizations, including grant agencies as a stock-taking effort to determine the accomplishments and weaknesses of the various AI techniques deployed so far during the pandemic. The findings should guide policy makers on the deployment and sponsorship of AI-related solutions in the health sector just as it would guide stakeholders on a possible trajectory for any possible future health concerns and eventualities.

1.2 Article organization

This article begins with the background in section 1, which highlights the research objectives and the significance of the research. Section 2 has the methodology that provides the search results, the taxonomy of areas of application of AI, and the impacts of AI in the areas of molecular, clinical, and societal medicines. In section 3, results are specified and this is followed by the discussions. The conclusion of the study is in section 4.

2. METHODS

The PRISMA serve as a roadmap for the review's methodology. Other theoretical bases for the study are specified in their relevant sections and subsections.

2.1 Eligibility, Data Source, and Search Strategy

The PICO framework was used to define the scope of this review, as well as the most important parts of the review question and the inclusion criteria (Table 1). Studies are deemed qualified for inclusion if they report the application of AI approaches to COVID-19 either for Prediction, Diagnosis, Treatment, or Prognosis. The relevant articles were identified on the ACM Digital and Science Direct databases. Google Scholar was also used to complement the collections and to ensure relevant primary studies were not left out. The articles selected were from an early stage of the pandemic which is from December 2019 when the WHO proclaimed COVID-19 a pandemic till July 2020. This time window was extended to December 2020 when the WHO recognized the Comirnaty COVID-19 mRNA as an emergency vaccination usage.

This made the Pfizer/BioNTech immunization the initial to acquire the organization's Emergency Use Listing (EUL). Previously, this time window was only extended to December 2019.

Table 1: Framework for Determining The Eligibility Of Studies (PICO)

Criteria	Description
Population	COVID-19 cases
Intervention	Artificial Intelligence interventions on the Prediction, Diagnosis, Treatment or Prognosis of COVID-19.
Comparison	Not applicable in this review
Outcome	Prevalence of AI interventions on COVID-19 Prediction, Diagnosis, Treatment, or Prognosis

A comprehensive search strategy for a systematic review requires the building of an adequate queryset from the key concepts of a study. The queryset is a connection of search terms and search phrases using Boolean operators (AND, OR, and NOT). The resultant query set from the initial search queries for each of the research questions is "("COVID-19" or "SARS-COV-2" or "Novel Corona" or "2019-ncov") and ("diagnostic model" otherwise "prognostic model" otherwise "prediction model" otherwise "machine learning" otherwise "artificial intelligence" or else "soft computing" otherwise "algorithm" otherwise "score" or "deep learning" or "regression"). The two distinct groups in the queryset are connected with the AND operators, just as the elements of each category are connected using the OR operator. This final query set used for the systematic literature review has been formulated to report the four investigative questions raised in this learning. The responses to the investigative questions, which constitute the contributions of this study are extractions, deductions, and derivations from AI-related studies on techniques, tools, and models for COVID-19 predictions, diagnosis, and prognosis.

2.2 Study selection

Four reviewers independently screened the publications in the respective databases. They considered the relevance of the title, keywords, and English language. The selected papers were collated into a library for further processing in the Endnote referencing software and literature screening program. The eligibility criterion was used to filter the initial collections for abstract and full-text screening. All disagreements arising from using the eligibility criterion to select studies were resolved through discussion and consensus.

2.3 Data extraction and synthesis

Significant data were obtained and harmonized by all authors. The data included title, first author, publication year, country, study design/type, Target population, COVID-19 areas, sampling method, dataset type, and AI technique.

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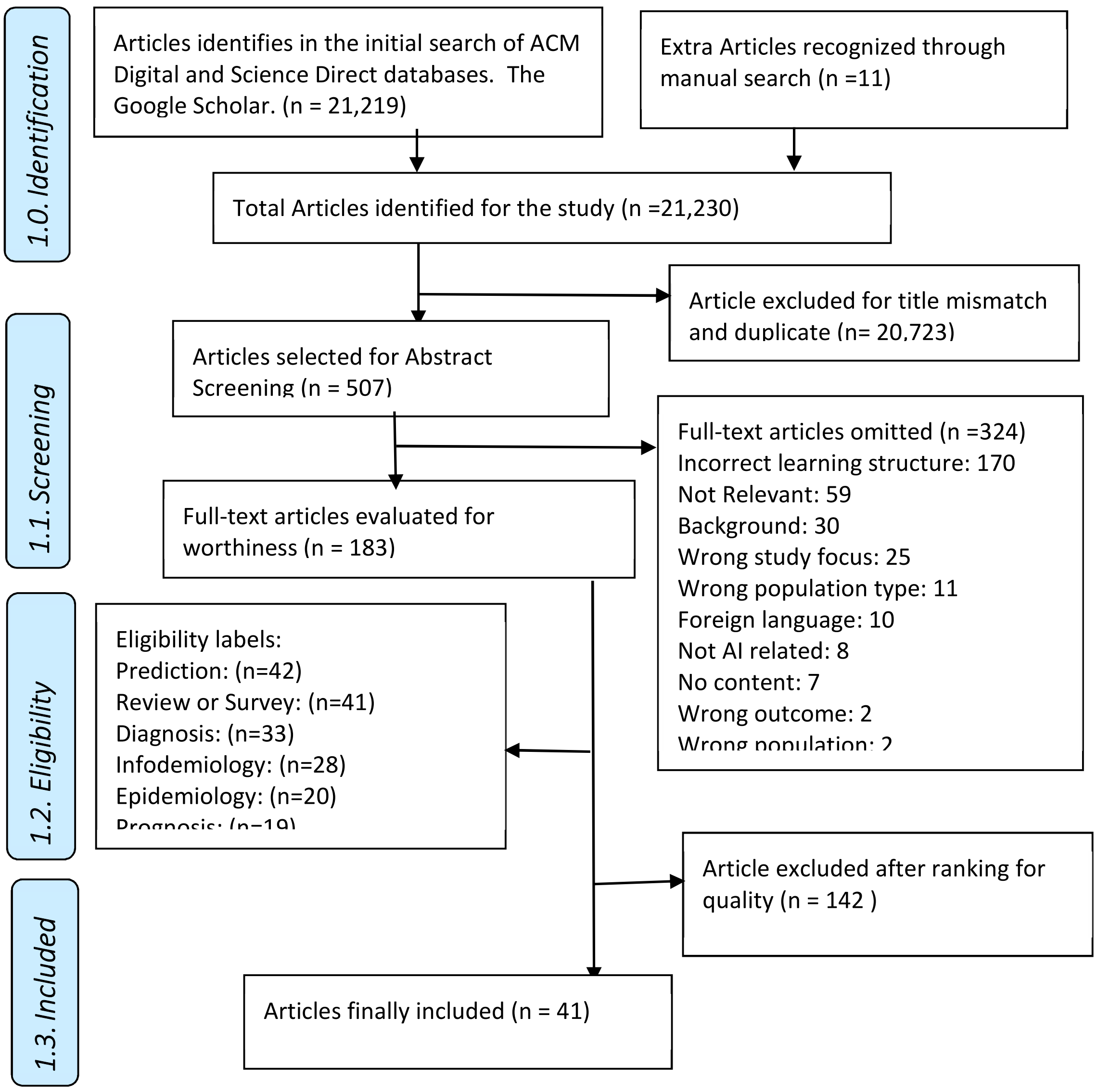

Figure 1: The PRISMA Diagram Describing the Selection of Artificial Intelligence Applications for COVID-19 articles[3]

3. RESULTS AND DISCUSSIONS

The four-level processes in the PRISMA model were used to select the articles required to gain insight into the contributions of AI technologies to COVID-19 from its discovery in December 2019 through July 2020 to December 2020.

3.1 Search Results and Study Characteristic

The relevant articles collected from the Science Direct databases, Google Scholar, and ACM Digital were 3,679, 17,500, and 40 respectively which add up to 21,219. The addition of the 11 articles that were manually sourced gives the total number of articles to 21,230. After the application of the eligibility criteria, 507 of the articles were considered for abstract screening, and 20,723 were dropped for duplication and title mismatch. 183 of the articles screened for abstract were divided among the authors for further processing, the remaining 324 were dropped. The reasons for the exclusion of articles include wrong study design, non-AI, background article, wrong study focus, wrong publication type, foreign language, and no content (Figure 1).

In all, 943 keywords were auto-extracted from the 183 Articles. Ranking of the articles by weights of the 'included keywords' revealed the 41 articles with the highest concentrations of the keywords. This provided a pointer that such articles shall be good sources of the needed information about the AI models, techniques, and interventions for COVID-19. The forty-one (41) papers in this category were taken further to the full paper review stage. The co-occurrence keywords were determined using 86 keywords with a minimum number of 3 occurrences.

Exploration of the network reveals the prominent nodes on the network for the application areas of COVID-19 as forecasting, prognosis, epidemiology, triage, and oncology. Others include otolaryngology, palliative care, infection control, humanism, and healthcare worker safety. On the AI technology and techniques, the nodes are deep learning, intelligence, and algorithms. The nodes on dataset types include computed tomography, lung, chest, and biological maker. The nodes on consequences and outcomes show mortality, stroke, inflammation, thrombosis, hyposmia, and anosmia. The countries in the network include Italy and Brazil (Figure 2).

The general overview of the referenced papers is in Appendix A. They are categorized into application areas of AI / AI models/technologies for COVID-19. The fourth category is the Dataset and Data Source for COVID-19. The deductions from these collections were used to respond to the formulated investigative questions. Also, the list of abbreviations and acronyms employed in this research is listed in Appendix B for better clarification.

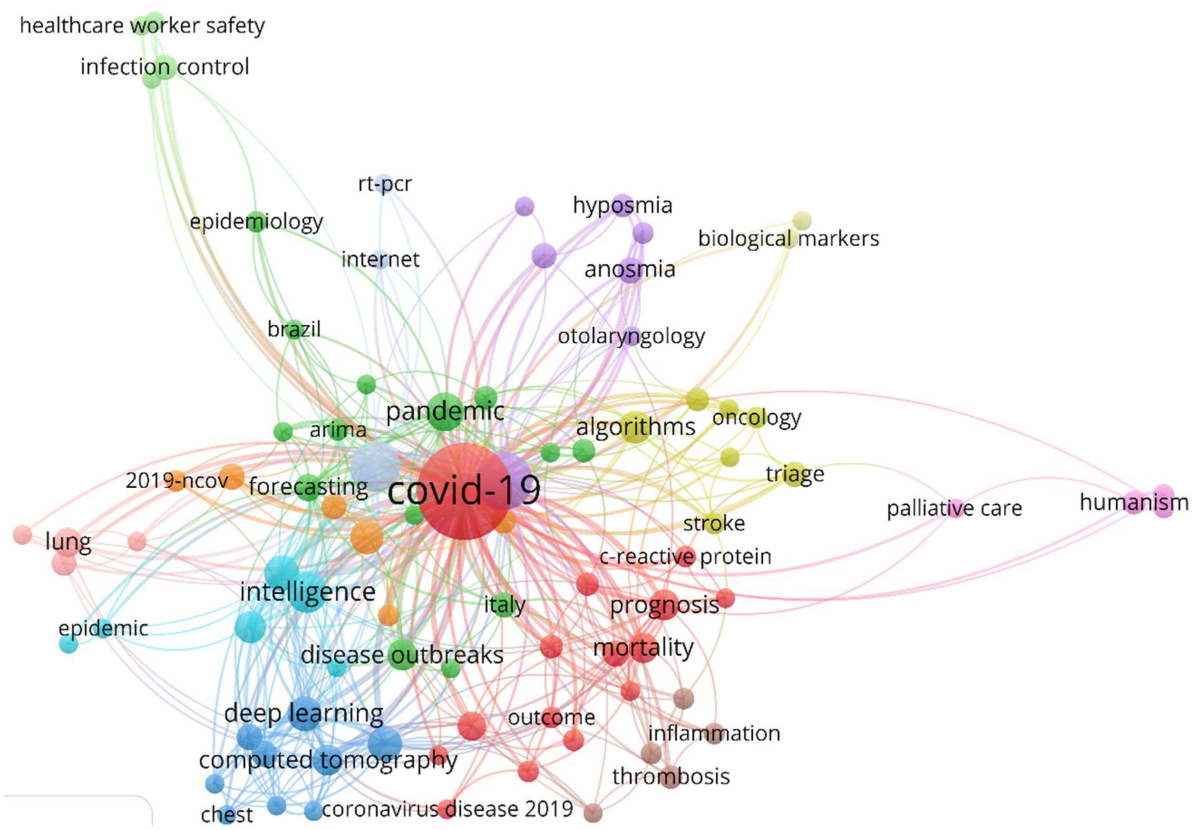

Figure 2: Network Visualization of AI for COVID-19 Co-Occurrence Keywords

Furthermore, the analysis of the authors and co-authors was done to identify the major researchers and researching nations on the COVID-19 AI applications during the period under review. The bibliometric analysis revealed 2173 authors and co-authors each having a minimum of one article. 93 of them have a minimum of 2 articles and 30 have a minimum of 3 articles. The Network Visualization of the 51 authors that are connected is shown in figure 3. Four (4) major clusters are formulated with 17 red clusters (China: 10, USA: 7), 12 green (China: 7, USA: 4, Europe: 1), 12 blue (China: 9, USA: 3) and 10 yellow (China: 6, USA: 4) authors.

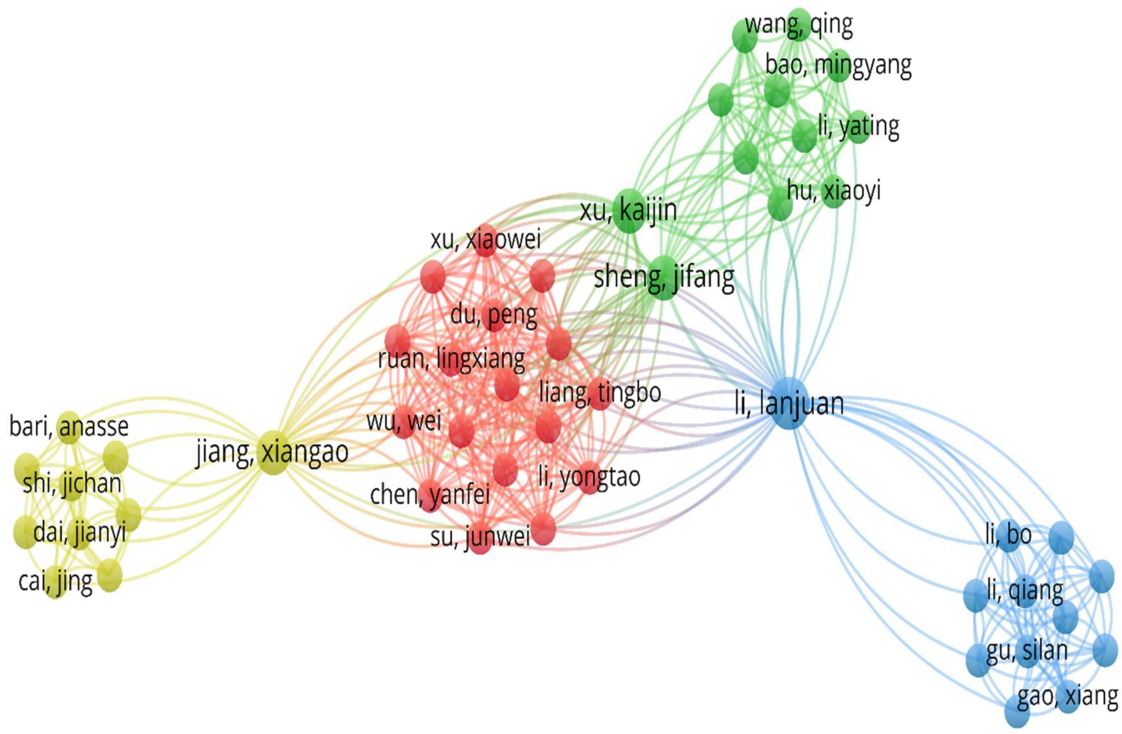

Figure 3: Network Visualization of the 51 Connected Authors on the AI application to COVID-19

The results indicate the most impactful and influential nations and authors. It also shows the intro and inter-relationship between and among the nations and the authors. The outcome shows that China (32 authors) and the United States (18 authors) have the most clusters of work on the AI application for COVID-19. Details of the 51 connected authors are shown in appendix E.

3.2 Taxonomy of areas of COVID-19 AI Applications and Open-Issues

The taxonomy of the AI application to the pandemic and the open issues are shown in Figure 4. The deductions from the survey reveal that application areas of AI to COVID-19 can be grouped either by types of medicine, by perspectives, or by public health concerns. The grouping by medicine is molecular, clinical, or societal [4]. The three grouping of application areas by perspectives is computational biology, patient, and medicine [20]. From the public health concerns or activities, COVID-19 AI applications include screening, treatment, and contact tracing. Others are prediction or forecasting, and drug and vaccine discovery. The most frequently applied AI technologies for COVID-19 are Deep Transfer Learning (DTL), Deep Learning (DL) in addition to Machine Learning (ML). Others are AI-embedded systems for example the Internet of Things (IoT) and Edge Computing (EC). Also, COVID-19 data sources are either opened or closed. The dataset types are text, sound, and image.

The open-issues identified from these earlier studies on the AI application to COVID-19 include Dataset and data source inadequacy, challenges of dataset availability and accessibility; Non-availability of model deployment standardization and benchmark framework; lack of ascendable methods to information and model distribution; inadequate open-source information curation and retrieval in numerous directions; Perception of AI procedures for COVID-19 control measures and prevention; Balancing the public health concerns and privacy. The review of each category is presented in the subsequent sections.

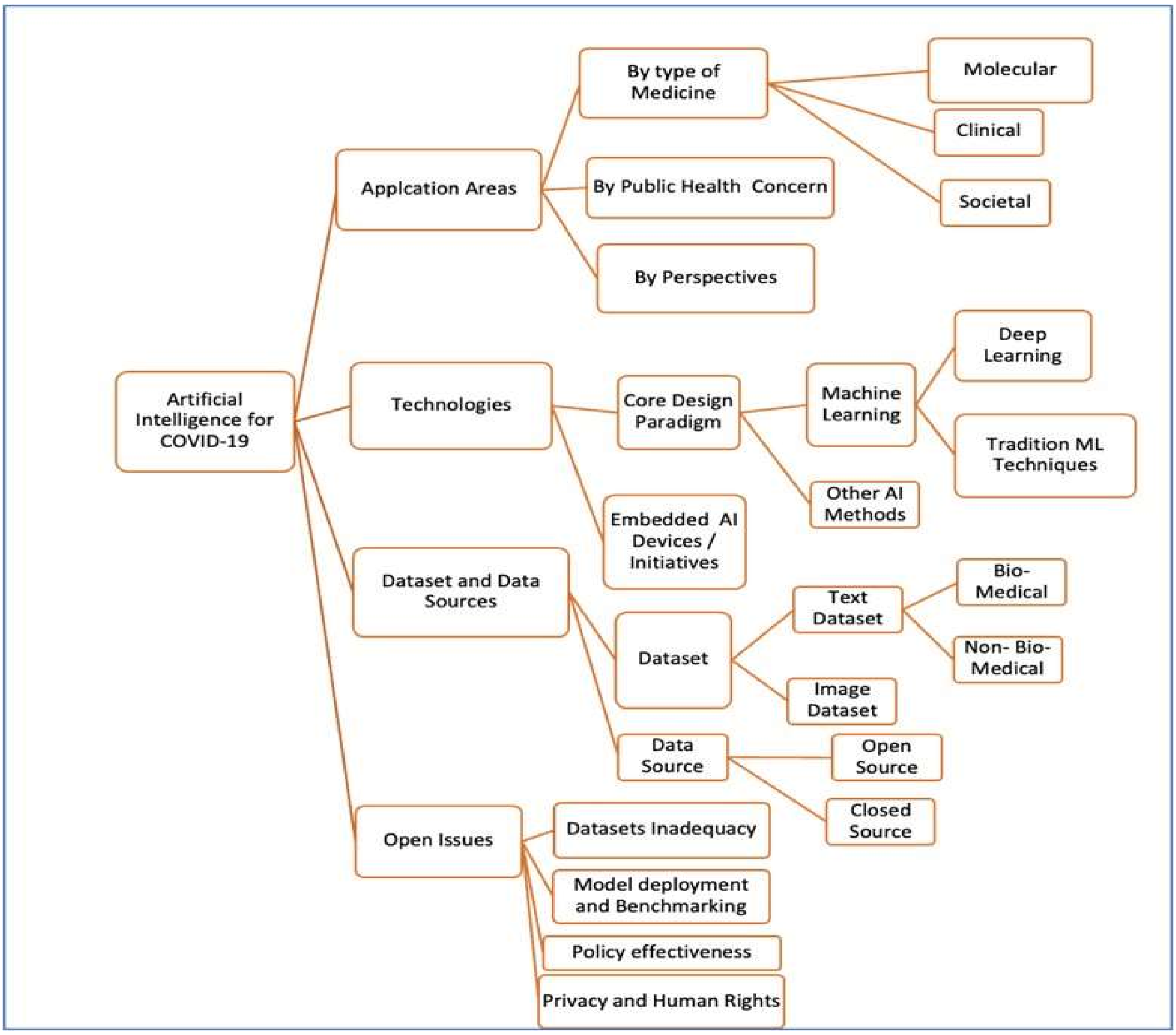

Figure 4. Taxonomy of the Application Areas of AI and the Open Issues on COVID-19

3.3 Application Areas of AI to COVID-19

From the submissions of [4], [3], and [21] the classification of AI to COVID-19 can be encapsulated as molecular, clinical, and societal (Table 2). The following subsections 3.4, 3.5, and 3.6 respectively present the molecular, clinical, and societal application areas of AI to COVID-19.

Table 2: Applicable Areas of AI for COVID-19

Types of Medicine		
Molecular	Clinical	Societal
Computational Biology	Patient	
-Protein structure predictions -Drug repurposing -Docking simulation -Drug /vaccine discovery	-Diagnosis/screening -Treatment -Non-invasive disease tracking -Patient outcome prediction	**Epidemiology:** -Modeling, prediction, and forecasting; -Tracking and Clustering; -Efficiency & public policy; -Risk assessment and bayesian analysis -Societal control **Infodemiology:** -Spread and interactions of COVID-19 -Hate speech and positive action

3.4 Molecular Application of AI to COVID-19

Physical, chemical, biological, bioinformatics, and medicinal approaches are utilized to describe molecular structures in molecular medicine, which is a vast discipline of medicine [22]. The term molecular is used to demonstrate how particular genes, molecules, and cellular activities can become faulty in disorders like cancer. AI has been utilized for COVID-19 membrane protein predictions, therapeutic targets, docking simulation, and vaccine candidates' development at the molecular level.

3.4.1 Contribution of AI to COVID-19 protein structure predictions and drug repurposing

The scientific community realized very early that understanding the pathobiology of COVID-19 was a necessity for the discovery of potent antivirals. Computation and machine learning-based technologies have yielded significant results thus far. New candidate medications and vaccines were discovered in silico using computer approaches. Similarly, effective viral therapeutics are provided by machine learning-based algorithms that have been trained on specific proteins. Machine learning techniques can suggest inhibitory prospects in a structural-based approach given a targeted membrane protein and enough data.

Consequently, [23] provided CoronaDB-AI, a collection containing chemicals, peptides, and determinants found either in-vitro or silico that may be utilized to train models for COVID-19 therapy extraction. The data and information given can be utilized to build DL techniques and speed up the development of successful viral medicines. A COVID-19 predicting model referred to as "pLoc_Deep-mHum" that incorporates the DL technique was developed as an advancement over "pLoc_bal-mHum" in [24]. They were to identify the sub-cellular localization of human proteins. Despite the performance of the pLoc_bal-mHum predictor, it was dropped for a more efficient DL "pLoc_Deep-mHum" predictor because of the "DL algorithm" integration.

The worldwide total true rate attained by "pLoc_Deep-mHum" was over 81% and its local accuracy was over 90%. The user-friendly webserver established for the predictor can be accessed at http://www.jci-bioinfo.cn/pLoc_Deep-mHum/. In addition, a pre-trained deep learning-based drug-target interface strategy termed Molecule Transformer-Drug Target Interaction (MT-DTI) was used [25] to recognize over-the-counter medications that may perform on SARS-CoV-2 epidemiologic proteins. This strategy is recognized as the MT-DTI. The most effective chemical in the trial was atazanavir, an antiretroviral medication used to treat and prevent Human Immunodeficiency Virus (HIV). With a Kd of 94.94 nM, it was proven to be effective against the SARS-CoV-2 3C-like proteinase. The study recommended a list of antiviral drugs for consideration in the strategies for the treatment of SARS-CoV-2.

Influenced by the fact that the implementation of an appropriate COVID-19 vaccine depends on the discovery of drug-target (DT) relations that use commercially obtainable medications to find possible inhibitors, the DeepH-DTA framework was proposed by [26] for predicting DT conformations for varied drugs. Extensive tests were conducted against cutting-edge methodologies utilizing Davis and KIBA general populace data sources to assess DeepH-performance. The DTA's databases include a variety of kinase protein samples as well as relevant inhibitors. On the Davis and KIBA datasets, DeepH-DTA achieved the best Congruence Index (CI) of 0.924 and 0.927, respectively, with mean square error (MSE) of 0.195 and 0.111.

Furthermore, medication repurposing was identified as a possible path for the formulation of COVID-19 preventive and treatment options. CoV-KGE is an associative, network-based deep-learning technology developed by [27] to pinpoint repurposable medicines for the pandemic. Using a vast technical corpus of 24 million PubMed papers, the researchers created a complete knowledge network with 15 million links linking drugs, illnesses, proteins/genes, and pathways. CoV-KGE was created by combining network-based deep learning technology with AWS computing resources from Amazon. Transcriptomic and proteomic information in SARS-CoV-2-disease-ridden living organisms, as well as information from clinical trials, were used to identify 27 repurposable medicines having therapeutic correlations with COVID-19.

Summarily, a collation of some repurposable antiviral drugs that were tried and proved to have good potential for accelerated therapeutic development for COVID-19 is shown in Appendix C. In the collection, the name of the drugs, the manufacturer, and the country of the company are provided. Also provided is a brief description of the identified drugs. The total drugs listed are 25, 10 are from the US, 4 each from UK and India, 2 from China, and 1 each from France, Germany, Russia, Spain, and Switzerland.

3.4.2 Contribution of AI to COVID-19 drug and vaccine discovery

This crucial component of the COVID-19 mitigating technique benefited substantially from AI capabilities. The strategy was considered essential because there was no effective COVID-19 medical treatment, and vaccine development was urgently needed. As a result, [50] suggested an in silico DL method for the estimate and conception of a multi-epitope shot (DeepVacPred). The model was made up of a deep neural network and in silico immune informatics. DeepVacPred provides 26 potential vaccine components based on the available SARS-CoV-2 spike protein sequence.

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A lack of overall protection as well as safety issues were discovered in the clinical trial survey on the spike (S), nucleocapsid (N), and membrane (M) proteins studied for SARS and MERS vaccine development. To anticipate the COVID-19 vaccine candidates [51] used the Vaxign and the machine learning-based Vaxign-ML reverse vaccinology tools. The SARS-CoV-2 N protein sequence was conserved with SARS-CoV and MERS-CoV, but not with the other four human coronaviruses that cause moderate symptoms, according to the Vaxign research. Table 3 shows the candidates and vaccinations suggested and approved on the information retrieved bases from the official website WHO as of April 2021[106].

Table 3: Candidates and Recommended Vaccines

Name	Age limit	Number of shots	Limitations
Pfizer-BioNTech/ BNT162b2/COMIRNATY Tozinameran (INN)	12 years and older	2	One should not get an mRNA COVID-19 immunization if a severe allergic response (anaphylaxis) or an acute allergic reaction, even a mild one, to any component of the vaccine has already occurred (such as polyethylene glycol). If the first dosage of any mRNA COVID-19 immunization resulted in a severe or rapid adverse response, a second dose shouldn't be acquired.
Moderna/ mRNA-1273	18 years and older	2	Same as Pfizer-BioNTech above
Johnson & Johnson's Janssen/ Ad26.COV2	18 years and older	1	If you have ever experienced an acute allergic response, even a mild one, to any ingredient in the J&J/JanssenCOVID-19 vaccine, or if you have ever had a severe allergic reaction (anaphylaxis) (such as polysorbate). prior history of anaphylaxis or a severe allergic reaction to any substance, regardless of strength.
Sinova COVID-19/ Coronavac	18 years and older	2	Anaphylaxis to slightly component of the injection should be avoided. Infected individuals should not be vaccinated until they are well enough to be removed from isolation. Those with a fever of 38°C or higher should delay vaccination.
Sinopharm COVID-19/ InCoV	18 years and older	2	Individuals who have had anaphylaxis to any element of the vaccine in the past should avoid it.
Oxford/AstraZeneca COVID-19/ AZD1222 Vaxzevria	18 years and older	2	The Vaccine should be avoided if there is previous experience of a simple sensitive response to any element of the vaccine.

As shown, a total of six (6) approved vaccines focus on the age limit, the number of shots required, and the limitation associated with each of the vaccines. As indicated in the limitation, it is obvious that the major hindrance to the receipt of the vaccines was anaphylaxis. Anaphylaxis is a systemic reaction portrayed by rapid onset and possibly deadly consequences of airway, respiratory, or circulatory involvement. [113]. After the presentation of a successful vaccine, the frequency of new cases diminishes, but adverse effect shows up due to anaphylaxis and can become hazardous.Also, the age limit proves to be a major setback to these vaccines, with only the Pfizer COVID-19 vaccine having the approval to get those below the age of 18 vaccinated but just down to the age of 12. Concerning the Centers for Disease Control and Prevention (CDC), young ones below the age of 12 have limited chances of being infected. The recommendation given in this regard is for those from the ages of 12 and above to get vaccinated, so as not to infect those who cannot get vaccinated.

3.5 Clinical Application of AI to COVID-19

Clinical medicine is a type of scientific medicine that gives more emphasis on the direct observation of the patient. Unlike other fields that concentrate on the theoretical and basics of medical science, clinical medicine heals patients through direct diagnosis, treatment, surgery, and prognosis. AI techniques have been used for COVID-19 diagnosis, treatment, non-invasive disease tracking, and patient outcome prediction - Prognosis. This section discusses the clinical application of AI in these areas.

3.5.1 Contribution of AI to COVID-19 diagnosis using cough and medical images

The conventional diagnosis method for COVID-19 is a laboratory test. The process is expensive and requires a specialized laboratory. This led to the growth in popularity of magnetic resonance imaging (MRI) and computed tomography (CT) for identifying COVID-19 affected role, however other data types like cough, voice, and breathing have also been utilized sparingly. In [52] AI technology over computed tomography was employed to foster a speedy and precise method for the analysis of COVID-19. CT scan, or computed tomography, is an analytical imaging method that shows imageries of the internal part of the body system utilizing a grouping of computer technology and X-rays. It could show comprehensive analyses of the skeletons, physiques, fat, tissues, and blood vessel in every segment of the human body.

The study included 1020 CT slices from 108 COVID-19 patients and 86 patients with various atypical and viral pneumonia illnesses. AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101, and Xception were designed to identify COVID-19 infection from non-COVID-19 groups. The two networks with the best performance were ResNet-101 and Xception. ResNet-101 distinguished COVID-19 patients from non-COVID-19 cases with an AUC of 0.994. (Sensitivity, 100 percent; specificity, 99.02 percent accuracy, 99.51 percent). In contrast, Xception has an AUC of 0.994. (98.04 percent sensitivity, 99.02 percent accuracy, and 100 percent specificity) As a result, ResNet-101 can be used to define and diagnose COVID-19 infections with great sensitivity.

Also, [53] A deep learning-based image classification strategy was utilized to detect COVID-19 Chest X-Ray pictures (CXR). Using transfer learning, a CNN classifier was utilized to describe the normal-healthy photos from the COVID-19 images. The accuracy, precision, recall, and F1-score criteria were used to evaluate the system's outputs. The research also contains an automated comparison of many optimizers, such as Stochastic Gradient Descent (SGD), AdamW Adam, and Adamax.

The LR Scheduler and Loss Function were used to achieve the highest possible accuracy for the proposed system. The Adamax optimizer outperformed the competition, obtaining 98.45% accuracy for normal-healthy CXR images and 98.32% accuracy for COVID-19 images. Similarly, [54] investigated the efficacy of a VGG16-based DL model for noticing pneumonia and COVID-19 using torso radiographs - X-ray Pulmonary Imaginings. The results reveal that COVID-19 can be identified with 100 percent sensitivity and a gradation of specificity, indicating it may be utilized as a transmission examination. For all classes considered, AUCs on ROC curvatures are more than 0.9.

Publically obtainable CT imageries of COVID-19 pneumonia and lung cancer were employed by [55] in the same way. There are 349 COVID-19 CT pictures and 397 non-COVID-19 CT images in this COVID-19 collection. The CT scan data was included in the 760 COVID-19-related preprints on medRxiv and bioRxiv. As a result, a substantial amount of label data from a lung cancer CT dataset was gathered, and the model used this data to build a COVID-19 dataset and learn the COVID-19 ground glass opacity (GGO) style using a CycleGAN model. The COVID-19 dataset was produced by training deep learning (DL) classification algorithms on 512 512 x 3 2D lung cancer CT scan pictures. The generated dataset was used to train the deep learning-based COVID-19 classification models VGG16, ResNet-50, Inception ResNet v2, Inception v3, and DenseNet-169. 1000 images of synthetic COVID-19 and 1000 photographs of non-COVID-19 made up the dataset. The F1 score, recall, accuracy, and precision of the models were evaluated. All average metrics in the study are greater than 90%, indicating reliability in diagnosing COVID-19 using synthetic data, which can aid in the development of a deep learning-based COVID-19 diagnostic tool.

Complementarily, [56], identified chest X-ray imagery knowledge as a useful tool for finding Chest X-ray imaging is used to demonstrate Magnetic Resonance Imaging (MRI), which employs radio waves and magnets to examine stuff inside the body. They are widely used to diagnose problems with the heart, brain, blood vessels, breast, joints, and breast tissue. By analyzing COVID-19 patient X-ray images, experts are offered extra diagnosis recommendations, which may assist them manage aspects of their tasks more simply. As a result, the study combined five pre-trained DL models with traditional transfer learning approaches. The Xception model has nearly perfect effects and a diagnosis accuracy of 96.75 percent. To improve diagnostic accuracy, an end-to-end diagnostic model was developed that combines deep features with ML classification. According to experimental results on two distinct datasets, the diagnostic accuracy of Xception+SVM rose by 2.58 percent when compared to the baseline Xception model and reached a maximum of 99.33 percent when compared to the baseline Xception model. This model's sensitivity, specificity, and AUC were respectively 99.27 percent, 99.38 percent, and 99.32 percent.

Away from medical imaging, [57], hypothesized that utilizing AI, COVID-19 participants and asymptomatic may accurately be distinguished through a forced-cough mobile phone record. The MIT Open Voice model was created using a pipeline of COVID-19 cough recordings as training data at opensigma.mit.edu. With 5,320 samples, the biggest audio COVID-19 cough-balanced dataset was generated in May 2020. Using acoustic biomarker feature extractors, the system pre-screens cough recordings for COVID-19 and develops a unique patient saliency map, enabling real-time, non-invasive, and low-variable-cost longitudinal patient monitoring.

The cough recordings are utilized to create a convolutional neural network (CNN)-based architecture that gives a binary pre-screening diagnostic by employing one Poisson biomarker layer and three pre-trained ResNet50 layers in parallel. The CNN-based models were trained on 4256 focuses before being evaluated on the remaining 1064.

Transfer learning, which learns biomarker characteristics on bigger datasets and has formerly been effectively tested in the test center on Alzheimer's, enhanced the COVID-19 insight accurateness of the design. When tested on people who had been diagnosed with COVID-19 using an approved test, the result was 98.5 percent sensitivity and 94.2 percent specificity (AUC: 0.97). It has a specificity of 83.2 percent and a sensitivity of 100 percent in asymptomatic people. AI techniques were found to be capable of producing a permitted, non-aggressive, real-time, anytime, instantaneously distributable, large-scale COVID-19 asymptomatic transmission tool to supplement existing COVID-19 containment strategies. Students, workers, and the general public might be screened daily in places like schools, employment, and trains.

Also, information investigation of a large-scale crowd-sourced dataset was reported in [58]. The collection contains respiratory coughs and breathing sounds recorded for COVID-19 diagnosis. The study compares COVID-19 sounds to those of asthmatics and healthy individuals using coughs and breathing. The researchers created three binary tasks to distinguish COVID-19-positive users from healthy users, COVID-19-positive users with a cough from healthy users with a cough, and COVID-19-positive users with a cough from asthma sufferers who report having a cough. For all three tasks, the results show that performance remained over 80% area under the curve (AUC). With an AUC of 80% (Task 1), 82 percent (Task 2), and 80% (Task 3), the study properly categorized healthy and COVID-19 sounds (Task 3). The research shows how automatically analyzed breathing patterns can be used as pre-screening indications to help diagnose COVID-19.

Based on the coughing echoes characteristics and indications metadata, [59] created an explainable COVID-19 analysis AI system, a model which comprises of two subnetworks that procedure the information from diverse modes (a TabNet network that processes featured indications & Demographic information, while the other network processes the auditory indicator from cough. A medical dataset of 30000 audio segments, 328 cough sounds from 150 persons, four types of cough, symptoms, and demographic data were used to evaluate the framework's effectiveness (COVID-19, Asthma, Bronchitis, and Healthy). According to the experimental results, the model captures a strong and robust feature embedding to discriminate between COVID-19 patient coughs and other forms of non-COVID-19 coughs with specificity and accuracy of 95.04 0.18 percent and 96.83 0.18 percent, respectively.

Federated learning (FL) was utilized to predict clinical outcomes in COVID-19 patients while respecting data privacy. FL enables the training of AI models using data from several sources while maintaining data privacy. The EXAM (electronic medical record (EMR) chest X-ray AI model) predicts the future oxygen demands of symptomatic COVID-19 patients based on vital signs, laboratory data, and chest X-rays. EXAM delivered a 16% increase in average AUC assessed across all participating sites and a 38% increase in generalizability when compared to models trained at a single site using that site's data for predicting outcomes after 24 and 72 hours after the first visit to the emergency department [100].

For categories with few samples, the FL significantly improves the average AUC performance of the local models trained on an unbalanced dataset. When compared to the local models, the FL model likewise produced greater true-positive rates and lower false-positive rates. Typically, the receiver-operator characteristic (ROC) plot and the area under the ROC curve (AUC) usually describe the effects or consequences of threshold adjustments on false positives and negatives in ML models, [114]. Class-imbalanced issues develop when the number of samples in one of the classes, typically the class of interest, is much lower than the number of samples in the other, it is crucial to utilize appropriate evaluation criteria to accurately measure the value of pursued algorithms and evaluate their impact realistically.

Methods for evaluating classifiers on datasets with class imbalance are well-known and have been exhaustively documented in the past. In numerous real-world classification situations, the class of interest is disproportionately underrepresented. The standard set of appropriate evaluation criteria is well-known, but the common assumption is that the imbalance in the test dataset mirrors the imbalance in the actual world. This assumption is frequently disproved in practice for a variety of reasons. Consequently, the published results are frequently overly optimistic and may lead to erroneous inferences on the industrial impact and applicability of proposed procedures. Without accessing local data, the FL can successfully address the problem of data silos and create a shared model. In order to remove COVID-19 from chest X-ray pictures, a collaborative federated learning architecture that was presented in could make use of DL [101].

This work investigated essential properties and aspects of federated learning environments, including naturally occurring non-IID and unbalanced data distributions. The test demonstrated that the federated learning framework generated outcomes similar to those of models built utilizing shared data. These results motivate health care providers to collaborate and use the wealth of personal data to swiftly create a powerful model for COVID-19 screening.

Furthermore, Dynamic-Fusion-Based Federated Learning and Blockchain-federated-learning have also been used for COVID-19 detection. Dynamic-Fusion-Based Federated Learning used health analytical image investigation to improve model performance and communication efficiency of COVID-19 prediction. This allowed us to schedule the model fusion based on how well the participating customers' local models performed and to dynamically choose clients to join based on their training times. It also provides a variety of medical diagnostic image datasets with COVID-19 detection capability for machine learning image analysis. The study's findings demonstrated that the proposed technique was feasible and beat the federated learning system's default configuration in terms of model performance, efficient communication, and fault tolerance [102]

In [103], DL models and Blockchain-based federated learning were used for COVID-19 detection using CT imaging. The project's main goal is to develop a system that leverages a little quantity of data from several sources to train a global deep learning model utilizing blockchain-based federated learning (various hospitals). The data was validated with blockchain technology, the model was trained globally via federated learning, and the company's name was hidden. Because the data came from a variety of institutions utilizing various types of Computed Tomography (CT) scanners, the study provides a data normalization approach to cope with data heterogeneity.

The suggested approach may benefit from new data, increasing the ability to identify CT images. The results revealed that the sensitivity of COVID-19 patient identification has improved.

3.5.2 Contribution of AI to COVID-19 Non-Invasive Tracking and Patient Outcome Prediction

Prognosis, or patient outcome prediction, is a medical term for forecasting the likely result or course of an illness, as well as the likelihood of recovery or recurrence [60]. The impact of AI on this component of COVID-19 is conspicuous. The importance of developing a predictive tool to recognize risky patients was emphasized by [61] to aid in the construction of treatment strategies. The study included 366 patients with severe COVID-19 from four different sites, of whom 296 survived longer or received a cure, compared to 70 who passed away within 14 days of their initial CT scan. Patients in these two groups were categorized as high-risk and low-risk, respectively. With the use of a 3D densely coupled convolutional neural network, CT and clinical data were examined to determine whether COVID-19 patients were more likely to fall into the high-risk or low-risk categories. The area under the curve (AUC) for the De-COVID-19-Net model is 0.952. De-COVID-19-Net has shown its capability to predict the patient's impending death non-invasively using the patient's initial CT scan. Thus, the technique may be used to identify high-risk individuals and provide therapy early.

Similarly, the need for early COVID-19 diagnosis and the identification of risky patients with a poor prediction for early inhibition and therapeutic resource optimization was stressed in [56]. The researchers suggested a completely automated DL approach for COVID-19 diagnosis and predictive investigation using regular computed imaging. A reflective report of 5372 patients with computed imaging scans was conducted in seven cities or provinces. For external validation of the DL system, pre-training was done with computed CT scans of 4106 patients and 1266 patients from six cities or provinces. The DL algorithm distinguished COVID-19 from further pneumonia with an AUC of 0.87 and viral pneumonia with an AUC of 0.86. As a result, the DL system can emphasize on anomalous areas with consistent features with reported radiological findings without the need for human intervention. It was successful in categorizing patients into high-risk and low-risk categories, with significant differences in hospital stay time of p=0.013 and p=0.014, correspondingly.

In [62], a collection of 58 clinical and biological factors, as well as chest CT scan information, from 1003 COVID-19-infected patients from two French clinics was done to discover predictors of COVID-19 severity and priority. To predict severity, a DL model based on CT scans was built. Urea, gender, oxygenation, platelet, and age are among the five multimodal clinical and biological factors used to create AI severity scores. The neural network analysis of CT images provides unique prognostic information that outperformed 11 previous AI-severity ratings significantly.

The lack of a defined COVID-19 stage description and progression characterization [63] was identified as a snag [63]. As a result, a temporal DL strategy based on a time-aware long short-term memory (T-LSTM) neural network has been presented. The model can understand active relations in sporadically tested time series after being trained with blood samples from 485 patients. By taking into account both biomarkers and irregular periods, it can predict the fate of COVID-19 patients. Finally, the T-LSTM unit for patient representations was employed to subtyped the patient phases and explain COVID-19 disease development. There were four (4) phases of COVID-19 evolution identified, each with differing patient ranks and death concerns.

A total of forty (40) biomarkers associated with the condition were ranked, with reference values for each stage provided. Lymph, LDH, hs-CRP, Indirect Bilirubin, and Creatinine's are the top five. Myocardial injury, liver function damage, and renal function damage are also three complications discovered. Predicting which of the four phases a patient is in, can aid clinicians in improved assessing and treating the patient. At 12 days, the accuracy of the model's forecast results was over 90%, and at 3, 6, and 9 days, it was 98, 95, and 93%, correspondingly.

3.6 Societal Application of AI to COVID-19:

Socialized healthcare, often known as socioeconomic pharmaceuticals, is a scientific, multidisciplinary area of medicine that analyzes population health and healthcare systems in a broader social context [64]. As part of public health, social medicine focuses on population-based health issues, their characteristics and factors, and the possibility of controlling them [65]. Rather than viewing disease as a singular entity, social medicine views the health-illness dialectic as a fluid, multifaceted interaction between the normal and abnormal. Epidemiology, biostatistics, and social psychology are the scientific and methodological foundations of social medicine; others include sociology, law, economics, managerial sciences, philosophy, and history. The Epidemiology and Infodemiology scales are the two divisions of social medicine.

3.6.1 Contribution of AI to COVID-19 Epidemiology and Infodemiology

Epidemiology is a branch of medicine that studies the causes of disease and health outcomes in communities. Modeling and forecasting statistics, clustering, efficiency and public policy, risk assessment, and Bayesian analysis are some of the topics covered. Information dissemination and variables in a population or an electronic medium, notably the Internet, are studied in info-epidemiology with the ultimate goal of informing public health and public policy [66]. It comprises information on the frequency and outlines of data on internet site, public media, and chatting platforms, as well as auto-aggregation and analysis. COVID-19 distribution and interactions hate speech, and positive action is among the info-epidemiology signs. The following sections describe some of the studies on AI applications in epidemiology and info-epidemiology.

A hybrid DL system was presented in [67] to handle the unsupervised anomaly discovery problem in multivariate Spatiotemporal data. The suggested method uses unlabeled data and makes no prior assumptions regarding abnormalities. The COVID-19 statistics from the Italian Department of Civil Protection were used as a case study. The framework was trained on COVID-19 data from Northern Italy regions and then used to spot any unusual patterns or upswings in COVID-19 data from Central and Southern Italy. Based on the reconstruction error, the proposed framework detected early COVID-19 pandemic signals in test regions.

On the Italian COVID-19 dataset, a rigorous assessment of advanced DL architectures was undertaken, along with 15 other algorithms. The experimental results indicated that the suggested framework improves unsupervised anomaly detection performance even in circumstances with limited data and a high contamination ratio. The suggested methodology provides significant information to suppress the reappearance of local new COVID-19 outbreaks, as timely detection is critical in the fight against any outbreak. One of the non-medical strategies regarded to be an adequate preventative measure against the development of COVID-19 is social distance. As a result, a DL platform for social distance tracking employing an overhead perspective was developed by [68].

To recognize persons in video sequences, the system employs the YOLOv3 object recognition paradigm. The transfer learning process is also used to improve the model's accuracy. In this method, the detection algorithm employs a pre-trained algorithm that is linked to an additional trained layer that utilizes an additional human data set. The detection model uses bounding box information to identify persons. The model's tracking accuracy improves from 92 percent to 98 percent using the transfer learning method.

In [69], deep learning-based time series techniques were investigated to anticipate worldwide COVID-19 cases in advance for short-term and medium-term dependencies using adaptive learning. A real-world COVID-19 dataset was used for preprocessing the data and extraction of features. Following that, Auto-Regressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), Stacked Long Short-Term Memory (SLSTM), and Prophet Approaches ware used to model the prediction of cumulative confirmed, death, and recovered global cases. Multivariate LSTM models were used to forecast COVID-19 cases over the long run. All of the models' performance indicators were computed, and the prediction results were compared to determine which model is the most dependable. In comparison to the other evaluated algorithms for the studied performance measures, the Stacked LSTM method produces superior accuracy with an error of less than 2%, according to the results.

The work in [8] was to inspect the dispersion of Arabic language conversations and break down the idea of Internet search practices connected with the worldwide COVID-19 pandemic through Twitter and Google Trends in Saudi Arabia. A bunch of Twitter Arabic information connected with COVID-19 was gathered and dissected. Utilizing Google Trends, web search practices connected with the pandemic were investigated. Well-being and hazard discernments and data connected with the reception of COVID-19 infodemic markers were explored. In addition, Google versatility information was utilized to survey the connection between different local area exercises and the pandemic transmission rate. Similar information was utilized to explore how changes in versatility could anticipate new COVID-19 cases. The outcomes show that the top COVID-19-related terms for deception on Twitter were people cures from bad quality sources. The quantity of COVID-19 cases in various Saudi regions has a solid negative relationship with COVID-19 hunt questions on Google Trends (Pearson $r = -0.63$) and measurable importance ($p < 0.05$). The decrease in portability profoundly corresponded with a diminished number of all-out cases in Saudi Arabia. At last, the absolute cases are the main indicator of the new COVID-19 cases.

Also, [99] investigated web search exercises and practices connected with the COVID-19 pandemic from February 20, 2020, to May 6, 2020, using Google Trends and Instagram hashtags. The research examined the names used to distinguish the infection, well-being, and hazard discernment, life during the lockdown, and data connected with the reception of COVID-19 infodemic monikers (query, hashtag, or phrase that generates or feeds fake news, misinterpretations, or discriminatory phenomena). The best six COVID-19-related terms looked in Google were “coronavirus,” “corona,” “COVID,” “virus,” “coronavirus,” and “COVID-19.” Countries with a larger number of COVID-19 cases had a bigger number of COVID-19 questions on Google. The monikers “coronavirus ozone,” “coronavirus laboratory,” “coronavirus 5G,” “coronavirus conspiracy,” and “coronavirus bill gates” were generally circled on the web. Around 66 (n=48,700,000, 66.1%) of Instagram clients utilized the hashtags "Coronavirus" and "Covid" to spread infection-related data.

3.7 Artificial Intelligence (AI) Technologies Deployed for COVID-19

The AI technologies that were employed to construct COVID-19 solutions are discussed in this section. The success of ML and AI applications in earlier pandemics provided the incentive for academics around the world to use AI technology to combat the COVID-19 (SARS-CoV-2) outbreak [3]. The next paragraphs cover some of the works that showcase these technologies and their usage. Although health requirements are not always available or known during the early stages of any outbreak, outbreaks are frequently controlled with existing capacity. Modern technology for COVID-19 mitigation has been recognized as Data Science and Deep Learning [1]. However, DL necessitates huge datasets and sophisticated computing resources, both of which are in short supply during a pandemic. Deep Transfer Learning (DTL) and Edge Computing were both seen as viable options. Edge Devices (ED) such as the Internet of Things (IoT), Webcams, Drones, Intelligent Medical Equipment, and Robots, among others, are useful in the pandemic. The primary computational methodologies reviewed in [2] are ML techniques and deep learning techniques, as well as mathematical and statistical methods in the domain of COVID-19 categorization, prediction, and prevention.

The Deep Convolutional Network, CNN, and Support Vector Machine are the technologies identified by [4] for the screening and treatment of COVID-19. For contact tracing, mobile applications were created using various technologies such as Bluetooth, GPS, and social graphs. Models were created using stacking-ensemble with the support vector regression algorithm and the supervised multi-layered recursive classifier XGBoost for prediction and forecasting. In addition, a Deep Neural Network model was developed to aid in the development of new medications and vaccines. From the standpoint of the patients, Deep-CNN, 2D deep Convolutional Neural Network, 3-dimensional DL, and Modified Inception Transfer-Learning Model were among the AI technologies highlighted by [70] for diagnosis using radiological pictures. To estimate infected persons, identify respiratory patterns, and forecast the trajectory of an outbreak, the Time Dependent Susceptible-Infected-Recovered (SIR) model, GRU Neural Network, and SEIR (Susceptible, Exposed, Infectious, and Removed or Recovered) model were employed. Prediction models based on the Supervised XGBoost classifier and ML were used to predict mortality risk and the length of a patient's stay in the hospital, respectively, as AI technologies for patient health prediction.

Since COVID-19's discovery, smart city initiatives technology has been playing major roles in the handling. Sensor-based monitoring stations, social media data mining, and individual monitoring of health issues via devices or wearable sensors are some of the technologies utilized for monitoring and detecting outbreaks, as highlighted by [7]. Automated hospitals and healthcare systems, smart transportation, response teams, and alerting and notification messages are all part of the alert and mitigation strategy. Berlin - ambient-assisted living; web-based services; Helsinki - Helsinki smart region; London –Digital Health. program; New York -NYC; SHIN-NY; Seoul - big data, AI, blockchain; self-quarantine app, corona 100 m apps, Coronamap; New York -NYeC; SHIN-NY; Seoul - big data, AI, blockchain; self-quarantine app, corona 100 m app, Corona Shanghai - robots are driven by 5G; Singapore has a contact tracing tool, as well as a WhatsApp group, webpages, and educational games, My health record, secure texting in Sydney; records exchange, Alipay QR, quarantine code, smartphone tracking in Wuhan.

Some AI technologies used new insights into the prediction and management of COVID-19. The work of [71] included neural networks in the area of drug discovery, rough set theory, and other ML-based disease risk models in the area of disease prediction. ML and DL, nanomedicine, novel technologies, novel mathematical modeling, big data, and internet of things (IoT), telemedicine, robots, and 3D printing technology are among the emerging technologies that have aided in the study of COVID-19 [13]. Table 4 summarizes all AI technologies as well as the COVID-19 areas in which they are used.

Table 4: Technologies and Applicable Areas of AI for COVID-19

COVID-19 Application Areas	AI-ML Technologies and Devices Applicable
Prediction or forecasting	Stacking-ensemble, Neural Networks, Support vector, Regression algorithm, Deep learning algorithm, Supervised multi- layered recursive classifier called XGBoost. Exponential model, Logistic model, SIR Model, MetaWards, [72]; [73];[74];[75]; [76].
Screening or diagnosis	Deep Convolutional Network, Convolutional Neural Network, and Support Vector Machine. Edge Computing and Deep Transfer Learning (DTL). Meta-Analysis and Artificial Intelligence aided analysis. Ensemble methods like bagging and stacking, [77]; [78]; [79];[80].
Contact tracing	Mobile applications (using Social graphs, Global Positioning System (GPS), Bluetooth) Deep Transfer Learning (DTL) and Edge Computing, [81]; 1]; [82].
Prognosis	Deep learning algorithm [87]; [88];[89];[90]; [91];[92]
Drugs and vaccination discovery.	Deep Neural Network and Deep learning algorithm [93]; [94]; [95]; [96]

As shown in table 4, the DL is the most applied technique across all the areas and concerns of COVID-19. DL technology has been used for interventions in the areas of COVID-19 prediction, screening, contact tracing, prognosis, and for both drug and vaccine discovery.

3.8 COVID-19 Artificial Intelligence datasets and data sources

Medical images and textual data are the two main types of data sets for COVID-19. Computed Tomography (CT) scans and Magnetic Resonance Imaging (MRI) X-ray images are the medical images. Case reporting, transmission estimation, and prognosis using epidemiological, demographic, and mobility data are among the COVID-19 textual data. COVID-19 emotive and sentiment analysis from social media, knowledge-based discovery, and semantic analysis from a collection of COVID-19-related scientific articles are also used [97], [19]. So, right after the "first wave," [17] evaluated what was known about COVID-19 pneumonia imaging at the time. Though laboratory testing of nasopharyngeal aspirates for identification of SARS-CoV-2 by reverse transcriptase-polymerase chain reaction was the method of reference, it was claimed that chest computed tomography (CT) has become a speedy and effective ML diagnostic tool for COVID-19 (RT-PCR). However, RT-PCR takes several hours to produce findings, and the test's sensitivity was just 60 to 70%.

The data used for the Deep Convolutional Network, Convolutional Neural Network, and Support Vector Machine models constructed in [3] for diagnosis are also computer tomography (CT), radiography picture, and x-ray. For Bluetooth, Global Positioning System (GPS), and Social graph applications designed for contact tracing [9], the data types used included network-based API, mobile tracking data, card transaction data, and system physical address. A measure of social distancing policies, policy responses, and effectiveness models was constructed using the mobility dataset. The COVID-19 datasets and resources used for the molecular, clinical, and societal scales studies in [4] comprise case data, text data, and biomedical data.

The COVID-19 data types are collated in Appendix D. The distribution includes 9 - cases and deaths dataset, 4 - mobility reports dataset, 4 - government policy dataset, 3 - social-economic dataset, 2- vaccination dataset, 1- social media dataset, and 1 website data collection. Some of the datasets can be accessed on the host websites or through repositories such as the free public datasets for COVID-19 on UCI ML Repository, COVID-19 Open Research Dataset (CORD-19) of the Allen-Institute-for-AI and Google Cloud. These repositories can be accessed at https://cloud.google.com, https://archive.ics.uci.edu, and https://www.kaggle.com respectively.

3.9 COVID-19 Open – Issues and Future Agenda

Some challenges and unresolved areas of concern regarding the impact of Artificial Intelligence on COVID-19 are considered in this section. The effort is to provide insight into these issues and to offer a basis for future research agendas. The open issues range from the inadequacy of the dataset and the poor quality of model development to the effects of prevention and control measures on model validation and the inadequacy of model deployment testing facilities. Other issues identified are the lack of a benchmark framework and the challenge of ensuring a balance between privacy and public health solutions.

3.9.1 COVID-19 Artificial Intelligence Datasets Inadequacy, Non-Availability, and Inaccessibility Issues

Management of COVID-19 is deeply driven by data, the availability, accessibility, and adequacy of data are significant to the success of combating the scourge. Dataset is the lifeblood of AI solutions [98]. The influence and effect of dataset quality, size, and nature are of great concern to COVID-19 AI researchers. Some of the concerns are the implications of too little or too much data size [20], data source (open or closed), and dataset type (biomedical and non-biomedical, text, image, and sound) on the AI system.

The data size concern was because several months into the pandemic, the number of data points in many countries was extremely low. The statistics as of March 31, 2021, showed that the data of the early months was so low that it was difficult to train DL and most other ML models with such a small dataset. Another concern was noisy dataset [2]. A noisy dataset is traceable to inadequate testing facilities, social stigmas of the asymptotic patient, and the effects of various preventive measures. Another major challenge was the ethical and human right issue concerning the usage of the dataset and application of AI generally.

Hence, AI researchers should be concerned with the development of frameworks for robust data modeling and standardization. Also, malleable techniques that can be optimized or extrapolated available data at the initial stage of any future pandemics or similar occurrences should be explored.

3.9.2 Model Deployment and Benchmark Framework Concerns

Deployment of an inadequate model was identified in [3] as a challenge, it was one of the consequences of the non-availability of scalable approaches to data and model sharing using open repositories [4]. This situation was described in [21] as a lack of a benchmark framework to assess current AI techniques for the pandemic in real-world healthcare practice. In [19] the situation was referred to as a lack of a unified platform for AI-based detection of COVID-19. The framework if available will facilitate collaboration in the scientific community with open sharing of knowledge, tools, and expertise [13]. The AI community should aggregate efforts toward the development of a unified platform for medical imaging COVID-19 models and models of other dataset types.

3.9.3 Control Measures and Policy Effectiveness Concerns

It has been identified that a combination of AI technologies, effective healthcare treatment, and governance are required to subdue pandemics. Viable prospective technologies such as 5G, drones, the Internet of Things (IoT), and robot technologies were recommended for controlling the pandemic in areas such as surgery, medicine, hospital management, and delivery of goods [11]. Though in [7] the Smart cities initiatives were recognized as a great initiative that can be leveraged to face COVID-19 and any future pandemics. However, governments are expected to play a leading role for other non-governmental stakeholders in this process. Government action is required mostly in the formulation and enforcement of laws and budgets. Therefore, when the effects of the COVID-19 pandemic are relieved, the AI community should not rest on their oars but should commence preparation for the next pandemic by identifying effective AI-driven control measures.

3.9.4 Balancing Privacy, Human Rights and Public Health

No doubt, the discovery of the COVID-19 vaccine doused the tension generated by the pandemic and rekindled the hope of human survival. Nonetheless, the approved vaccines witnessed political and social challenges. For instance, there was growing safety concern on the COVID-19 AstraZeneca vaccine because of the reported cases of blood coagulation disorders among people who had received the vaccine. However, WHO in her statement of March 17, 2021, recommended the continuation of the vaccination pending the conclusion of the investigation because the benefits outweigh the risks [107].

As of March 31, 2021, a total of 547,727,346 vaccine doses had been administered [105]. Other concerns and unverifiable reasons for hesitancy in the collection of vaccines include the short development time that was considered to be inadequate for a genuine vaccine, the possibility of the vaccine altering body DNA, production from controversial substances, and many more. The bases for the anxiety as in [111] was the duration of preclinical stage (in vitro and in vivo) tests for COVID-19 that was shortened to allow developers to meet the target of 12-18 months instead of the historical 15-20 years duration for the development of a classical vaccine.

Several efforts have been made to correct these concerns, but, truly, the impressions are pointers to ethical and human issues regarding the development, validation, and administration of vaccines. The significant roles played by AI techniques in achieving this height are evident in the literature and the impacts are obvious on improved diagnosis, treatment, and health research. However, many of the techniques have also raised ethical, legal, and social concerns. The anxieties about AI in medicine range from deep-fake videos and photo fraud [110] to, the obscureness of AI processes especially the black-box approaches and potential job loss as a result of robotics [109]. Progress has been made to standardize ethics and legal implications of AI application in medicine, [112] extracted Ten Commandments of ethical medical AI, which is a clear concise checklist of understandable principles for stakeholders.

Also, the WHO (2021) report titled "WHO guidance on Ethics & Governance of AI for Health" identifies the ethical challenges and risks of the use of AI in health. These challenges include assessing whether AI should be used, issues of data collection and usage, accountability and responsibility for decision-making with AI, bias, and discrimination associated with AI, risks of AI technologies to safety and cybersecurity, and impacts of AI on labor and employment. The six consensus principles to ensure AI works to the public benefit of all countries are protecting autonomy; promoting human well-being, human safety, and the public interest; ensuring transparency, explainable and intelligibility; fostering responsibility and accountability; ensuring inclusiveness and equity; promoting AI that is responsive and sustainable. All these are open issues and pose a lot of challenges to the AI community in future research.

4. CONCLUSIONS

This study brings forth an interpretable review of the impact of AI on the global COVID-19 Pandemic. It provides the impacts of the technology on the molecular, clinical, and societal handling of the pandemic. An extended taxonomy of the areas of application of the technology was formulated and discussed. The systematic review revealed the generalizable capabilities of deep learning in various areas of the pandemic though spotted the roles of transfer learning and federated learning among other AI technologies. The work provides the implications and efficacies of various AI-developed models.

Furthermore, the paper explores the controversies that trailed the discovery of the COVID-19 vaccine and systematically sets future research agenda for the AI community on proactive control measures, and policy effectiveness as well as balancing the privacy and human right in the research on this and any future pandemics. It is envisaged that the open issues revealed in this study will spike further collaborative research in the adoption of AI for better assessment, treatment, and monitoring of infected patients. Extension of study beyond the range covered in this work is recommended, this will reveal the extent to which the identified open issues have been managed for better global health care and as efforts towards preparing the world for any future pandemic.

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Author contribution statement

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Appendix A: Reviews of AIs at the Early Stage of COVID-19

Author/Year	Year	Title	Aim/Objectives	Methodology and Comment (Methods used, conclusion, and limitation)
Application Areas of AI to COVID-19				
[1]	(2020)	An overview of machine learning and artificial intelligence strategies for the COVID-19 (SARS-CoV-2) outbreak	To examine the role of AI and machine learning as one important tool in the screenings, predicting, connection tracking, and drug discovery for SARS-CoV-2 and its linked epidemics.	The use of machine learning and artificial intelligence (ML and AI) innovation to fight the COVID-19 (SARS-CoV-2) occurrence was thoroughly covered for prevention and diagnosis, early detection, prognostication and prediction, medications, and flu vaccine materials in numerous medical systems. AI and machine learning are proactive approaches to COVID-19 tasks. They are proficient in battling the epidemic, though the systems have not been deployed enough to reveal their real-world full functionalities.
[2]	(2020)	Mapping the site of Artificial Intelligence applications against COVID-19	To spot the breadth of available AI applications to the COVID-19 outbreak and provide an early overview and development plan about how AI can aid the worldwide approach to the outbreak.	From January 2 through April 5, 2020, relevant literature and result relating to COVID-19 have been published. The research takes into account genetic, medicinal, and socioeconomic dimensions. In a variety of sectors, it has been demonstrated that machine learning and artificial intelligence can aid in the reaction to COVID-19. Sustainable dataset and model distribution utilizing open archives has been recognized as a significant strategy for accelerating the establishment of innovative systems in the interest of the public. In this setting, Artificial intelligence will necessitate exceptionally broad, diversified complementing teams as well as long-term collaborations, both of which are now scarce.
[3]	(2020)	Artificial Intelligence (AI) applications for the COVID-19 pandemic	To analyze the effect of Artificial intelligence as a significant technique for enhancing COVID-19 and current outbreak prevention, management, and appropriate decisions	The evaluation was based on materials gathered through PubMed, Scopus, and Google Scholars to determine and debate the potential Artificial intelligence for combating COVID-19. Early detection and treatment, diagnostic testing, connection tracking, incidence and death projections, and medication and vaccination research are among the fields of use mentioned.

Artificial Intelligence Models, Technologies, and Dataset for COVID-19				
[4]	(2020)	A methodical evaluation and critical analysis of COVID-19 infection prediction models for diagnosis and prognosis.	To evaluate and critically analyze authored and preprint findings of predictions for analysis and treatment of COVID-19 in patients suspected of having an infection, the initial diagnosis of COVID-19 patients, and sensing people in the overall population at an enhanced risk of getting involved with COVID-19 or being hospitalized with an infection.	There were 4909 papers reviewed, with 51 research detailing 66 predictive models cutting. Three approaches for determining hospitalization due to pneumonia as well as other incidents, 47 diagnostic algorithms for finding COVID-19, and 16 prognosis methods for determining mortality rate, development to chronic symptoms, or hospitalization were discovered in the analysis. Age, skin temperature, indications and symptoms, gender, and heart rate were the most commonly reported indicators of COVID-19 occurrence. Age and characteristics obtained from magnetic resonance scanning were the most often recognized analysis of severe outcomes in individuals with COVID-19.
[5]	(2020)	COVID-19 Epidemic: an overview of smart city strategies to combat new breakouts	To investigate innovation connected to the advancement of the smart city concept.	This report looks at new advancements that could still help present cities prepare for this and future epidemics, as well as monitoring technology and innovative solutions to the expansion of the smart city concept. The report highlights standard procedures and predicts interesting future growth. Furthermore, cities that are competitive and innovative in this developmental process are discussed, indicating possible paths to go, however, there is no basic principle. The authorities are projected to add useful mechanisms, rules, and resources for the establishment of Smart Cities.
[6]	(2020)	COVID-19 Prevention: A Survey of Deep Transfer Learning and Edge Computing	To Perform a comprehensive evaluation of studies that reflect the importance, drawbacks, and methodological bases of Big Data and Deep Transfer Learning, and Edge Computing for COVID-19 prevention	This study discusses the potential and drawbacks of Deep Learning, Deep Learning Algorithms, and Edge Computing for COVID-19 prevention. It has offered technical source material and assessments on existing situation methods. It also sees a DTL over Edge Computing approach as a research approach to help avoid a present pandemic or any future outbreaks.

[7]	(2020)	An Evaluation of COVID-2019 Information Computational Systems for Epidemic Detection, Medical Identification, National Policy agenda, and Care Coordination	To conduct a comprehensive analysis of data gathered from an operational standpoint, to handle collected information in COVID-19-related investigations at a preliminary phase.	The purpose of this study was to perform research from the standpoint of data-driven statistics. It looked into the most up-to-date options for epidemic computer models, medical assessment, legislative efficacy, and disease surveillance. Furthermore, models with the most recent data were reviewed to see how well they have performed since their original publication and to gather sources of data for research analysis.
[8]	(2020)	Cognitive computing's significance in COVID-19 diagnosis and treatment: An up-to-date evaluation	To give an understanding of the major machine learning algorithms utilized in COVID-19 prognosis, classifications, and prediction. Also, to compare the influence of machine learning and other competing strategies, such as modeling and simulation on the COVID-19 challenge.	The foundations of SARS-CoV-2 and its influence on world health are traced in this study. Machine learning algorithms, Deep learning methods, and Computational and Scientific strategies are explained as part of the established Computing techniques in the categorization, prognosis, and mitigation of COVID-19. Analytical inquiry and performance overview of different advanced computational methodologies, the effectiveness of the COVID-19 prediction method, and the development of COVID-19 academic publications by methodologies, papers, and nations are also completed. The data and information used in COVID-19-related studies, and the obstacles, were also reviewed. Furthermore, there are indeed significant drawbacks, perhaps with a lack of labeled medical data and learning on limited data samples.
[9]	(2020)	Evaluation of Machines and Learning Models for Coronavirus Classification and Prevention	To understand the disease epidemiology, identify major preventive measures and assess machine and deep learning-based architectures	A review was done based on a literature search of articles that have utilized machine and deep learning algorithms on medical images to solve a clinical problem. A comparison of the algorithms was also carried out based on output and performance

[10]	(2020)	A Consideration of Technological Aspects Methods for Controlling the COVID-19 Epidemic in Reorganized Social and Environmental issues	To identify different applied methods for COVID-19 management, predictions, detection, intervention, and impact.	Google Scholar, Elsevier, PubMed, and IEEE were used to conduct the evaluation. Trusted sources included the World Health Organization (WHO) as well as other recognized reporting and tracking sources such as the World Economy Forum, Stats, MIT technology evaluations, and headlines. Publications that matched the acceptance requirements were divided into two categories: pandemic-controlling technical techniques and pandemic-supporting scientific methods. According to the findings, implementing AI technology in the battle against COVID-19 can boost the infected defensive structure. The investigation does caution, nevertheless, that this is up to people to stop the infection from spreading.
[12]	(2020)	Review Of the literature on Machine Learning for COVID-19 Medical Image Recognition and Prevention	To offer insight into current and novel COVID-19 medical image detection technologies powered by AI investigations.	A systematic review of the literature was carried out on different digital databases including Science Direct, Scopus, IEEE, Web of Science, and PubMed between 2010 and May 5, 2020. 11 articles met all the inclusion criteria with the following distribution across the databases: 4 from Science Direct, 3 from IEEE, 2 from PubMed, 2 from Scopus and none from Web of science. The remaining publications were grouped into two groups: a review of the research groupings, with one literature review and ten scientific articles in each group. Binaries, multi-class, multi-variable, and structured and multi-class categorization were the four sub-groups of the concepts and tools. Following that, a technique for analyzing and evaluating the COVID-19 subgroups classification was developed.
[13]	(2020)	New Technology for the Investigation, Diagnostics, and Medication of COVID-19 Individuals	To provide an overview of technology advancement being used in the research, diagnosis, and medication of COVID-19.	An evaluation of the strategies used to combat COVID-19 was conducted. Artificial intelligence (AI), computational intelligence, nanotechnologies, innovative vaccination and medicinal innovations, innovative computational analysis, deep learning, internet - of - things (IoT), telehealth, robotics, and 3D printing technology are among the innovations. The paper finishes by emphasizing the importance of collaboration as a key to the public acquisition of information, techniques, and skills. Innovation can be used to help the scientific profession react immediately to the increasing population and impact of COVID-19.

[14]	(2020)	A Computational Approach to Recognize SARS-Cov-2 Affected Patients' Early-Stage Symptoms	To investigate patient features, case history, contraindications, indications, diagnostics, and prognosis to make quick medication and isolation recommendations.	The most significant clinical COVID-19 predictive features were (in descending order) respiratory infection, sore throat, pneumonia, sneezing, health records, flu, isolation, age, sore muscles, diarrhea, and gender. According to this investigation, developed and implemented a variety of machine learning techniques to generate models to use the predictor to forecast the degree of COVID-19.
[15]	(2020)	COVID-19 epidemic prediction with machine learning	To evaluate the suggested ML models' prediction performance and accuracy for various lead-times	In total instances over 30 days, data was acquired from https://www.worldometers.info/coronavirus/country for five countries: Italy, Germany, Iran, the United States, and China. To create the needed model, logic, linear, logarithm, quadratic, cubic, compound, powers, and exponential formulas were used. Evolutionary techniques such as GA, particle swarm optimizer, and grey wolf optimizer were used to estimate the parameters. The root means square error (RMSE) and correlation coefficient were used to assess the results. Improvement of model results with high dimensionality would be impossible due to inherent disparities between outbreaks in distinct countries. A single epidemic is unlikely to be duplicated elsewhere, as several studies have seen and documented.
[16]	(2020)	For the COVID-19 pandemic, the intelligent Internet of Medical Things will be used.	To solve the worldwide dilemma, the Cognitive Medical Things Internet (CIoMT), a unique application of cognitive radio (CR)-based IoT precise for the medical area, is being investigated. The CIoT concept is well suited to the epidemic	CIoMT is a capable technology for fast detection, integrated surveillance, and tracking, improved care, and management, without spreading the virus to others. In Google Scholar, Scopus, PubMed, ResearchGate, and IEEE Xplore databases, a comprehensive literature survey is undertaken using the words "COVID-19" and "Cognitive IoT" or "Coronavirus" and "IoMT." The most recent evidence and references from government websites and records are used to further evaluate and examine the application areas

Dataset and Data source				
[17]	(2020)	Chest CT in COVID-19 pneumonia: A review	To review and update the current knowledge on COVID-19 pneumonia imaging (Chest computed tomography (CT)).	A survey is done on the role of chest CT in the management of suspected COVID-19 patients. The typical and atypical CT presentation, the evolution of CT findings, the sign of severity, and complications. AI techniques were suggested could make it feasible to automate the proper diagnosis and the subsequent measurement of defects in the coming years, and maybe, enable the extraction of biomarkers to determine the prognosis of COVID-19 cases, in the coming years. In asymptomatic patients, chest CT scans must not be conducted for diagnostic imaging. For the identification of COVID-19, either chest X-ray or ultrasound is suggested, as their efficiency seems to be substantially lowered to that of a CT-Scan.
[18]	(2020)	COVID-19 Open Source Data Sets: A Comprehensive Survey	To survey and analyze research works based on open-source data sets concerning the COVID-19 pandemic.	The study offered a thorough examination of COVID-19 accessible sets of data. The review was divided into sections based on the data and application types. The most common data kinds were text and medical picture data. COVID-19 diagnosis, infection prediction, movement, and epidemiological associations, social economic evaluation, and sentiment classification were among the applications of the accessible set of data. Despite the rapid expansion of scientific investigation on COVID-19, there is still room for information sharing collection and extraction in a variety of ways, such as augmenting pre-existing CT scan sets of data for deep learning applications and compiling cough collections. In the domains of data curation for cough-based COVID-19 diagnostics and extending CT scans, strategies can be implemented on research directions paths and issues affecting COVID-19 accessible sets of data.
[19]	(2020)	Current Landscape of Imaging and the Role of AI in the Management of COVID-19	To examine the existing landscape of imaging modalities and Artificial Intelligence as applied in the management of COVID-19	The current imaging modalities in COVID-19 management and their strengths and limitations were reviewed. The role of AI in COVID-19 imaging was also reviewed. Consequently, the experiences gained along with the trained AI models can help optimize the imaging-based management of COVID-19.

Appendix B: Definition of Abbreviations and Acronyms

ACRONYMS AND ABBREVIATIONS	DEFINITIONS
AI	Artificial Intelligence
AIDS	Acquired Immunodeficiency Syndrome
AOC	Area under the ROC Curve
ARIMA	Auto-Regressive Integrated Moving Average
CDC	Centers for Disease Control and Prevention
CI	Concordance Index
CIoMT	Cognitive Internet of Medical Things
CNN	Convolutional Neural Networks
COVID-19	Coronavirus Disease of 2019
CR	Cognitive Radio
CT	Computed Tomography
CTL	Cytotoxic T Lymphocytes
CXR	Chest X-Ray
DL	Deep Learning
DT	Drug Target
DTL	Deep Transfer Learning
EC	Edge Computing
ED	Edge Devices
GPS	Global Positioning System
HGAT	Heterogenous Graph Attention
HIV	Human Immunodeficiency Virus
HTL	Helper T Lymphocytes
IoT	Internet of Things
LSTM	Long Short-Term Memory
ML	Machine Learning
MRI	Magnetic Resonance Imaging
MT-DTI	Molecule Transformer- Drug Target Interaction
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-analyses
ROC	Receiver Operating Characteristics
SARS	Severe Acute Respiratory Syndrome
SEIR	Susceptible, Exposed, Infectious, and Removed or Recovered
SLSTM	Stacked Long Short-Term Memory
SMILES	Simplified Modified Input Line Entry System
SVM	Support Vector Machine
TLSTM	Time aware Long Short-term Memory

Appendix C: Repurpose-able Drugs Manufacturers and Description

S/N	Drugs	Manufacturer	Country	Description
1	Remdesivir	Zydos	India	Remdesivir is an antiviral medication used to treat coronavirus disease 2019 (COVID-19 infection) caused by the SARS-CoV-2 virus in hospitalized adults and children aged 12 and up who weigh at least 88 pounds (40 kg). Remdesivir belongs to the antiviral drug class. It functions by preventing microorganisms from growing throughout the system [28].
2	Favipiravir	Biophore India	India	Favipiravir (T-705) is a synthesized antibiotic that was identified while evaluating the antimicrobial activities of chemical agents effective against influenza in the Toyoma compounds chemicals bank. A/PR/8/34 later renamed T-1105, and its compounds were discovered to have antioxidant properties [29].
3	RIBAVIRIN	Genentech, Merck Sharp & Dohme	USA	Ribavirin has the rare virtue of being clinically effective against viruses from many families. Respiratory tract infections caused by the respiratory syncytial virus and flu, measles, herpes virus infections, hemorrhagic fever with renal syndrome, Lassa fever, and chronic hepatitis C virus are all part of its scope of activity [30].
4	ELBASVIR	Merck & Co.	USA	The FDA has approved elbasvir/grazoprevir as an antiviral prescription drug for the treatment of chronic hepatitis C virus infection (HCV). HCV is an HIV-related opportunistic infection (OI) [31].

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5	CEPHARANTHINE	Atkin Chemicals	China	Cepharanthine (CEP) is a medication that is used to diagnose a range of acute and chronic conditions, such as leukopenia, snake bites, xerostomia, and alopecia. In the broad class of bisbenzylisoquinoline alkaloids, it is the sole medication licensed for human use [32].
6	IDX-184	Idenix	USA	IDX-184 is an antimicrobial agent that acts as an NS5B RNA polymerase inhibitor and was established as a therapy for hepatitis C. [33].
7	SOFOSBURIN	Gilead Sciences	USA	C22H29FN3O9P is an antiviral medication that is administered orally alongside other antiretroviral drugs (such as ribavirin) to combat hepatitis C infection [34].
8	LOPINAVIR-RITRONAVIR	AbbVie Inc.	USA	It is used to treat HIV infection (the virus that causes AIDS). It's also being researched for use in the treatments of some cancers. Lopinavir/ritonavir inhibits HIV's capacity to replicate itself, which may improve the efficacy of other anticancer medications or inhibit cancer cell proliferation [35].
9	DARUNAVIR	AbbVie Inc	USA	Darunavir belongs to a class of drugs known as protease inhibitors. It helps to lower HIV levels in the bloodstream.
10	ARBIDOL	Pharmstandard	Russia	Arbidol is a Russian antiviral drug that appears to be efficient against a variety of viruses, such as influenza A, B, and C, respiratory syncytial virus (RSV), SARS-related coronavirus (SARS-CoV), adenovirus, parainfluenza, poliovirus, rhinovirus, coxsackievirus, Zika virus, and hepatitis B and C. [35].

11	ANGIOTENSIN RECEPTOR BLOCKER	La Jolla Pharmaceutical *Company*	USA	Angiotensin is a hormone produced by the kidneys that cause blood arteries to constrict. It keeps levels of blood pressure and bone metabolism in check [36].
12	NAFAMOSTAT	Tocris Bioscience.	UK	In vitro investigations demonstrated that nafamostat mesylate possesses antiviral efficacy against the SARS-CoV-2 coronavirus, as well as anti-inflammatory and anti-coagulant properties. However, no clinical investigations on the efficiency of nafamostat in COVID-19 patients have been conducted [37].
13	CHLOROQUINE AND HYDROCHLOROQUINE	Sanofi	France	The antimalarial medication chloroquine was first created in 1934. In 1946, hydroxychloroquine, a chloroquine homologue, was created. In addition to malaria, hydroxychloroquine is used to treat autoimmune illnesses such as systemic lupus erythematosus and rheumatoid arthritis [38].
14	PLURIFLOXACIN	Ranbaxy	India	Urinary Tract Infection has been studied with the drug prulifloxacin. Prulifloxacin is a fluoroquinolone antibiotic with a broad spectrum of action that is used to treat several bacterial illnesses [39].
15	NELFINAVIR	Agouron Pharmaceuticals	USA	Nelfinavir is an orally accessible immune deficiency infection HIV-1 protease inhibitor (Ki=2nM) that is commonly prescribed for HIV infection in association with HIV recombinant medications [32].

16	AZITHROMYCIN	Pfizer	USA	Azithromycin is an antibiotic that is used to treat many different types of bacterial illnesses. It belongs to the macrolide family of antibiotics. It works by preventing bacteria from growing. This medicine is ineffective against infectious diseases (such as the common cold, and flu). Any antibiotic's effectiveness can be reduced if it is used or misused unnecessarily [40].
17	DOXYCYCLINE	Pfizer	USA	Pimples, urinary tract diseases, intestinal infections, lung problems, eye diseases, chlamydia, gonorrhea, hepatitis, periodontist (tooth cancer), as well as other microbial diseases are asymptomatic with doxycycline [41].
18	TOCILIZUNAB	Roche	Switzerland	Tocilizumab (Actemra) is a reverse transcriptase humanized anti-human interleukin (IL)-6 antibody recombinant immune response signified for limiting clinical symptoms in older patients with tolerably to sometimes several rheumatoid arthritis (RA) who had insufficient reactions between one or even more disease-modifying antirheumatic drugs [42].
19	AURANAFIN	Medichem	Spain	Rheumatoid arthritis is treated with auranofin, as well as rest and nondrug treatments. It alleviates arthritic signs such as aching or sensitive bones, swelling, and extreme fatigue [43].
20	TRAMETINIB	GlaxoSmithKline	UK	Trametinib is being used to treat melanoma (skin cancer) which has expanded or cannot be surgically removed, either alone or in combined application with dabrafenib. It is also used in combination with dabrafenib to assist in keeping melanoma from returning after surgery [44].

21	WITHAFERIN A	Kavya Pharma	India	Withaferin A is a steroidal-structured natural substance. With its anti-inflammatory, anticarcinogenic, and neuroprotective characteristics, withaferin A offers a wide range of potential therapeutic applications. It's been utilized as a flavor and fragrance ingredient as well [45].
22	PARTHENOLIDE	Tocris Bioscience	UK	Parthenolide is a germacranolide sesquiterpene lactone that naturally occurs in the plant chaste berry (Tanacetum parthenium), which it will be termed. The largest concentrations are found in the flowers. Parthenolide's viability as a medicine is limited by its inability to absorb water and its poor bioavailability [46].
23	SORAFENIB	Bayer	Germany	Sorafenib is a drug that is used to treat advanced renal cell carcinoma, liver cancer (hepatocellular carcinoma) that cannot be cured surgically, and distinct thyroid cancer which has returned or disseminated to other body regions. Sorafenib is a cancer-fighting drug called antineoplastic. [47].
24	AURANOFIN	Henan Daken Chemicals	China	Auranofin is used to treat rheumatoid arthritis, primarily chronic rheumatoid arthritis that has not responded to chemotherapeutic drugs [48].
25	SELUMETINIB	AstraZeneca	UK	Selumetinib is a small chemical with potential antineoplastic action that can be taken orally. It inhibits mitogen-activated protein kinase (MEK or MAPK/ERK kinase) without requiring ATP. 1, 2, and 3. MEK 1 and 2 are dual specificity kinases that are important mediators in the activation of the RAS/RAF/MEK/ERK pathway [49]

Appendix D: Sources of COVID-19 Dataset, Types, and Description

S/N	SOURCE NAME	Dataset TYPE	DESCRIPTION	LINK
1	Johns Hopkins University Center for Systems Science and Engineering (JHU CCSE)	Cases and death	The data was compiled by the Johns Hopkins University Center for Systems Science and Engineering (JHU CCSE) from a variety of sources, including the World Health Organization (WHO), DXY.cn, BNO News, the National Health Commission of the People's Republic of China (NHC), China CDC (CCDC), Hong Kong Department of Health, Macau Government, Taiwan CDC, US CDC, Government of Canada, and the Australian Government Department.	https://github.com/CSSEGISandData/COVID-19
2	OCHA ROAP	Cases and deaths	The number of confirmed cases, recoveries, and fatalities caused by the COVID-19 pandemic in Indonesia are listed in this dataset.	https://docs.google.com/spreadsheets/d/1ma1T9hWbec1pXIwZ89WakRk-OfVUQZsOCFI4FwZxzVw/htmlview#
3	CARE Bangladesh	Mobility report	The data represents the number of returnee migrants who are currently quarantined by the district.	https://docs.google.com/spreadsheets/u/1/d/e/2PACX-1vQgQAWwIQYF4XTxVT8sYP5wwqz_KxaWfVNQk9B0FIyPPpDphAIv1cRIMV4ve_1gNbewGjcbkKNpi3Wm/pub?gid=624602850#
4	Blavatnik School of Government, University of Oxford	Government Policy	The OxCGRT methodically collects data on a variety of common policy responses implemented by governments, assesses the stringency of these actions, and aggregates the results into a single Stringency Index.	https://www.bsg.ox.ac.uk/research/research-projects/oxford-COVID-19-government-response-tracker
5	Facebook	Socio-economic	This bucket provides FAIR COVID-19 forecast data at the county level in the United States.	https://data.humdata.org/dataset/29d5f1e8-062e-4d30-be0c-bc50fab2a7c1/resource/4c934a8f-123c-45e3-8191-cfa8ce5c3158/download/covid19_forecast_file_formatted_2021-07-12.zip

6	UNESCO	Government policy	To limit the global pandemic, governments all around the world have closed educational institutions. Over 100 nations adopted nationwide closures, affecting more than half of the world's student population, according to UNESCO monitoring. Several other countries have enacted limited school closures, and if these closures become widespread, millions more students would be affected.	https://en.unesco.org/sites/default/files/covid_impact_education.csv
7	HDX	Vaccination	For nations with Humanitarian Response Plans, this information covers COVID-19 vaccine dosage availability projections as well as actual delivery. The vaccine availability projections were manually taken from COVAX's Facility Interim Distribution Forecast, which was released on February 3, 2021. The dataset includes the source(s) for each such vaccination delivery, such as press releases, official announcements, or articles.	https://docs.google.com/spreadsheets/d/e/2PACX-1vTVzu79PPTfaA2syevOQfyRRjy63dJWitqu0fFbXIQCzoUn9K9TiMWMRvFGg1RBsnLmgYugzSEiAye2/pub?gid=992438980&single=true&output=csv
8	HDX	Cases and deaths	This data offers a summary of COVID-19 monitoring in the 34 UCPM Participating States plus Switzerland, based on sub-national statistics (admin level 1) on numbers of infections and deaths acquired directly from National Authoritative Sources (National monitoring websites, when available).	https://raw.githubusercontent.com/ec-jrc/COVID-19/master/data-by-region/jrc-COVID-19-all-days-by-regions.csv
9	HDX	Cases and deaths	The number of confirmed cases, recoveries, and fatalities caused by the COVID-19 pandemic in Afghanistan are listed in this dataset.	https://proxy.hxlstandard.org/data.csv?dest=data_view&url=https%3A%2F%2Fdocs.google.com%2Fspreadsheets%2Fd%2F1F-AMEDtqK78EA6LYME2oOsWQsgJi4CT3V_G4Uo-47Rg%2Fedit%23gid%3D1539509351

10	ACAPS	Government policies	This dataset compiles all the steps taken by governments around the world in response to the COVID-19 pandemic. The information that has been gathered falls into five categories: Social estrangement, Restrictions on movement, Measures to improve public health, and Economic and social indicators. Each category is subdivided into several different sorts of measurements. ACAPS used information from the government, the media, the United Nations and others	https://data.humdata.org/dataset/e1a91ae0-292d-4434-bc75-bf863d4608ba/resource/4fb08b98-9af5-43d7-8dae-89076dbf5ead/download/acaps_covid19_government_measures_dataset.xlsx
11	HERA - Humanitarian Emergency Response Africa	Cases and deaths	Infections (new cases), Deaths, Recoveries, and Gender data per region for COVID-19 in Nigeria daily (only April - October).	https://data.humdata.org/dataset/f5c35452-d766-468a-a272-4bd82d0a3be0/resource/cba924c0-2bce-4832-bd30-8b8c662fa484/download/nga_subnational_covid19_hera.xlsx
12	HDX	Cases and deaths	The number of tested cases, confirmed cases, recoveries, and fatalities due to the COVID-19 pandemic in Myanmar are all included in this dataset.	https://docs.google.com/spreadsheets/d/e/2PACX-1vQ9GWIx9wsSxy253wGLjRqq79cQ1n4_X5N4dx6JemV7evq3DeGXSDdpnu4M9K4Rceujw3rt_CJRS5aD/pub?output=csv
13	iMMAP	Mobility Report	While communities throughout the world struggle with COVID-19, health officials have disclosed that the same type of aggregated and anonymized data that they use in Google Maps could help them make crucial decisions in the fight against the virus. The goal of these Local Mobility Reports is to give useful information on changes in people's mobility because of initiatives implemented to prevent COVID-19. These studies detail movement trends over time in several kinds of venues, such as shops and recreational spaces, supermarkets and pharmacies, parks, public transportation stations, workplaces, and residential areas, and are organized by geographical areas.	https://www.gstatic.com/covid19/mobility/Global_Mobility_Report.csv?cachebust=2dcf78defb92930a

14	Dalberg	Government policies	The database contains data for 20 nations in the Global South — as well as six countries in the Global North for reference – where Dalberg employees are either based or have extensive knowledge. The database's material is based on publicly available data and, more importantly, on-the-ground knowledge from Dalberg employees. The database includes a comprehensive list of 100 non-pharmaceutical interventions, which are grouped in a framework that makes it easier to spot common differences in the scope of key interventions	https://docs.google.com/spreadsheets/d/e/2PACX-1vR87PvMa1iClyXiyna6tPfp8w9aGPxWEKk3ILidVTwgYlqe0X1md0xcoRL6IIFRnxCxOHLRKm00aLMj/pub?output=xlsx
15	HDX	Cases and deaths	The number of confirmed cases, fatalities, and recoveries related to the COVID-19 pandemic in Mozambique are all included in this dataset.	https://data.humdata.org/dataset/96f9bc99-28ee-4046-8a96-9f7c1a1462d7/resource/2857979e-a528-429e-b7ce-e4b1c3317718/download/mozambique-COVID-19-cases.xlsx
16	ISI Foundation / Cuebiq Inc	Mobility report	Estimates of changes in human mobility during the COVID-19 outbreak in Italy are included in the dataset.	https://data.humdata.org/dataset/40a9ea9e-0edb-49f7-a440-6aee3015961b/resource/5319b9e6-17e5-43ce-81be-c4a801c9a454/download/od_matrix_daily_flows_norm_full_2020_01_18_2020_06_26.csv
17	HDX	Mobility report	Since the beginning of the COVID-19 pandemic, a few organizations have been tracking PHSM deployment around the world, utilizing various data-gathering methods, database designs, and classification schemes. WHO, the London School of Hygiene and Tropical Medicine, ACAPS, the University of Oxford, the Global Public Health Intelligence Network, US Centers for Disease Control and Prevention, and the Complexity Science Hub Vienna collaborated to bring these datasets together into open-content for public use	https://data.humdata.org/dataset/b8a55c73-8491-4c89-96fb-61850d1a3547/resource/fb5b2952-26df-4a44-9056-576ffa0e42a7/download/clean_data_2020_04_29.csv

18	World Bank Group	Socio-economic	The collection contains standardized metrics derived from World Bank and partner high-frequency phone surveys. The surveys document the socioeconomic effects of the COVID-19 pandemic on homes and individuals throughout the world. Over 90 indicators in 14 theme categories, including education, food security, income, safety nets, and others, are available.	https://development-data-hub-s3-public.s3.amazonaws.com/ddhfiles/1235981/data-coviddash-latest.xlsx
19	Code for Venezuela	Mobility Report	The Premise Data mobile application was used to crowdsource data from Venezuelans. Users are only asked to complete the survey once, and it attempts to gather current COVID-19 awareness about testing availability and symptoms, as well as users who have migrated to a different state in the previous year.	https://data.humdata.org/dataset/76f85e19-9b9a-45d4-977c-7a563e8f75d3/resource/e1826a77-691d-4b2e-a5f5-c1956e283a14/download/open_one_time_covid_impact.csv
20	HERA - Humanitarian Emergency Response Africa	Cases and deaths	Since the outbreak began, Ethiopia has had COVID-19 cases (infections, recoveries, deaths, and cumulative cases) as contained in this dataset	https://globalhealth5050.org/?_covid-data=datasettable&_extype=csv
21	HDX	Cases and deaths	This dataset shows the number of confirmed cases, recoveries, and fatalities in Palestine as a result of the COVID-19 pandemic.	https://docs.google.com/spreadsheets/d/e/2PACX-1vSLwvIS7euU8VhMkrijPKU-3Iz0PQU01et7zWn8o7EFMqE1NApp-ITX6dpLP-2peUJmeZaIrmrkNN_J/pub?gid=1539509351&single=true&output=csv
22	Qatar Computing Research Institute	Social Media	At three layers, this dataset depicts the geographical distribution of Twitter users and messages connected to the COVID-19 pandemic. The AIDR system gathered and analyzed the information.	https://data.humdata.org/dataset/70c2c71b-1322-4d44-83fc-6135e450b098/resource/06394e45-2833-490b-a15a-6562bfe0fe6e/download/cc_geo_place.xlsx

23	United Nations Development Coordination Office	Socio-economic	An inter-agency task committee led by UNDP and DCO produced the UN framework for the immediate socio-economic response to COVID-19 (approved in April 2020) to guide the reaction over the next 12 to 18 months. UN entities established a simple monitoring framework with 18 programming indicators to gauge the UN's support for the socioeconomic response and recovery (endorsed by the UNSDG in July 2020). Lead entities were nominated to lead the production of methodological notes for each indicator and the collection of data at the country level, based on their mandate and comparative advantage. Every quarter, through UN Info, these main bodies reported the collective UN results through the Office of the Resident Coordinators. By March 2021, all 2020 statistics had been reported. This is the first thorough assessment of the UN development system's collective programming contribution and outcomes.	https://data.humdata.org/dataset/6b32fade-9f68-4269-b3e2-308aab2a22d6/resource/a69f5f7e-0bae-491e-be79-991bb72ec8e5/download/serp-programme-indicators-results-2020.xlsm
24	Metabiota	Websites	The dataset comprises data from multiple sources at multiple spatial resolutions in cumulative and non-cumulative forms. This repository is designed to give a single point of access to data from a variety of sources.	https://data.humdata.org/dataset/c8b99f91-79be-46f9-a6f0-4bd92cee959c/resource/8403502a-5c61-4a17-9567-dd1c50829f0f/download/data_ncov2019.csv
25	Mobile Accord, Inc. (GeoPoll)	Vaccination	SMS conducted this research in late November in Côte d'Ivoire, the Democratic Republic of Congo, Kenya, Mozambique, Nigeria, and South Africa. The continued effects of COVID-19 on finances, physical and mental health and consumer spending are all discussed. The study also looks at people's opinions on vaccine safety and effectiveness, as well as their willingness to get the COVID-19 vaccine.	https://data.humdata.org/dataset/42f41a4b-17d6-4897-92f5-5369766a1509/resource/3ceed8ae-1a92-469b-9018-b2ef38f0824d/download/geopoll-year-end-study-raw-data_no-adm.xlsx

Appendix E:
Names and Affiliations of the 51 connected researchers on the application of AI to COVID-19

S/N	Cluster	Researcher	Affiliation	Address
1	Red	Qiu yunqing	Zhejiang University	China
2	Red	Lv Shuangzhi	Hospital of China Medical University	China
3	Red	Xu Xiaowei	China Pharmaceutical University	China
4	Red	Liu Jun	Pacific Northwest National Laboratory	United States
5	Red	Du peng	Peking University	China
6	Red	Ni qin	Johns Hopkins University	United States
7	Red	Liang tingbo	Zhejiang University School of Medicine	China
8	Red	Zhao Hong	Feinberg School of Medicine, Northwestern University	United States
9	Red	li yongtao	Montclair State University	United States
10	Red	lang quanjing	Zhejiang University	China
11	Red	su junwei	Xi'an Jiaotong University	China
12	Red	Chen yanfei	University of Pittsburgh	United States
13	Red	Wu Wei	Zhejiang Ocean University	China
14	Red	ruan lingxiang	Nanjing Medical University	China
15	Red	Yu Liang	The University of Tennessee at Chattanooga	United States
16	Red	li xukun	Kansas State University	United States
17	Red	ma Chun Lian	Wuhan Sports University	China
18	Green	xu kaijin	Zhejiang University	China
19	Green	Sheng Jiang	Zhejiang University	China
20	Green	wu jinging	China Medical University	China
21	Green	wang qing	University College Dublin	Europe
22	Green	wu wenrui	University of Waterloo	United States
23	Green	bao ming yang	Fudan University, Shanghai	China
24	Green	li yating	Duke University	United States
25	Green	hu xiaoyi	Massachusetts Institute of Technology	United States

S/N	Cluster	Researcher	Affiliation	Address
26	Green	shi ding	Portland State University	United States
27	Green	fang dating	Zhejiang University	China
28	Green	wang kaicen	Southeast University (China), Nanjing	China
29	Green	Xie jiao jiao	Zhejiang University	China
30	Blue	li Qiang	Harvard Medical School/Dana-Farber Cancer Institute	United States
31	Blue	li bo	hong kong university of science and technology	China
32	Blue	tang lingling	Nanjing University of Chinese Medicine	China
33	Blue	zhang jiaying	Beijing Normal University	China
34	Blue	zhang yuanyuan	Beijing Normal University	China
35	Blue	lu Haifeng	East China University of Science and Technology	China
36	Blue	Gao Xiang	Zhejiang University	China
37	Blue	gong yiwen	Ohio State University	United States
38	Blue	gu silan	Zhejiang University	China
39	Blue	zhang ruhong	Michigan Tech	United States
40	Blue	wu zhengjie	Tsinghua University	China
41	Blue	li lanjuan	Zhejiang University	China
42	Yellow	Xinyue Jiang	University of Minnesota	United States
43	Yellow	zhang tian xiao	Xi'an Jiaotong University	China
44	Yellow	Junzhang Wang	New York University	United States
45	Yellow	Huang Jianping	Lanzhou University	China
46	Yellow	Megan Coffee	NYU Grossman School of Medicine and Columbia Mailman School of Public Health	United States
47	Yellow	Anasse Bari	New York University	United States
48	Yellow	chi jichan	Wenzhou Medical University	China
49	Yellow	dai jianyi	Wenzhou Medical University	China
50	Yellow	cai jing	The Hong Kong Polytechnic University	China
51	Yellow	Jiang xiangao	Wenzhou People's Hospital	China