Artificial Intelligence in COVID-19 Management: A Systematic Review

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Abstract: With the development of modern technologies in the field of healthcare, the use of Artificial Intelligence (AI) in disease management is increasing. AI methods may assist healthcare providers in the COVID-19 era. The current study aimed to observe the efficacy and importance of AI for managing the COVID-19 pandemic. An organized search was conducted, utilizing PubMed, Web of Science, Scopus, Embase, and Cochrane up to September 2022. Studies were considered qualified for inclusion if they met the inclusion criterion. We conducted review according to the Preferred Reporting Items for Systematic reviews and Meta Analyses (PRISMA) guidelines. There were 52 documents that met the eligibility criteria to be included in the review. The most common item using AI during the COVID-19 era was predictive models to foretell pneumonia and mortality risks in people with COVID-19 based on medical and experimental parameters. COVID-19 mortality was related to being male and elderly based on the Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) logistic regression analysis of demographics, clinical data, and laboratory tests of hospitalized COVID-19 patients. AI can predict, diagnose and model COVID-19 by using techniques such as support vector machines, decision trees, and neural networks. It is suggested that future research should deal with the design and development of AI-based tools for the management of chronic diseases such as COVID-19.
Keywords: COVID-19, SARS-CoV-2, Artificial Intelligence (AI), Deep Learning, Machine Learning, Predicting

Introduction

SARS-CoV-2 the cause of coronavirus disease (COVID-19) primarily emerged in Wuhan, China, in December 2019 and the World Health Organization (WHO) acknowledged a COVID-19 worldwide disease on March 11th, 2020 (WHO, 2020a; Mehraeen et al., 2021). The severity of the disease ranges from flu like symptoms including fever, fatigue, cough, headache, diarrhea, myalgia, and sore throat, to atypical pneumonia causing Acute Respiratory Distress Syndrome (ARDS) with dyspnea, loss of consciousness, and chest pain (WHO, 2020b). According to the latest WHO reports, as of August 2nd, 2022, this ongoing catastrophic pandemic has infected 575,887,049 cases and led to 6,398,412 deaths (WHO, 2022). COVID-19's long asymptomatic incubation period, relatively high reproduction numbers, and high mortality rates mostly among vulnerable patients (e.g., >65 years, immunocompromised, morbidities) have put an unprecedented burden on healthcare organizations everywhere. The combat against COVID-19 seemed an arduous task since the beginning due to overwhelmed hospitals, exhausted healthcare providers, medical supplies shortage, and detection tool kits (real time polymerase chain reaction) (Dadras et al., 2022). To control the pandemic and halt the rapid spread of the disease, many vaccines were introduced and granted emergent safety approvals by the Food and Drug Administration (FDA) and WHO. As of July 26th, 2022, 12,248,795,623 vaccine doses have been ordered globally. However, despite the efficacy of COVID-19 vaccines, they are not yet a definitive solution because of vaccine inequality, vaccine hesitancy, and new variants of the virus (WHO, 2022; Oliaei et al., 2021).

Thus, all these barriers signify the importance of new technologic methods in controlling the pandemic. For this reason, the use of Artificial Intelligence (AI) and Machine Learning (ML) has gained great popularity in different health systems globally over the past two decades. This has occurred due to the easy accessibility of data, the ubiquity of computers, and increasing computational power. Thus, AI and ML-based solutions have the exceptional capability in addressing the aforementioned issues (Shamsabadi et al., 2022; Hamet and Tremblay, 2017; Mehraeen et al., 2022).

AI and ML can be used in the diagnosis of COVID-19 through image processing and analysis of X-rays, CT scans, and ultrasounds. For instance, these methods can be used to differentiate between COVID-19 and other causes of pneumonia (Ulhaq et al., 2020). In addition, AI-based methods are used in COVID-19 control and prevention; deep learning models have been used to recognize mask wearing, infrared thermography techniques were utilized for fever detection (Somboonkaew et al., 2017) and mobile based applications were available for self-claimed COVID-19 symptomatic patients (Lahiri et al., 2012). Additionally, AI has been used in the clinical management of COVID-19 by selecting the most efficient treatment based on the severity of the disease and the patient's clinical condition (Siam et al., 2020). Finally, AI-based technique has also been used in the COVID-19 vaccine and medication development to find the most efficient lead components and chemical substances (Tang et al., 2022).

Recently, AI technologies such as ML-based prototypes trained on specific biomolecules have provided low cost and fast implementation approaches for the detection of practical viral treatments. However, there are not many articles on the application of this technology for pandemic management and so we aimed to investigate AI and ML’s use, efficacy, and importance amid the COVID-19 pandemic and find the key differences between various ML models.

Materials and Methods

This study is an organized review of current literature pertinent to AI-based detection of COVID-19 disease. We have studied papers available in the English language as of September 2021. With the purpose of reliability and authenticity of the outcomes, this investigation adheres to the Preferred Reporting Items for Systematic reviews and Meta Analyses (PRISMA) checklist (Moher et al., 2009).

Data Sources

A search from December 2019 to September 2022 was directed using the following databases: PubMed, Web of Science, Scopus, Embase, and Cochrane. The search strategy employed combining the terms: “COVID-19” OR “SARS-CoV-2” OR “Coronavirus” AND ”Artificial Intelligence (AI)” OR “deep learning” OR “machine learning” OR “data mining” OR “artificial neural networks” OR “deep neural networks” OR “convolutional neural networks” AND “detection” OR “diagnosis” OR “prognoses” OR “prognosis” OR “assessment” OR “distinction” OR “recognition”. Searches were limited to documents available in the English language. Titles and abstracts of recovered articles were individually evaluated by five authors to assess their eligibility for review. Any disagreements unable to be solved following discussion were adjudicated amongst the authors. When abstracts did not provide sufficient information to examine study eligibility, the full text was retrieved for evaluation. Subsequently, each study selected in the previous stage was fully evaluated and selected by four reviewers.
Eligibility Criteria

Studies were suitable for inclusion if they met the following measures: (1) Documents published in English; (2) Human studies, original articles, and papers with the experimental data. Studies were excluded if they met the following criteria: (1) Reviews, non-original editorials, and meta analyses; (2) Literature without available full texts, abstract papers, or conference abstracts; (3) Literature with doubts about duplication and/or reliability of results; and (4) Clinical Trials which were in progress without published outcomes and (5) Studies that did not explain the implemented AI-model.

Data Extraction

Four members of our research team individually assessed the full text documents and accompanied data extraction, using a regular template/spreadsheet. Data extracted included first author (reference) ID, type of study, country of study, target population, type of AI program, the purpose of using AI, type of data used, model and type of AI technique used, a sample size of training, classification measures and other information related to the aims of this review. To eliminate possible repetitions and/or crossovers, the selected publications and extracted data were checked by other researchers.

Results

The database search achieved 617 qualified studies and following the screening 52 full text documents met the inclusion standards and included in the final evaluation (Fig. 1).

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Fig. 1: PRISMA flow diagram of study retrieval process
The included studies were conducted in 10 countries (China = 10, USA = 8, Spain = 5, Italy = 3, Korea = 3, Turkey = 3, Saudi Arabia = 2, Switzerland = 2, Taiwan = 2, India = 2, Brazil = 2 and 1 study from the UK, Australia, Israel, Egypt, Pakistan, Iran, Iraq, Bangladesh, and Mexico. One of the articles was a report on multi-national scientific collaborations (Table 1 shows a summary of the findings).

<table>
<thead>
<tr>
<th>First Author</th>
<th>Country</th>
<th>N</th>
<th>Type of disease</th>
<th>Purpose of study</th>
<th>Type of data used</th>
<th>Sample size of Training</th>
<th>Classification measure</th>
<th>Other findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Abdulkareem et al. (2021)</td>
<td>Brazil</td>
<td>600</td>
<td>30 with COVID-19 520 without COVID-19</td>
<td>Diagnosis</td>
<td>Laboratory findings</td>
<td>Random Forest (RF)/Naive Bayes (NB)/Support Vector Machine (SVM)</td>
<td>94.96% RF/92.16% NB/95% SVM</td>
<td>SVM model had the best diagnostic performance (up to 95%)</td>
</tr>
<tr>
<td>2 Akter et al. (2021)</td>
<td>Bangladesh</td>
<td>545</td>
<td>Confirmed positive COVID-19</td>
<td>Modelling</td>
<td>Blood sample results</td>
<td>Decision Random Forest (RF)/Gradient Boosting Machine (GBM)/Extreme gradient Boosting (XGBoost)/Support Vector Machines (SVM)/Light Gradient Boosting Machine (LGBM)/K nearest Neighbor (KNN)/Artificial Neural Network (ANN)</td>
<td>43.82% DT/95% RF</td>
<td>RF and GBM had the highest AUC (99%)</td>
</tr>
<tr>
<td>3 Al-Waisy et al. (2021)</td>
<td>Iraq</td>
<td>800</td>
<td>400 COVID-19 cases/400 normal cases</td>
<td>Diagnosis</td>
<td>chest X-ray</td>
<td>Support Vector Machine (SVM)/K nearest Neighbor (KNN)</td>
<td>80% SVM/85% KNN/97.14%</td>
<td>The CNN model showed a great success, it had optimal accuracy, effectiveness, and robustness for diagnosing COVID-19</td>
</tr>
<tr>
<td>4 Al-Subaie et al. (2021)</td>
<td>Saudi Arabia</td>
<td>245</td>
<td>140 COVID-19 images/95 normal images/10 SARS images</td>
<td>Classification</td>
<td>Support Vector Machine (SVM)/K nearest Neighbor (KNN)</td>
<td>-</td>
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<td>-</td>
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<tr>
<td>5 Andrea-Peza et al. (2021)</td>
<td>Spain and Mexico</td>
<td>1358</td>
<td>2,239 COVID-19 positive/641 COVID-19 negative</td>
<td>Diagnosis</td>
<td>Cough sound/quantitative RT-PCR/electrocardiogram</td>
<td>CNN</td>
<td>-</td>
<td>-</td>
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<tr>
<td>6 Ayrid et al. (2021)</td>
<td>USA</td>
<td>4087</td>
<td>11.03% of patients were imputed/COVID-19 positive/88.97% of patients</td>
<td>Prognostication of patients diagnosed/Long COVID-19 expected</td>
<td>Demographic, clinical, and laboratory data</td>
<td>Ensemble weighted tree-based neighbor/SVM/Random Forest (RF)/Logistic regression/Deep learning</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>7 Baksh et al. (2021)</td>
<td>UK</td>
<td>405</td>
<td>Adults/40% male/18-60 years old</td>
<td>Screening</td>
<td>Routine blood test</td>
<td>Ensemble weighted tree-based neighbor/SVM/Random Forest (RF)/Logistic regression</td>
<td>81.79% EBT/78.5% KNN/73.76% SVM/74.48% discriminant analysis classifier</td>
<td>A machine learning model applying routine laboratory tests can detect atypical and asymptomatic presentations of COVID-19 and could be used for screening</td>
</tr>
<tr>
<td>8 Bolouzani et al. (2021)</td>
<td>USA</td>
<td>11,525</td>
<td>42% female/30 years old</td>
<td>Predictive respiratory failure within 48 h of admission</td>
<td>XGBoost/Logistic regression</td>
<td>-</td>
<td>-</td>
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<tr>
<td>9 Booth et al. (2021)</td>
<td>USA</td>
<td>398</td>
<td>43 expired/355 non-expired</td>
<td>Modelling for mortality</td>
<td>Logistic regression/Support Vector Machine (SVM)</td>
<td>-</td>
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<tr>
<td>10 Butt et al. (2021)</td>
<td>China</td>
<td>618</td>
<td>219 CT images from 170 patents with COVID-19/224 CT images from 224 Influenza-A patients with viral pneumonia/173 CT samples from healthy people</td>
<td>Diagnosis</td>
<td>Transverse-section CT images</td>
<td>Convolutional Neural Network (CNN)</td>
<td>96.7%</td>
<td>The XGBoost model had the best accuracy (91.9%). The predictive ability of XGBoost showed that the model could be used for predicting 48-hour respiratory failure in COVID-19 patients</td>
</tr>
<tr>
<td>11 Cabrita et al. (2021)</td>
<td>Italy</td>
<td>1624</td>
<td>52% COVID-19 positive/48% COVID-19 negative</td>
<td>Diagnosis</td>
<td>Routine blood test</td>
<td>Random Forest (RF)/naive Bayes (NB)/logistic regression (LR)/Support Vector Machine (SVM)/K nearest Neighbor (KNN)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>12 Chen et al. (2021)</td>
<td>China</td>
<td>362</td>
<td>Patients with COVID-19</td>
<td>Modelling</td>
<td>Clinical characteristics, severe and non-laboratory test</td>
<td>Random Forest (RF)</td>
<td>81%</td>
<td>Clinical input accuracy &gt;90% Laboratory</td>
</tr>
</tbody>
</table>

Table 1: Description of the findings reported in the eligible studies
<table>
<thead>
<tr>
<th>Study ID</th>
<th>Country</th>
<th>Methodology</th>
<th>Patients</th>
<th>Classification</th>
<th>Result</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>Spain</td>
<td>306 CXR</td>
<td>COVID-19 + Pneumonia cases</td>
<td>Diagnose Lung X-Ray images</td>
<td>105 COVID-19 CXR classification, convolutional neural network model (VGG16)</td>
<td>95.9%</td>
<td>100%</td>
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<tr>
<td>14</td>
<td>Brazil</td>
<td>337 435 People Using the app</td>
<td>Predicting Combination of symptoms</td>
<td>Logistic Regression (LR) &amp; support vector machine (SVM)</td>
<td>357,626 users selected according to the model</td>
<td>97.3%</td>
<td>100%</td>
</tr>
<tr>
<td>15</td>
<td>South Korea</td>
<td>3524 COVID-19</td>
<td>To predict mortality among COVID-19 patients</td>
<td>3074 patients' chest X-ray images with logistic regression</td>
<td>-</td>
<td>87.9%</td>
<td>-</td>
</tr>
<tr>
<td>16</td>
<td>Spain</td>
<td>2547 patients</td>
<td>Medical records of COVID-19 patients</td>
<td>Predicting the severity of infection and mortality</td>
<td>Age &lt; 60 or Lab values &gt; 32 in total</td>
<td>-</td>
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<tr>
<td>17</td>
<td>Spain</td>
<td>2020 COVID-19</td>
<td>Diagnosis</td>
<td>Chest X-ray images</td>
<td>CNN model</td>
<td>-</td>
<td>-</td>
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<tr>
<td>18</td>
<td>Switzerland</td>
<td>7960 Normal and 5451 Pneumonia patients</td>
<td>to detect COVID-19 pneumonia on chest radiographs (CXR)</td>
<td>Learntable stroke convolution + inverted bottleneck blocks</td>
<td>7960 normal cases, 5451 with other pneumonia and 258 CXR COVID-19 pneumonia</td>
<td>Sensitivity 94.3, Specificity 97.2</td>
<td>-</td>
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<tr>
<td>19</td>
<td>China</td>
<td>2160 COVID-19</td>
<td>Mortality risk prediction model for COVID-19 (MyBPRC)</td>
<td>34 clinical features, eventually only 14 were chosen as the model</td>
<td>Logistic regression, support vector machine, gradient boosted decision tree and neural network</td>
<td>2520 COVID-19 patients with known outcomes</td>
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<tr>
<td>20</td>
<td>Iran</td>
<td>10153 people with pneumonia and 99 people without pneumonia</td>
<td>Design a highly efficient Computer Aided Detection (CAD) system for COVID-19</td>
<td>CT Scans</td>
<td>Neural search Architecture network (NASNet)-based algorithms</td>
<td>10,153 CT scans of 190 patients with COVID-19</td>
<td>-</td>
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<tr>
<td>21</td>
<td>Italy</td>
<td>852 patients</td>
<td>Prediction</td>
<td>Patients' medical history, demographics and clinical data were collected using a computer health record system</td>
<td>Chest X-ray images</td>
<td>852 patients with COVID-19</td>
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<tr>
<td>22</td>
<td>South Korea</td>
<td>332 patients</td>
<td>COVID-19</td>
<td>Computer Aided Detection (CAD)</td>
<td>Deep-learning algorithm</td>
<td>54221 normal CXR and 35613 abnormal CXR</td>
<td>-</td>
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<tr>
<td>23</td>
<td>South Korea</td>
<td>172 patients</td>
<td>COVID-19</td>
<td>Computer Aided Detection system (CAD)</td>
<td>Deep-learning based CAD</td>
<td>The CAD was initially trained using 54,221 normal CXRs and 35,613 abnormal CXRs</td>
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<tr>
<td>24</td>
<td>USA</td>
<td>4313 COVID-19</td>
<td>Prediction</td>
<td>Systolic and diastolic blood pressure, age, pulse oximetry</td>
<td>Open-source HAPI at annotation package (GM and Data from 4313 patients</td>
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<td>Table 1: Continue</td>
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<td>25</td>
<td>Imak (2020) Turkey 4575 COVID-19 Classifying level,hood sore cough level,leucocyte deroysenes level, D-dimer level,respiratory rate and Charlston comorbidity score X-ray image Convolutional Neural Network (CNN) 1428 images for training for task 1/245 for task 2 98.92% average accuracy on COVID vs normal 98.27% on COVID vs pneumonia Accuracy of 90% as early as 16 days before the outcome - Of 4575 total CXRs: 1524 COVID 1524 normal 1527 pneumonia</td>
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<td>26</td>
<td>Karthikyan et al (2021) China 2729 1766 deep into after the process COVID-19 Prediction Neutrophils,lymphocytes,Lactate Dehydrogenase (LDH), High-sensitivity C-Reactive Protein (hs-CRP) and age CXR XGBoost feature importance and neural network classification 1418 dataset for training and 348 datasets for testing -</td>
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<td>27</td>
<td>Khan (2021) Saudi Arabia 340 CXRs 170 healthy and 170 COVID-19 Direction SVM-based classifier (showed better results than CNN) 64 training CXR Accuracy up to 84.12% - 272 testing CXR</td>
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<td>28</td>
<td>Lang et al. (2020) Italy 199 Patients with influenza-like symptoms COVID-19 patients Diagnosis Clinical data and CXR images Neural network 100 91.4% - --</td>
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<td>29</td>
<td>Lin et al. (2021) China 2024 COVID-19 patients Prediction Clinical data Logistic regression Simplified logistic regression gradient boosting decision tree 2339 GBDT: 88.9% Logistic regression: 86.8% Simplified LR: 84.7% - Mortality occurred in 0 mild cases and 98.4% in moderate cases, 20.8% in severe cases and 62.2% in critically severe cases. 8.8% of patients died during hospitalization. There is a correlation between COVID-19 mortality and being male and elderly</td>
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<td>30</td>
<td>Liu et al. (2021) Taiwan 467 Hospitalized COVID-19 patients Prediction Demographics, clinical data, Laboratory tests Artificial neural network convolutional neural network random forest random tree logistic Logitronic regression random forest 361 ANN: 99% CBR: 82% -</td>
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<td>31</td>
<td>Muro et al. (2021) Spain 1270 Hospitalized COVID-19 patients Prediction Demographics, comorbidities, clinical data, chronic treatment Logistic regression random forest XGBoost ventilation Patients 918 - - 36.3% of patients died, or required mechanical ventilation with older age (average of 79.2), cardiovascular, central nervous system kidney diseases and cancer had more severe prognosis. 52.8% of patients survived, and 47.2% died during hospitalization. The best prediction performance was observed with XGBoost. The mortality rate was 17% and overall median time to death was 6.5 days (range of 1-25.4)</td>
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<td>32</td>
<td>Pan et al. (2020) China 123 ICU patients with COVID-19 Prediction Baseline information, Clinical diagnosis, vital signs, laboratory tests, treatments Logistic regression Gradient Boosting Decision Tree (GBDT) XGBoost CallBoost 98 XGBoost &amp; CallBoost: 84% Logistic regression &amp; AdaBoost &amp; GBDT: 76% -</td>
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<td>33</td>
<td>Puchett et al. (2022) USA 567 Hospitalized COVID-19 patients Prediction Demographics, Vital signs, laboratory test results, ECG results Random forest 396 65.5% - The mortality rate was 17% and overall median time to death was 6.5 days (range of 1-25.4)</td>
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<td>34</td>
<td>Quitro et al. (2021) Australia 346 Patients with COVID-19 Diagnosed through RT-PCR test Modelling: severity assessment &amp; prioritization treatment Clinical data, symptoms, comorbidities, laboratory tests, CT scan Logistic regression Gradient boosted trees NN 230 - - Differences between patients with severe COVID-19 and those with mild COVID-19 is related to comorbidities such as cardiovascular diseases (P = 0.042), hypertension (P = 0.002), diabetes (P = 0.001) and cancer (P = 0.001) and among all symptoms and symptoms, increased respiratory rate (P = 0.082) and dysnea (p&lt;0.001) were more common among patients with severe COVID-19</td>
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<td>35</td>
<td>Renni et al. Israel 2675 Hospitalized COVID-19 patients Prediction Demographics, Patient history, clinical data, hospital course, Laboratory tests Cox regression - - - -</td>
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<td>36</td>
<td>Sankaranarayanan US et al. (2021) 11007 Prediction on positive PCR test Prediction Demographics, Patient history, clinical data, hospital course, Laboratory tests Cox regression 80% 78% in prospective &amp; 89% in cross validation - -</td>
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<td>37</td>
<td>Zhang et al. Egypt Decoding a offline analysis model -1080 analysis model COVID-19 Coronavirus Predicting Prediction on twitter streaming data AI and machine learning AI and machine learning 1000-3000 94.7% And 81.7% And 85.3% - SVM and logistic regression</td>
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<td>38</td>
<td>Yuan et al. USA 6.12 million reports infectious disease Modelling: Reporting Odds Ratio (ROR), data mining the algorithm US food and drug antiviral agents such as antibiotics, such as the anthracycin algorithm Reporting Odds Ratio (ROR), a feature mining 6.12 million reports from 2015-2020 Not used this feature - - The current pharmacotherapy for COVID-19 are associated with increased the risks of</td>
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</table>
Table 1: Continued

<table>
<thead>
<tr>
<th>ID</th>
<th>Country</th>
<th>Work on</th>
<th>COVID-19</th>
<th>Modelling:</th>
<th>Data repository and clinical databases</th>
<th>Deep learning techniques, LSTM algorithm</th>
<th>Records from</th>
<th>Model accuracy</th>
<th>Disease</th>
<th>Additional details</th>
</tr>
</thead>
<tbody>
<tr>
<td>39</td>
<td>China</td>
<td>2021</td>
<td>COVID-19</td>
<td>China</td>
<td>Clinical databases</td>
<td>LSTM algorithm</td>
<td>6,388,931</td>
<td>-</td>
<td>LSTM</td>
<td>-</td>
</tr>
<tr>
<td>40</td>
<td>China</td>
<td>2020</td>
<td>COVID-19</td>
<td>China</td>
<td>Clinical databases</td>
<td>Region Proposals</td>
<td>224 patient and 618 CT samples</td>
<td>Average F1-score and the overall accuracy rate were 0.7580-0.764 and 78.7, 79.4%</td>
<td>-</td>
<td>In the test set training set, whereas it had an AUC of 0.808 (0.828-0.911) and an accuracy of 81.9%</td>
</tr>
<tr>
<td>41</td>
<td>China</td>
<td>2019</td>
<td>COVID-19</td>
<td>China</td>
<td>Clinical databases</td>
<td>Neural network deep learning models</td>
<td>408 confirmed COVID-19 patients,</td>
<td>Accuracy 97.4</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>42</td>
<td>China</td>
<td>2020</td>
<td>COVID-19</td>
<td>China</td>
<td>Clinical databases</td>
<td>Tomography images</td>
<td>5372 images from patients</td>
<td>Sensitivity 79.99%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>43</td>
<td>Turkey</td>
<td>2020</td>
<td>COVID-19</td>
<td>Turkey</td>
<td>Clinical databases</td>
<td>Support Vector Machines (SVM), Long Short Term Memory (LSTM)</td>
<td>110130 confirmed cases</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>44</td>
<td>Turkey</td>
<td>2021</td>
<td>COVID-19</td>
<td>Turkey</td>
<td>Clinical databases</td>
<td>Deep neural networks</td>
<td>346 CT-scan images</td>
<td>Accuracy 98.36</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>45</td>
<td>China</td>
<td>2021</td>
<td>COVID-19</td>
<td>China</td>
<td>Clinical databases</td>
<td>Multilayer Perceptron (MLP)</td>
<td>543 samples</td>
<td>93.73% for achieving maximum precision 90.8% to select relevant features for predicting satisfactory status Sensitivity 0.83</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>46</td>
<td>USA</td>
<td>2021</td>
<td>COVID-19</td>
<td>USA</td>
<td>Clinical databases</td>
<td>Logistic Regression (LR), Decision Tree (DT), Gradient Boosting decision trees (GB), support vector machines (SVM) and Neural Network (NN)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>47</td>
<td>India</td>
<td>2022</td>
<td>COVID-19</td>
<td>India</td>
<td>Clinical databases</td>
<td>PCR laboratory</td>
<td>Two datasets, 4356 CT-scan</td>
<td>Sensitivity and specificity of system achieves 0.44, 59.8, and 65.0% respectively Accuracy 0.003</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>48</td>
<td>Pakistan</td>
<td>2021</td>
<td>COVID-19</td>
<td>Pakistan</td>
<td>Clinical databases</td>
<td>Computer Tomography (CT) scan images</td>
<td>527 images of the dataset</td>
<td>Sensitivity specificity for training 60.87% and 98.20% respectively Accuracy 0.003</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>49</td>
<td>India</td>
<td>2022</td>
<td>COVID-19</td>
<td>India</td>
<td>Clinical databases</td>
<td>Data from open data set the countries reported curve artificial</td>
<td>Suspected Infected (SIB) model deep learning 28,657 from the recurrent neural network used in deep learning a Short Long Term Memory (LSTM)</td>
<td>Actual count patient was given as 99.82% accuracy reported</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>50</td>
<td>Switzerland</td>
<td>2021</td>
<td>COVID-19</td>
<td>Switzerland</td>
<td>Medical history and laboratory values hospital group DR</td>
<td>Medical history and laboratory values hospital group DR</td>
<td>419 out patient 0.96 (SVM) accuracy</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>51</td>
<td>China</td>
<td>2020</td>
<td>COVID-19</td>
<td>China</td>
<td>Clinical databases</td>
<td>Deep learning</td>
<td>4804 Patients with more than 3 consecutive CT</td>
<td>0.98</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>52</td>
<td>Japan</td>
<td>2022</td>
<td>COVID-19</td>
<td>Japan</td>
<td>Clinical databases</td>
<td>Machine Learning (ML)-based algorithm</td>
<td>87.5%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
The result of this study showed that forecasting or prediction was the main reason for applying AI in COVID-19 management; online AI for forecasting outpatients’ COVID-19 disease severity (Schöning et al., 2021; Dominguez-Olmedo et al., 2021; Xiao et al., 2020; Yu et al., 2021), differentiating severe and non-severe COVID-19 (Chen et al., 2021), predicting outpatients’ respiratory failure (Bolourani et al., 2021) and risk of intubation (Arvind et al., 2021).

Most of the included studies (n = 24) stated “prediction” as the purpose of using AI for managing COVID-19. Other AI objectives, in order of frequency, were: "diagnosis", "detection", "modeling", "deep learning" and "classifying" (Fig. 2).

Various predictive models to predict mortality (Das et al., 2020; Ünlü and Namli, 2020; Booth et al., 2021; Gao et al., 2020; Karthikeyan et al., 2021; Marcos et al., 2021; Pan et al., 2020; Stachiel et al., 2021) based on clinical and laboratory parameters of confirmed COVID-19 patients were the most used technologies of AI in COVID-19 pandemic management. Other studies predicted a 30-day mortality risk in patients with COVID-19 pneumonia (Halasz et al., 2021) and patients’ chances of surviving a SARS-CoV-2 infection (Ikemura et al., 2021). For instance, there was a correlation between COVID-19 mortality and being male and elderly in the Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) logistic regression analysis of demographics, clinical data, and laboratory tests of hospitalized COVID-19 patients (Lin et al., 2021).

Building a predictive model as a screening tool to identify people and areas with a higher risk of SARS-CoV-2 infection to be prioritized for testing (Booth et al., 2021; Dantas et al., 2021; Singh et al., 2022), early detection of COVID-19 (Siddiqui et al., 2021) and prediction system for discharged patients based on Computer Tomography (CT) scan images, (Shah et al., 2022) was reported by several studies.

In a related article, this vital finding mentioned that data mining could be used as a model to predict the side effects of COVID-19 (Yang et al., 2021). Another study reported the Odds Ratio (OR) and a data mining algorithm to investigate the risks of cardiac adverse events associated with the possible pharmacotherapies for COVID-19 outpatients (Yuan et al., 2021). Deep Neural Network and Convolutional Neural Network (CNN) models were used to detect coronavirus disease from CT Scan images (Turkoglu, 2021). We also identified that the presence of several techniques was used (logistic regression, Support Vector Machine (SVM), K-nearest neighbor, random forest, and gradient boosting) to diagnose and predict mortality among confirmed COVID-19 patients (Schöning et al., 2021; Das et al., 2020; Ünlü and Namli, 2020; Singh et al., 2022; Abdulkareem et al., 2021; Zhang et al., 2020).

A review of the articles showed that predicting systems had good efficiency and the accuracy ranged from 73 (Dantas et al., 2021) to 99.8% (Al-Waisy et al., 2021) (mostly above 90%) (Chen et al., 2021; Duran-Lopez et al., 2020; Ghaderzadeh et al., 2021; Irmak, 2020). Therefore, they could be applied in clinical settings for diagnosing COVID-19 infection and treatment follow-up.

**Fig. 2:** The frequency of AI using purpose for the management of COVID-19
Discussion

The main objective of this study was to consider AI and ML’s use, efficacy, and importance amid the COVID-19 pandemic and find the main variances among various ML models. Our results demonstrated that AI methods such as data mining, machine learning, deep learning, logistic regression, support vector machine, neural networks, K-nearest neighbor, random forest, and gradient boosting could help manage COVID-19. A similar article (Ohno et al., 2022) reported that ML-based CT texture analysis is equally or more useful for predicting the time until CT for favipiravir treatment on COVID-19 patients than CT disease severity score (Ohno et al., 2022). Also, Liang et al. (2022) in a related article concluded that a new AI system based on deep learning and federated learning has high reliability in diagnosing COVID-19 based on CT, with or without clinical data (Liang et al., 2022). Finally, existing literature on the use of AI during the COVID-19 epidemic determines the benefits of AI use in the pandemic such as early diagnosis, predictions, and even though modeling of treatments.

Discussing the type of program and the purpose of each study simultaneously provides a helpful understanding of the setting of each study. Many studies shared the same frameworks, like using AI to diagnose COVID-19 patients, but they applied different methods such as deep learning, data mining, machine learning, logistic regression, and support vector machines on targeted populations. But simply said, the diagnosis and prognosis of COVID-19 were the global aims of these studies. Interestingly, 11 studies used models to predict the prognosis of COVID-19 patients. This was the most abundant framework, followed by models diagnosing COVID-19, which was the setting of 9 studies. Mix methods of AI were also used in the management of COVID-19, such as using a model to develop an app to diagnose or assess the prognosis of patients. The outstanding results of each framework are discussed in detail below.

By using laboratory markers or chest radiograph imaging, researchers provided their models with data necessary for diagnosing COVID-19 regardless of patients’ history, manifestations, and physical exam results. Applying routine laboratory test results as data, (Baktash et al., 2021) established a ML model to detect asymptomatic individuals infected with COVID-19. The accuracy of their model covered a range of 74.48% up to 81.79% depending on the technique and algorithm (Baktash et al., 2021). By comparison of people’s signs and the results of traditional COVID tests Machine learning algorithms and models can predict COVID-19 infection. Populations, where access to testing is limited, can be examined by these diagnostic methods. During the COVID-19 pandemic mobile health apps that monitor patients, by gathering signs such as persistent coughing, fever, fatigue, and anosmia in daily reports on their health status, can predict COVID-19 infection. Development of a mobile application for self-management and self-monitoring among patients with COVID-19 allows data gathered to be used to forecast severe COVID-19 patients by ML models (Mohammad et al., 2021). ML algorithms allow identifying of COVID-19 patients. This method of AI is a tendency towards the application of innovative statistical approaches to defining results as a function of inputs. For example, (Cabitza et al., 2021) established compound ML models using data retrieved from 21 to 34 blood test results of 1624 patients reaching precisions of 75-78% to differentiate those infected with COVID-19 from those who were not (Cabitza et al., 2021).

Image processing and modeling for prediction were the two common methods of AI for the management of the pandemic. Clinical image processing is the basis of many diagnostic models, such as chest X-rays and chest CT scans that play a major role in diagnosing respiratory infections, especially COVID-19. AI image processing and interpretation algorithms can detect/recognize, assess, and classify COVID-19 by segmenting, detecting, and quantifying the images’ suspicious regions. Segmentation, localization, pattern classification, and extraction of Regions of Interest (ROIs) of chest X-rays or CT images play a particular role in Image classification (Kaheel et al., 2021). Outstanding results from different countries show that using image processing to analyze lung X-ray images, COVID-19 cases could be identified among pneumonia and healthy controls (Irma, 2020; Alsaaude et al., 2021; Civit-Masot et al., 2020; Fontanellaz et al., 2021; SeyedAlinaghi et al., 2022). Yang et al. (2021) designed a framework to find out the best architecture, pre-processing and training parameters by pre-trained Convolutional Neural Network (CNN) models and using deep learning techniques for the COVID-19 CT-scan classification tasks. The accuracy score was above 96% in the diagnosis of COVID-19 using CT-scan images that confirm the results (Yang et al., 2021).

Same as diagnosis, by predicting the diagnosis of COVID-19 patients, we require clinical data, upon which physicians provide the patient with less or more intensive care. Due to the characteristics of SARS-CoV-2 infection, to predict the outcome, we could focus on respiratory signs and symptoms. Bolourani et al., designed a model which was able to predict the 48 h respiratory failure of COVID-19 patients, using 10 parameters including oxygen delivery mode, ESI value, gender, and race (Bolourani et al., 2021). Another diagnostic model designed in Italy predicted 30-day mortality based on clinical data as well as medical history and demographics. This model showed high sensitivity (94%) but had low specificity (37%) (Halasz et al., 2021). Vital signs have also been involved in this process which includes: Systolic blood pressure, respiratory rate, and pulse oximetry level, as well as other laboratory test results. The
result is a prognostic model that predicts patients’ survival chances. In this method, by comparing the vital signs of a sick person with the vital signs of a healthy person, taking into account age and gender, the survival chances of COVID-19 patients are predicted (Ikemura et al., 2021). Ivano Lodato et al. (2022) developed a ML model to predict both the mortality and severity associated with COVID-19 based on data gathered from medical records and test results collected during their hospitalization. Decision tree, random forest, gradient, and RUS Boosting models of ML were used to test the accuracy of these models. Their results showed that random forest and gradient boosting classifiers were highly accurate in predicting patients’ mortality (average accuracy ∼of 99%) (Lodato et al., 2022). COVID-19 computer model using the biochemical markers, inflammatory biomarkers and a Complete Blood Count (CBC) was another method mentioned in most of the studies included in this review. This model helps the physicians form an idea about the patient’s overall status (Domínguez-Olmedo et al., 2021; Karthikeyan et al., 2021; Akhtar et al., 2021).

Biochemical markers, such as Arterial Blood Gases (ABG), including pH, HCO₃⁻, O₂, and CO₂, are useful indicators of hemoglobin saturation status and are of great importance in COVID-19. Using these values in combination with inflammatory markers and CBC results along with some demographics, (Arvind et al., 2021) developed a model skilled at predicting the COVID-19 patients’ necessity for intubation (Arvind et al., 2021). The unquestionable role of inflammatory biomarkers, during the course of COVID-19 made them one of the data targets for AI models and systems in COVID-19. Mimicking the follow-up protocols, some studies used inflammatory biomarkers as predictors of patients’ outcomes. Levels of Lactate Dehydrogenase (LDH) and high-sensitivity C-Reactive Protein (hs-CRP) as useful indicators of a patient’s inflammatory status helped with developing a model that predicted COVID-19 mortality with 90% accuracy 16 days before the outcome (Karthikeyan et al., 2021). Other laboratory values have also been integrated into AI models and systems. Some examples of these other laboratory markers include levels of D-dimer, troponin (Ikemura et al., 2021), and interleukin 6 (Chen et al., 2021).

Plain chest X-rays and chest CT scans are well-known diagnostic tools for COVID-19 and many other respiratory conditions and infections. Apart from COVID-19, interdisciplinary researchers have aimed to develop systems with the ability to interpret medical imaging modalities. Identifying chest radiographs or CT-scans that belong to known COVID-19 cases, while healthy and non-COVID-19 pneumonia cases were used as controls, describes the majority of study frameworks in this field (Ghaderzadeh et al., 2021; Irmak, 2020; Hwang et al., 2020; Khan, 2021; Xu et al., 2020; Sheikhhahaei et al., 2022; Behnoush et al., 2022). Age, demographics, chronic medical condition (Arvind et al., 2021), vital signs, exposures, and even gender were extracted from medical records and used to make the artificial models more realistic. In addition, novel approaches to diagnosis gathered attention among scientists. For instance, the system designed by Andreu-Perez et al. (2021) uses cough sounds in combination with quantitative RT-PCR and lymphocyte count to diagnose individuals infected with COVID-19 (Andreu-Perez et al., 2021).

One of the limitations of the current research was the breadth of methods and sub-branches of AI used in clinical care, so researchers had to study all the included articles in more detail and extract data in order to complete the table of results. Also, as interdisciplinary works, the included studies in this review were designed and conducted by researchers from different branches of science, mainly medicine, and computer sciences. Therefore, the interpretation of their results would have best been done through an interdisciplinary exchange of views. However, due to the specific aim of this review, it proceeded mostly from a medical point of view.

Conclusion

Managing difficult conditions in human life requires advanced technologies. COVID-19 is one of the important challenges in the health field that has involved the whole world. Information and communication technology tools such as AI can help manage this pandemic. In this research, the applications of artificial intelligence for managing COVID-19 were investigated and it was stated that AI can predict, diagnose and model COVID-19 by using techniques such as support vector machine, decision tree, and neural network. It is suggested that future research should deal with the design and development of AI-based tools for the management of chronic diseases such as COVID-19.

Declarations

Availability of Data and Material

The authors stated that all information provided in this article could be shared.

Acknowledgment

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Author’s Contributions

Samaneh Mohammadi: The conception and designed of the study.
SeyedAhmad SeyedAlinaghi, Esmaeil Mehraeen and Daniel Hackett: Final approval of the version to be submitted.
Mohammad Heydari, Parsa Mohammadi, Ghazal Arjmand, Yasna Soleiman, Ayein Azarnoush, Hengameh Mojdeganlou, Mohnes Dashti, Hadiseh Azadi Cheshmehkabodi, Sanaz Varshochi, Mohammad Mehrtak and Ahmadreza Shamsabadi: Drafted the article.
Zahra Pashaei, Pegah Mirzapour and Amirali Karimi: Acquisition of data.
Amir Masoud Afsahi and Peyman Mirghaderi: Analysis and interpretation of data.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

References


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