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Review

Applications of artificial intelligence in COVID-19 pandemic: A comprehensive review

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ARTICLE INFO

Keywords:
Artificial intelligence
Machine learning
COVID-19
SARS-CoV-2
Deep learning
Drug repurposing

ABSTRACT

During the current global public health emergency caused by novel coronavirus disease 19 (COVID-19), researchers and medical experts started working day and night to search for new technologies to mitigate the COVID-19 pandemic. Recent studies have shown that artificial intelligence (AI) has been successfully employed in the health sector for various healthcare procedures. This study comprehensively reviewed the research and development on state-of-the-art applications of artificial intelligence for combating the COVID-19 pandemic. In the process of literature retrieval, the relevant literature from citation databases including ScienceDirect, Google Scholar, and Preprints from arXiv, medRxiv, and bioRxiv was selected. Recent advances in the field of AI-based technologies are critically reviewed and summarized. Various challenges associated with the use of these technologies are highlighted and based on updated studies and critical analysis, research gaps and future recommendations are identified and discussed. The comparison between various machine learning (ML) and deep learning (DL) methods, the dominant AI-based technique, mostly used ML and DL methods for COVID-19 detection, diagnosis, screening, classification, drug repurposing, prediction, and forecasting, and insights about where the current research is heading are highlighted. Recent research and development in the field of artificial intelligence has greatly improved the COVID-19 screening, diagnostics, and prediction and results in better scale-up, timely response, most reliable, and efficient outcomes, and sometimes outperforms humans in certain healthcare tasks. This review article will help researchers, healthcare institutes and organizations, government officials, and policymakers with new insights into how AI can control the COVID-19 pandemic and drive more research and studies for mitigating the COVID-19 outbreak.

1. Introduction

A novel coronavirus disease 19, also referred to as COVID-19, is an infectious disease caused by severe respiratory syndrome coronavirus type 2 (SARS-CoV-2) (Awasthi et al., 2020; de Almeida et al., 2020; Manigandan et al., 2020). The most common symptoms experienced by COVID-19 infected patients are dry cough, loss of smell and taste, fever, fatigue, and respiratory illness such as shortness of breath (Ibrahim, 2020; Jalaber et al., 2020). The cross-sectional view of SARS-CoV-2 shown in Fig. 1, is comprised of spike protein (S), nucleocapsid protein (N), hemagglutinin-esterase dimer (HE), membrane glycoprotein/ matrix (M), an envelope protein (E), and single-strand RNA, non-segmented, enveloped (Su et al., 2020). The first case of coronavirus infected patient was recorded in December 2019 in Wuhan city, Hubei, China and afterward, the infected cases increased so rapidly throughout the world that the World Health Organization (WHO) has declared it a Public Health Emergency of International Concern (PHEIC) on January 30, 2020 (Deng et al., 2020; Sohrabi et al., 2020).

To control and mitigate the transmission of the novel virus, many countries have announced lockdowns and curfews with immediate effect. Paramedical staff, scientists, and researchers started working day and night to search for new technologies to mitigate the COVID-19 pandemic as a short-term strategy and started research on making a vaccine as an antidote for the virus as a long-term strategy (Li, 2020; Pontone et al., 2020). Currently, two types of standard tests are being applied. The first case of coronavirus infected patient was recorded in December 2019 in Wuhan city, Hubei, China and afterward, the infected cases increased so rapidly throughout the world that the World Health Organization (WHO) has declared it a Public Health Emergency of International Concern (PHEIC) on January 30, 2020 (Deng et al., 2020; Sohrabi et al., 2020).

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conducted for the detection of coronavirus disease, the diagnostic tests, and the antibody tests. These techniques are costly, time-consuming, need specific materials and instruments, and are not effective enough to give true positive rates. Therefore, the standard methods are not feasible for the rapid diagnosis and tracking of coronavirus disease (Tahamtan & Ardebili, 2020; Ai et al., 2020; Pham et al., 2020).

Recent studies have shown that artificial intelligence (AI) is a promising technology that can be employed in various sectors such as, in process industries, the agriculture sector, banking, computing, and healthcare (Wirtz et al., 2019; Liu et al., 2020; Abduljabbar et al., 2019). This emerging technology is used in various medical studies and results in better scale-up, timely, most reliable, and efficient outcomes, and sometimes outperforms humans in certain healthcare tasks (Coeckelbergh, 2010; Nadarzynski et al., 2019; Cossy-Gantner et al., 2018). Artificial intelligence is a subfield of computer science that emphasizes the design of intelligent systems that can learn from the data and make decisions and predictions accordingly. Machine learning (ML) and deep learning (DL) are the two main branches of AI out of many. ML is a subset of AI that can automatically learn and improve accordingly from experience without being programmed explicitly. ML-based algorithms depend on the characteristic features. Some of the dominant ML methods include artificial neural networks (ANN), random forest (RF), support vector machine (SVM), and decision tree (DT). While DL is the subset of machine learning that can solve complex schemes through representation learning. Some of the dominant DL methods include; convolutional neural network (CNN), recurrent neural network (RNN),

![Cross-sectional View of SARS-CoV-2](image)

**Fig. 1.** Cross-sectional View of SARS-CoV-2.
Artificial intelligence-based tools, particularly deep learning models, are the promising techniques used to assist radiologists in the early screening of coronavirus. Moreover, it reduces the workload of the radiologists, improves detection more accurately and efficiently, gives a timely response and accurate treatment for the patients of COVID-19 (Albahri et al., 2020; Swapnarekha et al., 2020; Sufian et al., 2020). AI coupled with drug repurposing can detect the drugs that can be used to combat novel diseases like COVID-19. The use of such emerging technologies has the potential to significantly alleviate the main issue associated with drug repurposing, which is the diagnosis and identification of the drug-disease relationship. Various applications of AI to combat the COVID-19 outbreak include virus identification, screening, and diagnostics, drug repurposing or repositioning, prediction and forecasting (Lin et al., 2020; Vaishya et al., 2020; Ahuja et al., 2020; Monshi et al., 2020).

Our focus is to highlight the applications of AI to combat the COVID-19 pandemic and to discuss the state-of-the-art solutions to tackle COVID-19 with the help of these emerging technologies. Moreover, various challenges associated with AI are highlighted, which inspired us to present a list of recommendations for researchers, academia, governments, and other communities working in a similar area. For this purpose, various citation databases available online were used to retrieve the relevant literature. The citation databases selected in this paper include ScienceDirect, Google Scholar, and preprints from arXiv, medRxiv, and bioRxiv. After screening and filtration, the final literature dataset of relevant articles was obtained and critically reviewed.

The remaining paper is organized as follows. Section 2 presents the applications of AI (ML and DL) to combat COVID-19. In section 3, challenges and limitations faced while using AI are discussed. Finally, the study is concluded in section 4.

2. Applications of AI to Combat Covid-19

Artificial intelligence (AI) based tools are widely used for the identification, classification, and diagnosis of medical images to control the spread of disease (Alsharif et al., 2020; Chen et al., 2020a). Recent research and development in the field of artificial intelligence has greatly improved the COVID-19 screening, diagnostics, and prediction and results in better scale-up, timely response, most reliable, and efficient outcomes, and sometimes outperforms humans in certain healthcare tasks (Sipior, 2020; Beck et al., 2020; Fant et al., 2020). Machine learning (ML) and deep learning (DL) are the two main branches of AI out of many. Applications of both ML and DL in combating and mitigating the COVID-19 pandemic are reviewed in the subsequent sections. Fig. 2 shows the schematic view of applications of machine learning and deep learning in combating COVID-19.

2.1. Applications of Machine Learning in COVID-19 Screening, Diagnostics, Classification, and Prediction

Machine learning is a subset of AI that can automatically learn and improve accordingly from experience without being programmed explicitly. ML-based algorithms primarily depend on characteristic features. A complex and huge amount of data can be developed by using ML-based techniques. These techniques have been widely used for finding the patterns of epidemics and for forecasting purposes. With regards to the COVID-19 pandemic, such techniques have been used by several researchers for screening, classification, diagnosis, drug repurposing, and prediction of COVID-19 (A. Kumar, Gupta, & et al., 2020; Mbunge, 2020; Salehi et al., 2020). Applications of some of the important ML methods including support vector machine (SVM), logistic regression (LR), random forest (RF), and decision tree (DT) in combating the COVID-19 pandemic are discussed.

![Fig. 2. Schematic view of applications of Artificial Intelligence for fighting COVID-19.](image-url)
2.1.1. Support Vector Machine (SVM)

Support vector machine (SVM) is a powerful tool used for solving classification and regression problems. It has been in numerous real-world applications, including the health sector, due to its high accuracy and performance. Therefore, recently, SVM has been used for combating the COVID-19 pandemic because of its superior performance (Singh, Poonia, & al., 2020; Ismael & Şengür, 2021). Various articles published on the detection (Hassanien et al., 2020; Yao et al., 2020; Sethy et al., 2020), classification (Barstugan et al., 2020; Randhawa et al., 2020), and prediction and forecasting (Hazarika & Gupta, 2020; Ribeiro et al., 2020; Pourhomayoun & Shakibi, 2020; Fang et al., 2020; Sun et al., 2020; Ella Hassanien et al., 2020; Batista et al., 2020) have been discussed in this sub-section.

For the early detection and diagnosis of COVID-19 cases, researchers (Hassanien et al., 2020) developed a model based on SVM using X-ray images. The dataset consists of 40 contrast-enhanced lungs X-ray images, among which 15 were normal lungs images while the other 25 were COVID-19 infected chest X-ray images. The suggested model showed high performance (sensitivity = 95.76%, specificity = 99.7%, and accuracy = 97.48%), showing the SVM-based model can be employed efficiently for the identification of novel coronavirus disease. Furthermore, authors (Barstugan et al., 2020) developed an ML-based model for the classification of COVID-19 using computed tomography (CT) images. The sample size comprises 150 CT abdominal images of the 53 infected cases. To enhance the classification performance, various feature extraction methods were applied followed by the classification of extracted features via SVM. During the classification process, 2-, 5-, and 10-fold cross-validations were implemented among which the 10-fold cross-validation achieved relatively high accuracy of (sensitivity = 97.56%, specificity = 99.68%, and accuracy = 98.71%). Finally, the authors suggested that the proposed model should be tested on another COVID-19 CT-images-based dataset.

To predict the symptoms of COVID-19 infected patients, the SVM model has been developed by (Sun et al., 2020) by analyzing more than 200 laboratory and clinical features. Results show the better performance of the suggested model with AUROC equals 0.996 for the training dataset and 0.9757 for the testing dataset. In another study, five ML-based models were developed to predict the diagnosis of COVID-19 in emergency care patients (Ella Hassanien et al., 2020). These models include NN, RF, LR, SVM, and GBT. These models were trained on the dataset collected from 235 adult hospitalized patients from 17th to 30th March 2020. It was concluded by the authors that among five ML-based methods, SVM achieved the best predictive results with an accuracy of 85%. The following Table 1 describes the usage of SVM models in the detection, classification, prediction, and forecasting of the COVID-19 pandemic.

2.1.2. Random Forest (RF)

The random forest algorithm (RF) is a statistical tool and is one of the most promising classifiers used to solve classification and regression problems. Multiple trees are used for the training and prediction of data samples. RF has been widely used in bioinformatics and chemometrics (Pavlov, 2019; Siekmann, 2005). In the context of COVID-19, RF has been extensively used by researchers for mitigating the COVID-19 pandemic. For the rapid and accurate screening of COVID-19, an infectious size aware rapid random forest (ISARF) model was developed by (Shi et al., 2020). In this work, the CT scans of 1658 (COVID-19 positive) and 1027 (CAP) were collected followed by preprocessing of these CT images. The suggested model achieved better results (accuracy = 87.9%, sensitivity = 90.7%, and specificity = 83.3%) in the screening of coronavirus diseases using the 5-fold cross-validation. Furthermore, it was suggested that by including the radionics feature, the proposed model showed more improvements in the results.

Due to the massive increase in the number of COVID-19 infected patients, the manual severity assessment of COVID-19 becomes difficult and time-consuming. Recently, the ML-based model suggested by (Tang et al., 2020) can be used to automatically identify the more severe and less severe cases of COVID-19 infected patients. The RF model is trained with the CT images of 176 COVID-19 positive patients for the severity assessment. The suggested model presented promising results with 87.5% accuracy using 3-fold cross-validation. According to the authors, various quantitative features were identified with the potential of assessing the severity of COVID-19.

A clinical model for the early prediction of severe cases of COVID-19 using five ML-based models was suggested by (Guan et al., 2020). In this work, the clinical history of 183 (COVID-19 severe) cases was used to

| References | Country | Purpose | Model | Data Type | Sample size | Performance |
|------------|---------|---------|-------|-----------|-------------|-------------|
| (Hassanien et al., 2020) | Egypt | Detection | SVM | X-Ray Images | 40 contrast-enhanced lungs X-ray 25 infected COVID-19 15 normal images | Sensitivity = 95.76 Specificity = 99.7 Accuracy = 97.48 |
| (Yao et al., 2020) | India | Detection | SVM | Blood and Urine Tests | 137 COVID-19 positive | RestNet50 plus SVM Accuracy = 95.33 Sensitivity = 95.33 Specificity = 97.96 Accuracy = 98.71 |
| (Sethy et al., 2020) | India | Detection | Resnet50 Plus SVM | X-Ray Images | —— | —— |
| (Barstugan et al., 2020) | Turkey | Classification | SVM | CT Images | 150 CT abdominal images, which belong the 53 infected cases | —— |
| (Randhawa et al., 2020) | Canada | Classification | SVM | Time series | 75,752 confirmed cases | Test#6 Classification Accuracy = 100 based on R² Average rank = 4.8 |
| (Hazarika & Gupta, 2020) | India | Forecasting | SVR | Time series | report on 10th July 2020 | —— |
| (Ribeiro et al., 2020) | Brazil | Forecasting | SVR | Time series | April 18 or 19 of 2020 | RS ODA [MAE = 8.17, nMAPE = 0.97] |
| (Pourhomayoun & Shakibi, 2020) | USA | Prediction | SVM | Clinical Data | 117,000 patients | Accuracy = 90.63 |
| (Fang et al., 2020) | China | Prediction | SVM | Clinical Data | 1,040 patients | Accuracy = 76.3 Sensitivity = 0.80 Specificity = 99.5 Recall rate, Training = 93.33 Testing = 100 MAE = 0.2155 |
| (Sun et al., 2020) | China | Prediction | SVM | Time series | 336 cases | —— |
| (Ella Hassanien et al., 2020) | Egypt | Prediction | SVM | ID, Age, Sex, City, Province, Country | 15 attributes of symptoms | —— |
| (Batista et al., 2020) | Brazil | Prediction | SVM | RT-PCR Tests | 235 adult patients | Sensitivity = 68 Specificity = 85 |
develop the model. These five ML-based models (RF, BFDA, LR, EN, and PLSR) were used for the feature selection and prediction of patient outcomes. The performance of the proposed models was measured using the area under the receiver operating characteristic curve (AUROC), which was 0.88 for the external validation and 0.895 for the derivation.

The following Table 2 describes the applications of RF in the detection, classification, prediction, and forecasting of the COVID-19 pandemic. 

### Table 2

Summary of Applications of Random Forest (RF) in Combating COVID-19.

| References | Country | Purpose | Model | Data type | Sample size | Performance |
|------------|---------|---------|-------|-----------|-------------|-------------|
| Wu et al., 2020 | China | Identification | RF | Blood test | 49 clinical available blood test data | Sensitivity – 95.12, Specificity – 96.97, Accuracy – 95.95 |
| Sarkar & Chakrabarti, 2020 | India | Identification | RF | Clinical Data | 1085 cases of COVID-19 | Area under the ROC curve 97 |
| Cobb & Seale, 2020 | USA | Examining | RFML | Time Series | COVID-19 cases (January 21 to March 31, 2020) | RFML, Accuracy – 92.3, MAPE – 92.3 |
| Shi et al., 2020 | China | Screening | iSARF | CT images | 1658 COVID-19 and 1027 CAP cases | Sensitivity – 90.7, Specificity – 83.3, Accuracy – 87.9 |
| Magar et al., 2020 | Pennsylvania | Antibodies Discovery Assessment | RF | Clinical Data | 1933 virus-antibody | RF, Performance – 89.18 |
| Tang et al., 2020 | China | Severity Assessment | RF | CT Images | CT images 176 patients (96 male and 80 female) COVID-19 | True positive rate – 93.3, True negative rate – 74.5 |
| Chen, Jiang, & et al., 2020; Chen, Wu, & et al., 2020; Chen, Hu, & et al., 2020 | China | Severity Assessment | RFS | Time Series | 106 COVID-19 patients 63 females 43 males | Accuracy – 87.5, Gender index of 0.022, Hypertension index of 0.035, age index of 0.007, cortisone index of 0.026, Sensitivity – 75.3, Specificity – 84.6 |
| Batista et al., 2020 | Brazil | Prediction | RF | RT-PCR Tests | 235 adult patients 102 received a positive diagnosis of COVID-19 | AUC = 92, Sensitivity = 75 Specificity = 100, AUROC = 92.2 |
| Middleton & Rowley, 2014 | China | Prediction | RF | CT Image | 52 patients | AUC = 92, Sensitivity = 75 Specificity = 100, AUROC = 92.2 |
| Guan et al., 2020 | China | Prediction | RF | Clinical Data | 183 severe COVID-19 patients | 10-fold cross-validation Accuracy – 91.88, GGP (g = 3) Accuracy = 98.18, Sensitivity = 99.16, Specificity = 97.26, Area under the ROC curve = 0.97 |
| Pourhomayoun & Shakibi, 2020 | USA | Prediction | RF | Clinical Data | 117,000 patients | Accuracy = 91.88, Sensitivity = 99.16, Specificity = 97.26 |
| Qiang et al., 2020 | China | Prediction | RF | Time Series | Protein sequences of 2666 coronaviruses | Sensitivity = 99.16, Specificity = 97.26 |
| Sarkar & Chakrabarti, 2020 | India | Prediction | RF | Clinical data | 1085 cases | Area under the ROC curve = 0.97 |
| da Silva et al., 2020 | Brazil | Forecasting | RF | Time Series | April 28th, 2020 | TDA [MAE = 6.39, sMAPE = 7.28] |
| Ribeiro et al., 2020 | Brazil | Forecasting | RF | Time Series | April 18 or 19 of 2020 | ODA, TDA, SDA [MAE = 179.5, sMAPE = 20.97] |
methods (LR, RF, PLSR, BFDA, and EN) were used for the feature selection and mortality rate prediction. For the performance evaluation, the area under the receiver operating characteristic curve (AUROC) was implemented. Moreover, 64 serious COVID-19 cases were used for the external validation of the ultimate predictive model. Four features including lymphocyte count, age, C-reactive protein, and d-dimer levels were selected by all models. The proposed model achieved high performance with different methods (LR, RF, PLSR, BFDA, and EN) were used for the feature selection and mortality rate prediction. For the performance evaluation, the area under the receiver operating characteristic curve (AUROC) was implemented. Moreover, 64 serious COVID-19 cases were used for the external validation of the ultimate predictive model. Four features including lymphocyte count, age, C-reactive protein, and d-dimer levels were selected by all models. The proposed model achieved high performance with different methods.

2.1.5. Other Machine Learning methods

Besides SVM, RF, DT, and LR, other ML-based approaches such as multilayer perceptron (MLP), xgboost, k-means, gaussian process regression (GPR), and neural networks have also been used in the screening, detection, prediction, and forecasting of COVID-19. The following Table 5 illustrates the applications of other methods in the detection, classification, prediction, and forecasting of the COVID-19 pandemic.

2.2. Applications of Deep Learning in COVID-19 Screening, Diagnostics, Classification, Drug Repurposing, and Prediction

Deep learning (DL) is the subset of machine learning, that can solve complex schemes through representation learning (Chan et al., 2020; Yan, 2016). Recently, deep learning-based algorithms have been used by various researchers for combating the COVID-19 pandemic, including convolutional neural network (CNN), recurrent neural network (RNN), and long short-term memory (LSTM) for the COVID-19 detection, classification, drug repurposing, prediction, and forecasting. (Bogu et al., 2020; Desai et al., 2020; Ghoshal & Tucker, 2020; He et al., 2020; Hu et al., 2020; Khurana et al., 2021; Mirza Rahim Baig et al., 2019; Pan et al., 2021; Sarv Ahrabi et al., 2021; Sedik et al., 2021; Soni & Roberts, 2020).

2.2.1. Convolutional Neural Network (CNN)

A convolutional neural network (CNN) is a deep learning algorithm...
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2021; Siswantining and efficiently, gives a timely response and accurate treatment for the in the early detection and diagnosis of coronavirus. Moreover, it reduces learning models, are the promising techniques used to assist radiologists huge workload. Artificial intelligence-based tools, particularly deep classification, prediction, and forecasting (Afifi et al., 2021; Cui pandemic. For instance, it is used for COVID-19 screening, diagnostics, (Indolia et al., 2018; Sony et al., 2021). CNN has several applications over traditional methods is that it requires much lower pre-processing primarily designed for image analysis. The main advantage of using CNN for combating the COVID-19 In this regard, the summary detection of COVID-19 using CT images has been proposed by (Jin et al., 2019). In this study, a dataset of 10,250 CT scans of COVID-19, community-acquired pneumonia (CAP), influenza, and non-pneumonia was collected. The proposed model achieved high performance (AUC = 97.17% and specificity = 95.76%). In another study by (Razzak et al., 2020), the authors used deep transfer learning and different CNN architectures for the detection of COVID-19 pneumonia using CT images. In this work, nine CNN architectures were used, including AlexNet, ResNet101, SqueezeNet, ResNet18, VGG16, GoogLeNet, MobileNet, ResNet50, and DenseNet. The dataset was divided into an 80% training set and a 20% validation set. Results showed that the model achieved a

| References | Country | Purpose | Model/Architecture | Data type | Sample size | Performance |
|------------|---------|---------|--------------------|-----------|-------------|-------------|
| (Magar et al., 2020) | USA | Screening | XGBoost | Text data | 1933 virus-antibody | XGBoost = 90.57 |
| (Mei et al., 2020) | China | Diagnosis | MLP | CT images | 905 patients | Sensitivity = 84.3 |
| (Zhang, Liu, & et al., 2020) | China | Diagnosis and Prognosis | U-net, DRUNET, FCN, SegNet, DeepLabv3, GRIDT | CT images | 617,775 CT images from 4,154 patients | Accuracy = 92.49 |
| (Al-karawi et al., 2020) | UK | Detection | FPT-Gabor scheme | CT images | Covid-19 275 positive and 195 negatives | Accuracy = 91.13 |
| (Carrillo-Larco & Castillo-Cana, 2020) | UK | Classification | k means | Text data | 155 countries | specificity 95.37 |
| (Bartugan et al., 2020) | Turkey | Classification | GLCM, LDP, GLRLM, GLSZM, DWT, SVM | CT images | 150 CT images | Accuracy = 99.6% with 10-fold |
| (Nemati et al., 2020) | USA | Prediction | IPCRidge, CPH, CSGB, GGB, FSVM, FR SVM | Clinical Data | 1,182 patients | Stage wise GB Prediction |
| (Guan et al., 2020) | China | Prediction | LR, PLsr, EN, RF, BFDA | Time series | 83 severe COVID-19 patients | Accuracies 71.47 |
| (Ribeiro et al., 2020) | Brazil | Forecasting | ARIMA, SVR, RF, RIDGE, CUBIST | Time series | until April 18 or 19 of 2020 | Error |
| (da Silva et al., 2020) | Brazil | Forecasting | GPR, BRNN, KNN, QRF, SVR | Time-series | April 28th, 2020 | One day 0.87-3.51 |
| (Fong et al., 2020a) | China | Forecasting | CMC, GROOMS + CMCM, BFGS + PNN | Time-series | 25 Jan 2020 to 25 Feb 2020 | Six days 0.95-6.90 |

Recently, the rapid increase in the number of publications on detection and diagnosis of COVID-19 with computed tomography (CT) images has been witnessed. The deep CNN-based model for the rapid detection of COVID-19 using CT images has been proposed by (Jin et al., 2019). In this study, a dataset of 10,250 CT scans of COVID-19, community-acquired pneumonia (CAP), influenza, and non-pneumonia was collected. The proposed model achieved high performance (AUC = 97.17% and specificity = 95.76%). In another study by (Razzak et al., 2020), the authors used deep transfer learning and different CNN architectures for the detection of COVID-19 pneumonia using CT images. In this work, nine CNN architectures were used, including AlexNet, ResNet101, SqueezeNet, ResNet18, VGG16, GoogLeNet, MobileNet, ResNet50, and DenseNet. The dataset was divided into an 80% training set and a 20% validation set. Results showed that the model achieved a
high accuracy of 98.75% using 10 k-fold. According to the authors, the proposed model could be successfully used for COVID-19 early screening.

Fast detection of COVID-19 is important to control its spread and take preventive steps. The DL-based model for detecting the COVID-19 using CT scans has been proposed by (Chen, Wu, & et al., 2020). The dataset of 46,096 unspecified scans taken from 106 patients was used to train the model. In this paper, UNEt++ architecture is used for image segmentation. Moreover, the model was also compared with the expert radiologist’s outcomes. Results showed that the suggested model performed well (sensitivity = 94.34%, specificity = 99.16%, and accuracy = 98.85%) than the expert radiologists in a very short time. The application of CNN in COVID-19 detection and diagnosis using CT images is depicted in Table 6.

ii. X-ray Images:
Besides CT images, X-ray images have also been used by many researchers in their DL-based models for the diagnosis of COVID-19. For instance, (Shibli et al., 2020) developed a deep learning-based model for the detection of COVID-19 using X-ray images. The VGG-16 (visual geometry group) network-based faster regions with CNN (Faster R-CNN) approach has been used in this study. The dataset comprises 5450 chest X-ray images of 2500 patients. The dataset was distributed into 90% of training and 10% of validation sets. According to the authors, the proposed model achieved high classification performance (accuracy = 97.36%, precision = 99.28%, and sensitivity = 97.65%). Similarly, (Hall et al., 2020) developed a deep CNN model for the detection of COVID-19 using X-ray images of 135 from COVID-19 cases and 320 from viral and bacterial pneumonia cases. Using 10-fold cross-validation, 102 COVID-19 cases and 102 viral and bacterial pneumonia cases were used to tune the Resnet50. Results presented that the suggested model accomplished an accuracy of 89.2%.

For the detection and diagnosis of COVID-19, DL-based models have been developed by (Hassantabar et al., 2020). In this article, CNN and CNN have been presented. In addition, for finding the infected tissues in lungs, a CNN architecture is used and achieved good performance (accuracy = 93.2% and sensitivity = 96.1%). According to the authors, their findings could be used for monitoring and controlling cases in of virus-infected regions. The applications of CNN in COVID-19 detection and diagnosis using X-rays are depicted in Table 7.

Table 7
Summary of Applications of CNN using X-ray images for Detection and Diagnosis of COVID-19.

| References                  | Country       | Purpose | Model/Architecture | Data Type | Sample Size | Performance                          |
|-----------------------------|---------------|---------|--------------------|-----------|-------------|--------------------------------------|
| (Shibli et al., 2020)       | Bangladesh    | Diagnosis | CNN               | X-Ray Images | Normal 300 non-COVID Pneumonia 950 | Sensitivity = 97.65                     |
| (Hall et al., 2020)         | USA           | Diagnosing | CNN               | X-Ray Images | 135 COVID-19 cases                  | Accuracy = 97.36                      |
| (Hassantabar et al., 2020)  | USA           | Detection and Diagnosis | CNN               | X-Ray Images | 315 images total 271 COVID-19 44 Non COVID-19 | Accuracy = 93.2 Sensitivity = 96.1 |
| (Khan et al., 2020)         | India         | Detection and Diagnosis | CNN CoroNet      | X-Ray Images | Normal 310 Pneumonia Bacterial 330 | Accuracy = 98.6 Precision = 90 Specificity = 96.4 |
| (Ouchicha et al., 2020)     | Morocco       | Detection | CVNet             | X-Ray Images | 219 COVID-19 1341 normal 1345 viral pneumonia | Precision = 96.72 Recall = 96.84 Accuracy = 96.69 |
| (Nour et al., 2020)         | Saudi Arabia  | Detection | CNN               | X-Ray Images | COVID-19 219 Normal 1341 Viral Pneumonia 1345 Total 2905 | Accuracy = 97.14 Sensitivity = 94.61 Specificity = 98.29 |
| (Karthik et al., 2020)      | India         | Detection | CSDB CNN          | X-Ray Images | 558 COVID-19 Chest X-rays           | Precision = 95.93 Accuracy = 93.42 F1 Score = 99.57 |
| (Alqudah et al., 2020)      | Jordan        | Detection | CNN-Softmax       | X-Ray Images | 71 chest X-ray images (48 cases for COVID-19 and 23 for Non-COVID-19) | Accuracy = 95.2 Sensitivity = 93.3 Specificity = 100 |
| (Ozturk et al., 2020)       | Turkey        | Detection | DarkCovidNet      | X-Ray Images | 127 X-ray images 43 Female 82 Male 26 Covid-19 Positive | Sensitivity = 95.13 Specificity = 92.3 Accuracy = 98.08 |
| (Heidari et al., 2020)      | USA           | Detection | CNN-based CAD scheme | X-Ray Images | 757 Cases 37 Covid 460 non Covid 260 | Accuracy = 94.5 Sensitivity = 98.4 Specificity = 98.0 |
| (Islam et al., 2020)        | Bangladesh    | Detection | CNN-LSTM          | X-Ray Images | 915 overall cases 305 Covid 305 non Covid 305 | Specificity = 99.3 Specificity = 99.2 |
| (Abbas et al., 2020)        | Egypt         | Detection | CNN DeTrAc        | X-Ray Images | norm 80 COVID19 105 SARS 11 | Accuracy = 95.12 Specificity = 97.91 Specificity = 91.87 |
| (Minaee et al., 2020)       | USA           | Detection | ResNet18 ResNet50 | X-Ray Images | 200 COVID-19 images 5,000 non-COVID images | Sensitivity = 98 Precision = 90 |
| (Haghanifar et al., 2020)   | Canada        | Detection | CheXNet COVID-CXNet | X-Ray Images | 3628 images 3,200 normal CXRs 428 | Accuracy = 87.21 |
| (Chowdhury et al., 2020)    | Bangladesh    | Detection | CNN               | X-Ray Images | 2905 chest X-ray images 219 COVID-19 positive 1341 normal 1345 viral pneumonia | Accuracy = 96.58 Precision = 96.58 Recall = 96.59 |
| (Apostolopoulos et al., 2020)| Greece       | Detection | CNN MobileNet v2  | X-Ray Images | 3905 X-ray images | Accuracy = 99.18 Sensitivity = 97.36 Specificity = 99.42 |
experimentation includes the use of image texture features, deep forward neural network, and convolutional neural network applied on the database of COVID-19 X-ray images. The dataset includes 338 images, among which 255 were COVID-19 images. In the end, the proposed model was compared with k-nearest neighbors (KNN) and support vector machines (SVM). Among these, the proposed model outperformed the rest of the approaches and achieved good performance (accuracy = 83.02% and AUC = 90.7%). The applications of CNN in the COVID-19 classification are depicted in Table 8.

c. Screening

With the rapid increase in the COVID-19 pandemic, the demand for screening COVID-19 cases has reached its peak. Healthcare providers, clinicians, and doctors are unable to screen such a massive number of cases efficiently. An alternative and automated way of screening mechanism of novel coronavirus disease is needed. The novel deep transfer learning-based model for the screening of COVID-19 has been proposed by (Basu et al., 2020) using X-ray images. In this study, based on deep CNN, a novel domain extension transfer learning (DETL) approach is employed. The dataset comprises 305 COVID-19 images, normal, 350, pneumonia 322, and other diseases 305 samples. Furthermore, 5-fold cross-validation is employed for the feasibility estimation of using X-ray images of the chest for the diagnosis of COVID-19. The proposed model performed well with an accuracy of 90.13% ± 0.14.

In another study, a shallow CNN-based model has been proposed by (Mukherjee et al., 2020) for COVID-19 pandemic screening using X-ray images of the chest. Fewer parameters are used for developing shallow CNN-tailored architecture compared to other DL-based approaches (This finding was validated by using 130 positive COVID-19 X-ray images). After successful implementation of the model, it was concluded by the authors that the proposed models achieved good performance (accuracy = 96.92%, specificity = 100%, and sensitivity = 94.24%). The applications of CNN in COVID-19 screening are depicted in Table 9.

d. Prediction and Severity Assessment

Besides the COVID-19 detection, diagnosis, screening, and classification, CNN has been widely used by many researchers for the prediction and severity assessment of the COVID-19 pandemic. For instance, (Cohen et al., 2020) proposed a deep learning-based model for the prediction of COVID-19 using X-ray images. In this work, a DenseNet model is trained on the 94-poster anterior chest x-ray images. The best correlation coefficient is achieved by the single “lung opacity” output was 0.80. In another work by (Kumar, Arora, & et al., 2020), the deep learning-based model is developed for the prediction of the COVID-19 pandemic using X-ray images. A deep feature learning model is used for feature extraction. The extracted features are used to train the ML-based classification models including random forest (RF) and xgboost. SMOTE was used for balancing data. The proposed predictive xgboost classifier achieved good performance (accuracy = 97.7% and specificity = 98.8%). According to the authors, their proposed model will help clinicians in screening COVID-19 images.

Table 9 shows the prediction and severity assessment of COVID-19 using CNN.

Table 10.

2.2.2. Long-Short Term Model (LSTM)

Long short-term memory (LSTM) networks are a type of recurrent neural network (RNN) with the capability of learning order dependence in sequence prediction problems. LSTM can store knowledge of previous states and can be used in memory-based problems. LSTM has been widely used for the time series sequential data prediction (DiPietro & Hager, 2019; Navares & Aznarte, 2020; Verma & Kumar, 2019). Recently, many researchers have used LSTM based models for COVID-19 detection, diagnosis, classification, prediction, and forecasting. A deep CNN-LSTM coupled approach has been proposed by (Islam et al., 2020) for COVID-19 detection using X-ray images. First, CNN is trained for the extraction of deep features and based on these extracted features, the LSTM model is trained for the detection of COVID-19. The dataset comprises 4575 X-ray images, among which 1525 images were from COVID-19 cases. The proposed model achieved high performance (accuracy = 99.4%, specificity = 99.2%, and sensitivity = 99.3%). According to the authors, their proposed model can help clinicians and doctors with rapid and automatic detection of COVID-19 using X-ray images.

Many studies reported the applications of LSTM in the time series prediction and forecasting of the COVID-19 pandemic. Three different deep learning-based models have been proposed by (Shahid et al., 2020) for the prediction of COVID-19. In this article, support vector regression (SVR), autoregressive integrated moving average (ARIMA), long short-term memory (LSTM), and bidirectional long short term memory (Bi-LSTM) were developed for the time series forecasting of confirmed infected cases, number of deaths and recoveries in different countries. The proposed models showed good performance with Bi-LSTM with the highest performance and lowest MAE (0.0070) and RMSE (0.0077) values followed by LSTM > GRU > SVR and ARIMA for the death cases. For the recovered cases, the best results of the correlation coefficient achieved were 0.9997. According to the authors, the Bi-LSTM outperformed the other models, showing its robustness and high prediction accuracy. Due to this, Bi-LSTM can successfully be used for the early prediction of a pandemic. That would help policymakers and government officials to take preventive steps. The applications of LSTM for COVID-19 detection, diagnosis, classification, prediction, and forecasting are depicted in Table 11.

2.2.3. Other Deep Learning methods

Besides CNN and LSTM, the applications of various deep learning (DL) methods for COVID-19 drug repurposing are discussed in this section.

a. Deep learning for drug repurposing

The COVID-19 pandemic is spreading very quickly, and to date, no vaccine has been developed since drug discovery is a complicated, prolonged, high-risk, and expensive process. Scientists and researchers are working day and night to formulate a drug for curing the novel disease (Mohanty et al., 2020a). Meanwhile, a quick and instant cure...
Drug repurposing or drug repositioning is a term that refers to the utilization of existing clinically approved drugs for the treatment of novel and challenging diseases, like COVID-19 (Mohanty et al., 2020b). For instance, Toremifene, a medicine used for the treatment of breast cancer. It is a first-generation non-steroidal drug approved in 1997 for the treatment of breast cancer in women. It was identified by the network. AI coupled with drug repurposing can detect the drugs that can be used for treating COVID-19 disease (Zhou et al., 2020). Toremifene can significantly be used for treating treatment of breast cancer in women. It was identified by the network.

### Table 9
Summary of Applications of LSTM for Diagnosis, Classification, and Prediction of COVID-19.

| References | Country | Purpose | Model/Architecture | Data Type | Sample size | Performance |
|------------|---------|---------|--------------------|-----------|-------------|-------------|
| (Basu et al., 2020) | India | Screening | AlexNet VGGNet ResNet DETL | X-Ray Images | normal 350 Pneumonia 322 other disease 300 Covid-19 305 | Accuracy = 90.13 |
| (Mukherjee et al., 2020) | India | Screening | MobileNet VGG16 Shallow CNN (proposed) | X-Ray Images | 130 COVID-19 positive 51 non-COVID-19 | Accuracy = 96.92 Sensitivity = 94.2 Specificity = 100 |
| (Hou et al., 2020) | USA | Screening | CNN ResNet ResNet23-based ResNet-18 | CT Images | 618 transverse-section CT samples | Accuracy = 86.7 Sensitivity = 98.2 Specificity = 92.2 |
| (Zhang, Saravanan, & et al., 2020) | China | Screening | DFCNN | CT Images | 18 patients 2019-nCoV | DFCNN Score ≥ 0.999 |
| (Wang, Zha, & et al., 2020) | China | Screening | CNN M-Inception | CT Images | 44 cases SARS-COV-2 55 cases typical viral pneumonia CT images (99 patients) | Accuracy = 82.9 Specificity = 84 Sensitivity = 81 |

### Table 10
Summary of Applications of CNN for prediction and Severity Assessment of COVID-19.

| References | Country | Purpose | Model/Architecture | Data Type | Sample size | Performance |
|------------|---------|---------|--------------------|-----------|-------------|-------------|
| (Cohen et al., 2020) | Canada | Prediction | DenseNet model | X-Ray Images | 94 images COVID-19 positive | Opacity Score R2 = 0.58 ± 0.09 MAE = 0.78 ± 0.05 MSE = 0.86 ± 0.11 |
| (Kumar et al., 2020) | India | Prediction | ResNet152 SMOTE algorithm | X-Ray Images | 5840 images, 5216 images for training 624 testing | XGBoost Accuracy = 97.7 Sensitivity = 97.7 Specificity = 98.8 MAE = 8.5% GRU = 2599.1 LSTM = 2992.976 MLP = 5710.293 CNN = 102.943 |
| (Takahashi et al., 2020) | China | Forecasting | CNN RNN LSTM GRU MLP | | | |
| (Obeid et al., 2020) | USA | Assessment | CNN | Telehealth | 6813 Total 498 tested positive 6315 tested negative 31 portable CXR 84 COVID-19 patients | Precision = 75.4 Recall = 45.3 F1 Score = 56.6 |
| (Zhu et al., 2020) | China | Prediction | CNN VGG16 Chest Radiographs | | | |

### Table 11
Summary of Applications of LSTM for Diagnosis, Classification, and Prediction of COVID-19.

| References | Country | Purpose | Model/Architecture | Data Type | Sample size | Performance |
|------------|---------|---------|--------------------|-----------|-------------|-------------|
| (Islam et al., 2020) | Bangladesh | Detection | CNN-LSTM | X-Ray Images | 915 overall cases 305 Covid 305 normal 305 pneumonia | Accuracy = 99.2 Sensitivity = 99.3 Specificity = 99.2 |
| (Alazzab et al., 2020) | Jordan | Detection | LSTM | Chest X-Ray Images | 1000 X-ray images of real patients | R2 = 0.98 Accuracy = 92.76 RMSE = 0.207 Deaths MAE values = 0.0077 RMSE values = 0.007 Epidemic Size = 95,911 |
| (Shahid et al., 2020) | Pakistan | Prediction | Bi-LSTM | Time Series | deaths and recovered cases of 158 samples | |
| (Yang, Zeng, & et al., 2020) | China | Prediction | LSTM | Time Series | No. of cumulative infection from Jan 16, 2020, to Jan 25,2020 (3845) | RMSE COVID-19 = 3293.3 Recovered = 747.2 Deaths = 211.0 |
| (Pal et al., 2020) | Norway | Prediction | LSTM-FCNS | Time Series | starts from 22 to 01-2020 to 10-03-2020 | RMSE 0.05 MAE = 0.05% MAE = 0.17 MAPE = 8.15% |
| (Zheng, Du, & et al., 2020) | China | Prediction | ISI + NLP + LSTM | Time Series | data before February 12, 2020 | MAPE = 0.05% MAE = 0.17 |
| (Yang, Yu, & et al., 2020) | China | Prediction | LSTM | Time Series | 13 436 confirmed cases on February 12, 2020 | Di does not exceed 0.03 |
| (Wang, Zheng, & et al., 2020) | China | Prediction | LSTM | Time Series | January 22– July 7 2020 | Long-Term RMSE = 45.70 Accuracy = 92.67 Low to High RMSE (2994.851, 3331.925) MAE (2992.976, 3224.591) |
| (Chimmula & Zhang, 2020) | China | Forecasting | LSTM | Time Series | confirmed cases until March 31, 2020 | |
| (Huang & Kwok, 2019) | China | Forecasting | LSTM | Time Series | January 23, 2020, to March 2, 2020 | |
used to combat novel diseases like COVID-19. The application of such emerging technologies has the potential to significantly alleviate the main issue associated with drug repurposing, which is the diagnosis and identification of the drug-disease relationship. Motivated by this, it was found by the researchers that the COVID-19 and the 2003 SARS virus have similarities between them. Based on the data available on SARS, AI-based models can be developed for the prediction of drug structures found by the researchers that the COVID-19 and the 2003 SARS virus main issue associated with drug repurposing, which is the diagnosis and input to the AI-empowered model for drug repurposing. The repurposed represents the AI-based strategy to be adopted for drug repurposing. The various healthcare organizations becomes accessible on one open platform (Riva et al., 2020; Shende et al., 2020; Wang & Guan, 2020). Fig. 4 represents the AI-based strategy to be adopted for drug repurposing. The input to the AI-empowered model for drug repurposing is a repurposed or repositioned drug database, and an open chemical or open drug database followed by the various algorithms to be applied to this input, and finally, the desired drug could be obtained.

3. Discussions

In this study, first, we have presented the applications of ML and DL in the COVID-19 screening, diagnostics, tracking, classification, drug repurposing, prediction, and forecasting. The applications of ML methods reviewed in this study include support vector machine (SVM), logistic regression (LR), random forest (RF), and decision tree (DT), multilayer perceptron (MLP), xgboost, k-means, gaussian process regression (GPR), and neural networks. While the applications of DL methods include convolutional neural networks (CNN) and long short-term memory (LSTM). All the general and technical data including author name, country, model used, sample size, data type, and performance of the applied model, associated with the implementation of AI for combating COVID-19 have been summarized and presented in Tables 1–11.

The datasets used to train and validate the ML and DL models comprise medical images (CT scans and X-ray images), time series, and clinical data. Among these, medical images were widely used as an input parameter to the ML and DL models. If the outbreak progresses, medical imaging will become increasingly important, particularly where access to RT-PCR tests is scarce or unavailable due to lack of resources. Furthermore, imaging meets more formal procedures and is less reliant on the expertise of the operator. The appearance of COVID-19 in medical images and scans has been linked to the seriousness of the disorder, allowing for the monitoring of its progression. The RT-PCR results, on the other hand, do not reveal the magnitude or stage of the disorder. Medical images (CT scans and X-ray images) play an important role in the treatment and control of COVID-19 and have also been recognized as the most sensitive imaging modality for detecting abnormalities due to their high sensitivity and easy accessibility.

Artificial intelligence-based tools, particularly deep learning models, are the promising techniques used to assist radiologists in the early screening of coronavirus. Moreover, it reduces the workload of the radiologists, improves detection more accurately and efficiently, gives a timely response and accurate treatment for the patients of COVID-19. Though the AI-based studies are not used on a large scale and are not clinically approved, they are very helpful and give fast responses, save time, and provide meaningful information to healthcare staff and government officials. However, many challenges and limitations are faced while building AI-based models due to the lack of massive data and the poor quality of data available. In this regard, research communities are working day and night to gather and extract more meaningful information from the available datasets. Moreover, it was observed that most of the AI models were lacking the implementation of cross-validation techniques, which should be employed to ensure the generalization of results for other unseen datasets.

We observed that the studies based on the conventional ML-based models (SVM, DT, RF, and MLP, etc.) showed poor performance while implemented standalone. However, hybrid ML models coupled with optimization techniques such as genetic algorithms or particle swarm optimization performed well. Recently, deep learning-based algorithms have been used by various researchers for combating the COVID-19 pandemic, including convolutional neural network (CNN), recurrent neural network (RNN), and long short-term memory (LSTM) for the COVID-19 detection, diagnosis, classification. Screening, drug repurposing, prediction, and forecasting. All these models performed well with exceptional accuracy compared to traditional ML-based models.

It is worth noting that even though certain COVID-19 patients are asymptomatic, they can become virus transmitters. Coronavirus victims with pneumonia symptoms can have a pattern on chest X-ray images or CT scans that is only mildly characteristic for doctors, even though the infection may be confirmed by a PCR. People that are currently afflicted with COVID-19 but are asymptomatic are difficult to identify. The ability to reliably identify contaminated patients with low false-negative rates determines the COVID-19 transmission rate. Meanwhile, efficient false-positive monitoring will reduce the pressure on the healthcare system by avoiding unwanted hospital quarantine.

Biomedical imaging (X-rays images and CT scans) allows for the visualization of pneumonia symptoms. In the fields of biomedicine and cancer detection, image processing approaches are appealing. It is

![Artificial intelligence (AI) empowered drug repurposing (Pham et al., 2020).](image-url)
common knowledge that AI-based biomedical picture diagnosis has had a lot of success. Methods such as machine learning and deep learning are useful in the identification of a variety of diseases. And if some patients have already been contaminated with SARS-Cov-2, their chest CT images are fine. As a result, chest CT images have a small negative predictive potential and do not fully rule out infection. The specificity of a single AI diagnosis is also being questioned. As a result, AI-based models are expected to integrate chest imaging with clinical signs, contact history, and laboratory testing in the detection of COVID-19 to satisfy healthcare needs.

The bibliometric analysis of the literature is shown in Fig. 5, which includes the percentage of articles published on AI applications for the COVID-19 pandemic, the type of data used for training the ML and DL based models including CT scans, X-ray images, Clinical data (Blood tests, PCR tests), and Time-series, and the percentage of articles on ML and DL for combating the COVID-19 pandemic. The share of articles published on ML and DL for combating the COVID-19 pandemic is shown in Fig. 5 (A). The statistics show that DL accounts for 53%, followed by the share of ML, which is 47%. The state-of-the-art DL-based models are a proven technology and can significantly be used for the COVID-19 pandemic. The individual shares of each ML and DL methods are shown in Fig. 5 (B). The individual distribution ML methods are as follows, RF 22%, SVM 17%, LR 16%, DT%, other ML methods 34% while that of DL methods is as follows, CNN 72% and LSTM 28%. The type of data used for training the ML and DL-based models includes CT scans, X-ray images, Clinical data (blood tests, PCR tests), and time-series as shown in Fig. 5 (C). From the literature survey, it is summarized that the dataset X-ray images account for 42% of the overall datasets used, followed by CT scans that account for 30%. Moreover, time series which combine X-ray images and CT scans, and clinical data account for 19%, 5%, and 4% respectively. Fig. 5 (D) shows that preprints such as medRxiv, bioRxiv, and arXiv accounted for 47% of the total, followed by Elsevier, whose number of published articles on the current topic accounted for 35%. The percentage of articles published in IEEE, Springer, and others were 8%, 4%, and 6% respectively.

4. Challenges and Perspectives

Artificial intelligence (AI) has great potential and can significantly be used for combating and mitigating the spread of the COVID-19 pandemic. Besides many advantages and positive outcomes, there are several challenges and limitations associated with the implementation of AI which need to be evaluated and addressed. Moreover, a useful outlook has been provided based on these challenges and limitations.

4.1. Unavailability of Standard Data

One of the main challenges associated with the use of AI is the lack of standard datasets. The implementation of these predictive tools requires a massive amount of data. Moreover, only the use of standard data can ensure both platforms a trustful and significant solution to combat COVID-19. In the literature reviewed above, various models of AI are presented but they were not tested using similar datasets. Due to the use of different samples, one cannot decide which model is best for the detection of coronavirus disease. Moreover, due to the lack of standard datasets, most of the datasets were generated by authors and researchers themselves by gathering data from various literature and platforms such as WHO. Such an issue can be addressed by the collaborative work of various well-known organizations like WHO or by generating more real-world datasets from the updated COVID-19 data. Similarly, a variety of
data can be provided by such sources, including CT scans, chest X-rays, personal information, and GPS data.

4.2. Cross-validation

There is always a possibility of gray areas and uncertainties in the research field based on historical data learning on rapidly produced data which ultimately leads towards the associated hidden risk. Most of the articles lack the cross-validation of their trained models, which leads to biases that could influence the decisions made by the government’s officials and healthcare organizations. Reproducing the proposed frameworks and models for finding uncertainties in the research can only ensure the validity of the data.

4.3. Privacy and Security

Personal privacy and security are the major challenges that need to be addressed. For the implementation of AI for combating COVID-19, a huge amount of data is needed to train the models. In the context of the COVID-19 pandemic, this data includes X-ray images, CT scans, travel history, patient history, GPS location, and routine activities. Such data is then used to train the models that can help in virus prediction, detection, policymaking, and vaccine production. However, if not officially announced or requested, no one wants to share their data with others due to privacy and security concerns.

4.4. Usage of advanced approaches

In this review, the most used data sources were CT scans and X-ray images. However, there are some other advanced approaches such as ultrasound scans and magnetic resonance imaging (MRI) which are barely discussed in combating COVID-19. These advanced approaches are proven technologies and have shown better performance than CT scans and X-ray images. Therefore, these approaches need to be considered in predictive modeling for COVID-19 which primarily depends upon the quality and standard dataset for training the models.

4.5. Variations in pandemic data pattern

The data available on open sources from across the globe has a complex pattern with variability in the data. Therefore, the credibility and reliability of the predictive models for the COVID-19 pandemic face lots of complexities and challenges. Moreover, different hospitals and laboratories have different criteria for sample collection, testing procedures, and results generation. Due to which variability in the dataset may occur, which ultimately questions the reliability of the predictive model based on an uncertain dataset.

4.6 Symptom's similarities

The differentiation of COVID-19 infection and other related viral infections is difficult due to similarities in their symptoms. Therefore, the recognition of an appropriate ML or DL-based model to screen, detect, diagnose, and classify the COVID-19 infected cases with optimum outcomes is a challenging task that needs to be addressed. Although many research articles have been published on the application of AI in fighting the COVID-19 pandemic, there is still a gap in the study and several research questions can be derived from this study that needs to be addressed. Moreover, medical images often face limited collections and the high cost of labeling. Some researchers have proposed various techniques but there remain unexplained gaps.

Further advances in the application of AI in combating the COVID-19 pandemic can be planned and solved through the following research gaps and prospects that are identified from the present study:

- To enhance the accuracy and reliability of the data analytics, the algorithms of AI must be optimized to ensure the better diagnosis and treatment of COVID-19.
- The incorporation of AI with other emerging techniques can offer effective and efficient solutions for combating COVID-19. For instance, data analysis tools from Oracle cloud computing are coupled to develop a vaccine for fighting the COVID-19 pandemic.
- Most of the ML-based models lack the implementation of cross-validation techniques, which should be employed to ensure the generalization of results for other unseen datasets.

The advanced approaches such as ultrasound scans and magnetic resonance imaging (MRI) are proven technologies and have shown better performance than CT scans and X-ray images. Therefore, these approaches need to be considered in predictive modeling for COVID-19 which primarily depends upon the quality and standard dataset for training the models.

5. Conclusions

Artificial intelligence (AI) is a promising technology that is widely used in various sectors, including the healthcare sector. In this study, a comprehensive review of state-of-the-art AI applications to combat the COVID-19 pandemic is highlighted. The application of AI includes screening and diagnostics, drug repurposing, and prediction and forecasting. It was discovered that the convolutional neural network (CNN) and its modified models were mostly used for COVID-19 pandemic prediction, whereas in the case of machine learning (ML), the support vector machine (SVM), k-means, linear regression (LR), and random forest (RF) were mostly used for COVID-19 pandemic combat. This paper also highlighted and addressed the challenges associated with the use of AI for the COVID-19 pandemic. Furthermore, in this study, the deep learning methods were the most popular and account for 53% of the total literature, showing its potential, robustness, and advancement among other methods. Most of the models, however, have not been deployed sufficiently to demonstrate their real-world functionality, but they are nevertheless capable of combating the pandemic. This paper will help researchers, healthcare institutes and organizations, government officials, and policymakers with new insights into how AI can control the COVID-19 pandemic and drive further research and studies into mitigating the COVID-19 outbreak.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abbas, A., Abdelhamea, M. M., & Gaber, M. M. (2020). Classification of COVID-19 in chest X-ray images using DeTrAc deep convolutional neural network. Applied Intelligence. https://doi.org/10.1007/s10489-020-01829-7.
Abdeljabbar, R., Dia, H., Liyanaage, S., & Bagloee, S. A. (2019). Applications of artificial intelligence in transport: An overview. Sustainability (Switzerland), 11(1), 189. https://doi.org/10.3390/su11010189
Afifi, A., Hafsa, N. E., Ali, M. A. S., Alhumam, A., & Alsalman, S. (2021). An ensemble of global and local-attention based convolutional neural networks for COVID-19 diagnosis on chest X-ray images. Symmetry, 13(1), 1–25. https://doi.org/10.3390/sym13010013
Ahuja, A. S., Reddy, V. P., & Marques, O. (2020). Artificial intelligence and COVID-19: A multidisciplinary approach. Integrative Medicine Research, 9(3), 100434. https://doi.org/10.1016/j.imr.2020.100434
Ai, T., Yang, Z., Hou, H., Zhan, C., Chen, C., & Lv, W., et al. (2020). Correlation of Chest CT and RT-PCR Testing for Coronavirus Disease 2019 (COVID-19) in China: A Report of 1014 Cases. Radiology, 296(2), E32–E40. https://doi.org/10.1148/ radiol.2020200642.
Al-karawi, D., Al-Zaidi, S., Polus, N., & Alsalman, S. (2020). Machine Learning Analysis of Chest CT Scan Images as a Complementary Digital Test of Coronavirus (COVID-19) Patients. April. https://doi.org/10.1101/2020.04.13.20063479.
Alanzah, M., Awaigan, A., Mesleh, A., Abraham, A., Jatana, V., & Alhyari, S. (2020). COVID-19 prediction and detection using deep learning. International Journal of Computer Information Systems and Industrial Management Applications, 12(June), 168-181.
Sipior, Janice C. (2020). Considerations for development and use of AI in response to COVID-19. https://doi.org/10.1007/s10096-020-03901-z

Shahid, F., Zameer, A., & Muneeb, M. (2020). Predictions for COVID-19 with deep learning based models of LSTM, GRU and Bi-LSTM. Chao, Solans and Fractals, 140. https://doi.org/10.1016/j.chaos.2020.110212

Sheng, P., Khanolkar, B., & Gaud, R. S. (2020). Drug repurposing: new strategies for addressing COVID-19 outbreak. Expert Review of Anti-Infective Therapy, 0(0). https://doi.org/10.1080/14787964.2020.1845019

Sheykhtahran, S., Mostafazadeh, S., & Vahdani, T. (2021). Developing an Efficient Deep Neural Network for Automatic Detection of COVID-19 Using Chest X-ray Images. Alexandria Engineering Journal. https://doi.org/10.1016/j.aej.2021.01.011

Shi, F., Liu, L., Shan, F., Wu, D., Wei, Y., Yuan, H., & et al. (2020). Large-scale screening of COVID-19 from community acquired pneumonia using infection size-aware classification. ArXiv.

Shibby, K. H., Dey, S. K., Islam, M. T. U., & Rahman, M. M. (2020). COVID faster R-CNN: A novel framework to Diagnose Novel Coronavirus Disease (COVID-19) in X-ray images. Informatics in Medicine Unlocked, 20, 100450. https://doi.org/10.1016/j.imu.2020.100450

Siekmann Machine Learning 2005.

Singh, D., Kumar, V., Vashishtha, K., & Meena, M. (2020). Classification of COVID-19 patients from chest CT images using multi-objective differential evolution based convolutional neural networks. European Journal of Clinical Microbiology and Infectious Diseases, 39(7), 1379–1389. https://doi.org/10.1007/s10096-020-03912-z

Singh, V., Poonia, R. C., Kumar, S., Dass, P., Aggarwal, P., Bhatnagar, V., & Raja, L. (2020). Prediction of COVID-19 coronavirus virus pandemic based on time series data using support vector machine. Journal of Discrete Mathematical Sciences and Cryptography, 23(8), 1583–1597. https://doi.org/10.1080/09725950.2017.1408562

Sipior, Janice C. (2020). Considerations for development and use of AI in response to COVID-19. International Journal of Information Management, 55, 102170. https://doi.org/10.1016/j.ijinfomgt.2020.102170

Siswanto, T., & Parlingdungan, R. (2021). Covid-19 classification using X-Ray image with ensemble learning. Journal of Physics: Conference Series, 1722, 012072. https://doi.org/10.1088/1742-6596/1722/1/012072

Sohail, C., Akif, Z., Khan, M., Khan, A., Shewan, A., Al-Jabri, A., Iosifidis, C., & Agha, R. (2020). World Health Organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19). International Journal of Surgery, 76 (February), 71–76. https://doi.org/10.1016/j.ijsu.2020.02.034

Song, Y., Zhang, S., Li, L., Zhang, X., Zhang, Z., Huang, Z., & et al. (2020). Deep learning Enables Accurate Diagnosis of Novel Coronavirus (COVID-19) with CT images. https://doi.org/10.1016/j.ijbiomac.2020.02.06930.

Son, S., & Roberts, K. (2020). An Evaluation of Two Commercial Deep Learning-Based Image Retrieval Systems for COVID-19 Literature. ArXiv, 28(November 2020), 132–137. https://doi.org/10.1093/jamia/ocz271

Sony, S., Dumpy, K., Sadhu, A., & Capretz, M. (2021). A systematic review of convolutional neural network-based structural condition assessment techniques. Engineering Structures, 226(October 2020), 111347. https://doi.org/10.1016/j.engstruct.2020.111347.

Stephen, O., Sain, M., Madhus, U. J., & Jeong, D. U. (2019). An Efficient Deep Learning Approach to Pneumonia Classification in Healthcare. Journal of Healthcare Engineering, 2019(3), 1–15. https://doi.org/10.1155/2019/4180949

Su, J., & Zhang, H. (2006). A fast decision tree learning algorithm. Proceedings of the National Conference on Artificial Intelligence, 1(Quinlan 1993), 500–505.

Su, Z., Bemley, B., & Shi, P. (2020). Artificial Intelligence-based Disease Surveillance Amid COVID-19 and Beyond: A Systematic Review Protocol. JAMA Network Open, 3(10), e201203. https://doi.org/10.1001/jamanetworkopen.2020.1203

Sufian, A., Ghosh, A., Sadig, A. S., & Smarandache, F. (2020). A Survey on Deep Transfer Learning to Edge Computing for Mitigating the COVID-19 Pandemic: DT-EC Journal of Systems Architecture, 108(June), Article 101830. https://doi.org/10.1016/j.sysarc.2020.101830

Sun, L., Song, F., Shi, N., Liu, F., Li, S., Li, P., & et al. (2020). Combination of four clinical indicators predicts the severity of critically ill COVID-19 patients. Journal of Clinical Virology, 128(May), 104431. https://doi.org/10.1016/j.jcv.2020.104431.
Zheng, N., Du, S., Wang, J., Zhang, H., Cai, W., Kang, Z., et al. (2020). Predicting COVID-19 in China Using Hybrid AI Model. IEEE Transactions on Cybernetics, 50(7), 28.

Zhou, Y., Wang, F., Tang, J., Nussinov, R., & Cheng, F. (2020). Artificial intelligence in COVID-19 drug repurposing. The Lancet Digital Health, 2(12), e667–e676. https://doi.org/10.1016/s2589-7500(20)30192-8

Zhu, J., Shen, B., Abbasi, A., Hoshmand-Kochi, M., Li, H., & Duong, T. Q. (2020). Deep transfer learning artificial intelligence accurately stages COVID-19 lung disease severity on portable chest radiographs. PLoS ONE, 15(7 July), 1–11. https://doi.org/10.1371/journal.pone.0236621