Fusion of intelligent learning for COVID-19: A state-of-the-art review and analysis on real medical data

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ABSTRACT

The unprecedented surge of a novel coronavirus in the month of December 2019, named as COVID-19 by the World Health organization has caused a serious impact on the health and socioeconomic activities of the public all over the world. Since its origin, the number of infected and deceased cases has been growing exponentially in almost all the affected countries of the world. The rapid spread of the novel coronavirus across the world results in the scarcity of medical resources and overburdened hospitals. As a result, the researchers and technocrats are continuously working across the world for the inculcation of efficient strategies which may assist the government and healthcare system in controlling and managing the spread of the COVID-19 pandemic. Therefore, this study provides an extensive review of the ongoing strategies such as diagnosis, prediction, drug and vaccine development and preventive measures used in combating the COVID-19 along with technologies used and limitations. Moreover, this review also provides a comparative analysis of the distinct type of data, emerging technologies, approaches used in diagnosis and prediction of COVID-19, statistics of contact tracing apps, vaccine production platforms used in the COVID-19 pandemic. Finally, the study highlights some challenges and pitfalls observed in the systematic review which may assist the researchers to develop more efficient strategies used in controlling and managing the spread of COVID-19.

1. Introduction

As the genome structure of novel coronavirus is identical to SARS-CoV (Severe Acute Respiratory Syndrome Coronavirus), it was initially known as SARS-CoV-2 by the International Committee on Taxonomy of Viruses (ICTV), which was later renamed as COVID-19 by the World Health Organization (WHO) on February 11, 2020 [1–3]. The healthcare system is overwhelmed by the COVID-19 cases because of the exponential growth in the number of cases throughout the world. In the month of January 2020, the WHO declared the coronavirus infection as public health emergency due to the accelerated growth in the number of COVID-19 cases. The announcement of the COVID-19 disease as pandemic by the WHO on March 11,2020 has led to the closure of national and international airports, travelling and lockdown restrictions and shutdown of nonessential services in order to inhibit the spread of the COVID-19 disease. The COVID-19 pandemic has greatly affected the daily activities of people, business and global economy of the countries all over the world because of lack of reliable information on how COVID-19 is transmitted in the early stage of pandemic. The following Table 1 displays the consequences of COVID-19 infection on the healthcare system and socio-economic conditions of the people throughout the world since from its origin.

The outbreak of COVID-19 pandemic has affected all most all the countries of the world. As SARS-CoV-2 virus is spreading rapidly from huma-to-human, if early diagnosis is not done it results in the increase in the number of cases. Due to the availability of the limited medical facilities, if number of cases increases it

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Table 1
Consequences of COVID-19 on the healthcare, social and economic conditions of the people.

Impact of COVID-19 on	Consequences of COVID-19 pandemic
Healthcare system	Interruption in the medical supply chain due to border restrictions
	Overburden on the medical practitioners and healthcare professionals due to the rapid increase in the number of cases
	Overload on medical shops due to the disruption of medical supply chain.
	Overwhelming of the existing healthcare systems because of the increase in the COVID-19 cases
	Patients with other diseases and disorders are neglected due to the overwhelming of existing healthcare system with COVID-19 cases
Social	Shutdown of hotels, restaurants and shopping malls to inhibit the spread of infection
	Closure of schools and postpone of competitive examinations
	Disruption in the supply chain of nonessential services
	Shutdown of national and international airports
	Shutdown of entertainment sectors such as theaters, gyms, swimming pools and so on.
	Postponement/cancellation of sports and tournaments
	Interruption in the celebrations of religious and festival events
Economic	Losses in national and international business
	Poor cash flow in the global market
	Decrease in GDP growth of countries due to disruption in the supply chain and closure of distinct sectors.

becomes difficult for healthcare system to provide proper treatment to all the infected patients. In addition, if diagnosis is not done at the early stage, there is a chance of developing severe symptoms by the patients which may result in increase in the mortality rate of the COIVID-19 disease. Therefore, identification and diagnosis of COVID-19 infection at early stage is the vital way to inhibit the spread of the disease [4]. The chances of spreading infection are severe in those countries that encounter shortage of RT-PCR (Reverse Transcription-Polymerase Chain Reaction) testing kits. Therefore, current measures depend on distinct preventive measures such as social distancing, wearing mask, hand sanitization, periodic temperature testing etc., in controlling the dissemination of COVID-19 infection [5].

Besides preventive measures, emerging technologies such as Artificial Intelligence (AI), Internet of Things (IoT), Internet of Medical Things (IoMT), 5G technology, Bigdata, Blockchain, Virtual reality, Additive manufacturing and drone-based or autonomous robots are essential in epidemiological modelling. AI is defined as the mechanism that allows computer to impersonate human intelligence and process things [6]. Presently, AI technologies have been extensively utilized in distinct fields of intelligent medicine such as analysis of medical images, surgery, health management system and integration of medical data [7]. Blockchain is a technology that consist of several inbuilt features including transparency, impermeable infrastructure and encryption tools. Blockchain technology has the capability to transform distinct industries including supply chain, healthcare and finance [8]. The IoT is defined as the connection of services and semantics through wireless protocols. IoT technology is specifically used to collect data from local and remote locations and has proven to be extensively utilized in the field of electronic-health management system [9]. Global mobile network is supported by the 5G technology referred as fifth generation wireless communication technology. IoMT is defined as the integration of medical services and software applications. Nowadays, IoT, 5G and IoMT technologies have been extensively used in healthcare sector [10]. This is mainly due to the fact that more number of mobile devices are now equipped with Near Field Communication (NFC) technology which allows them to interact with IT systems directly. As these technologies have been efficiently used in healthcare system, the present pandemic is also demanding these technologies to enhance the ability of global efforts in monitoring epidemic, tracking of infection, diagnosis of infection, development of vaccine and drug, allocation of resources and prediction of outbreak.

Therefore, the main objective of this study is to provide an extensive review of distinct strategies such as diagnosis of COVID-19, prediction of COVID-19, drug and vaccine development and prevention of COVID-19 that can be utilized in controlling the spread of COVID-19 pandemic. Further, the contributions of this survey are summarized as shown below.

a) Analysis of the types of data utilized in the COVID-19 research.
b) Analysis of different technologies used in combating COVID-19 and the effectiveness of the technologies.
c) Analysis of the approaches used in the diagnosis of COVID-19 pandemic and the effectiveness of the diagnosis models.
d) Analysis of distinct approaches in the prediction of COVID-19 pandemic and the effectiveness of the prediction models.
e) Analysis of the usage statistics of distinct contact tracing apps developed for the prevention of COVID-19.
f) Analysis of different vaccine production platforms used for COVID-19 pandemic.

The remaining part of the paper is structured as follows. Section 2 discusses about the distinct literature reviews performed in controlling the spread and management of COVID-19 pandemic. An in-depth analysis of the strategies such as diagnosis, prediction, treatment and prevention used in combating COVID-19 along with the technologies used and limitations has been presented in Section 3. Section 4 discusses about the critical analysis of the type of data, technologies, approaches used in diagnosis and prediction of COVID-19 along with their efficiency, usage statistics of contact tracing apps and distinct vaccine production platforms along with their advantages and limitations. Moreover, the future research directions and challenges in combating Covid-19 with intelligent approaches has been outlined in Section 5. Finally, the study ends with conclusion in Section 6. The following Fig. 1 depicts the overall framework of the study.

2. Literature review

Due to the exponential increase in the number of COVID-19 cases, the government and healthcare system all over the world are struggling a lot from the beginning of pandemic to control the spread of the infection. Several researchers are continuously working to develop effective diagnostic, prediction, treatment and preventive measures that may assist the government and healthcare system in efficiently combating the COVID-19 pandemic.

Shi et al. [11] have provided an overview of the application of AI technologies in providing effective and accurate imaging solutions for the diagnosis of COVID-19 infection. The efficacy of AI-assisted technologies in the diagnosis of COVID-19 can be explained through the use of two imaging modalities known as CT and X-ray. Further, a systematic study on imaging platforms for acquisition of images,
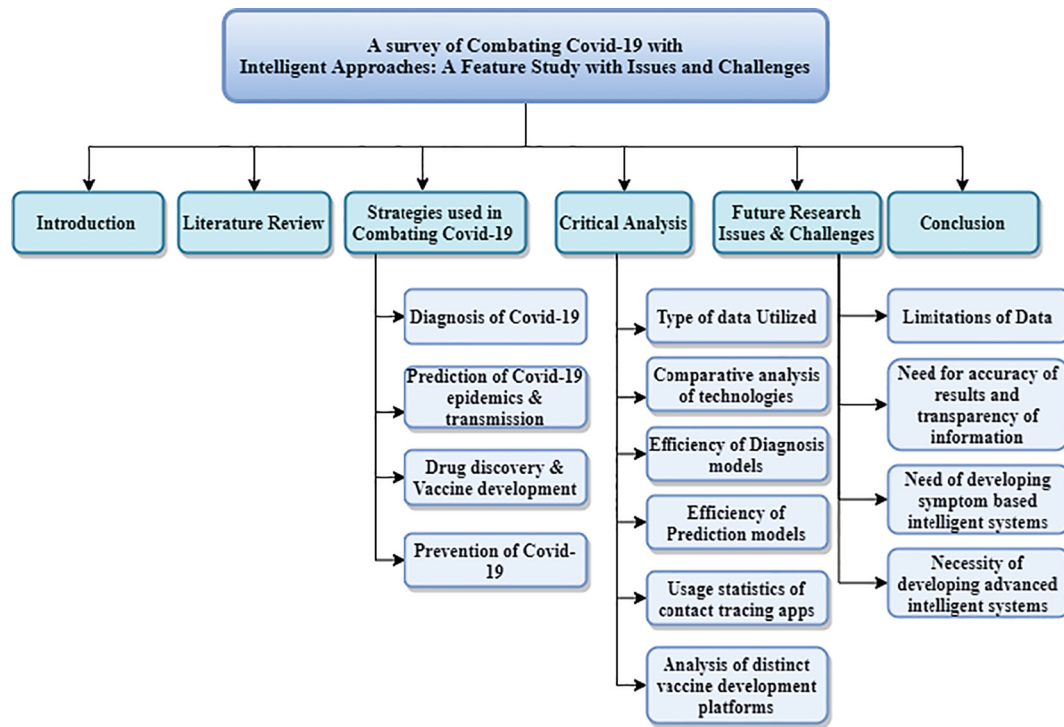
Fig. 1. Overall framework of the study.

segmentation and diagnosis of COVID-19 infected chest radiographs has been done using the abovementioned imaging modalities. It is observed from the review that the imaging provides only partial information about COVID-19 infected patients. To achieve better outcomes of the diagnosis, it is essential to merge imaging data with clinical indications and laboratory test results. A systematic review on the latest techniques and technologies that have been utilized for the diagnosis of COVID-19 infection has been presented by Taleghani et al. [12]. The study provides a detailed summary of various techniques developed by the distinct research institutions along with the commercial devices and kits manufactured by companies for the identification of the novel coronavirus. Further, the challenges and advantages of the existing methods have been highlighted in the review. Finally, some promising approaches has been suggested by author which helps in the accurate detection of COVID-19 infected and asymptomatic patients in the initial stage of the infection.

Mustafa et al. [13] has presented a systematic analysis of the existing mathematical models for analyzing and predicting the transmission of COVID-19 infection. A review on epidemiology of COVID-19, clinical presentations, transmission, susceptible population and mechanism of infection has been discussed by Lam et al. [14]. Further, the review also highlights about pharmacological agents such as anti-viral, immunomodulatory, adjunctive and other miscellaneous agents along with the efficacy of each agent.

An overview of the different stages of vaccine development, vaccine platforms along with their advantages and limitations, vaccine candidates, biological basis required for vaccine, ethical implications in the development of vaccine, vaccine coverage and the limitations and challenges in the vaccine development has been presented by Sharma et al. [15].

A comprehensive review on the social distancing measures has been presented by Gupta et al. [16]. Initially, a review of socioeconomic research on patterns of mobility, outcomes of labor market, behavior of consumer and population health during the initial phase of pandemic has been presented. Then, a simple microeconomic framework that considers the role distinct policy makers in implementing social distancing has been proposed by the authors. After, a review of typology of polices used during the closure and reopening phases has been presented. Further, an analysis on the data sources which plays an essential role in analyzing the behaviour of the population is performed. Finally, changes in the patterns of the mobility during the initial phase of pandemic have been presented. An extensive review has been done by Dehaghi et al. [17] to evaluate the efficacy of wearing face mask in controlling the spread of COVID-19 pandemic. This study includes the systematic review of five studies. Among the five studies, one study discussed about the differences between surgical and cotton masks and two studies have concentrated on the utilization of surgical mask by health practitioners. While the remaining studies concentrated on the usage of type of mask by the public. An extensive review of contact tracing apps has been presented by Ahmed et al. [18]. In addition, the papers also present a review of many tracing apps that were utilized countrywide along with the concerns that were reported during their usage such as battery usage, compatibility of the operating system versions, transparency and so on. Further, it discusses the challenges of contact tracing apps that needs to be addressed to improve the tracing capability and performance of the apps in future. The analysis of other systematic reviews carried out in combating COVID-19 infection are discussed in detail in Table 2.

3. Strategies used in battling COVID-19 pandemic.

In December 2019, the outbreak of SARS-CoV-2 virus was first reported in Wuhan City. Since its origin the virus is continuously disseminating around the world. As the virus progresses, it creates a threat to the health and socio-economic activities of the public all over the world. To solve these rapidly emerging problems, new strategies are being developed every day. Therefore, this section describes the various strategies such as diagnosis of COVID-19

Table 2
comparative analysis of the other literature review used in combating COVID-19.

Author & year	Focused Area	Activity reviewed	Limitations	Ref
Ozsahin et al. & 2020	Diagnosis using AI	Classification studies of COVID-19 / Normal, COVID-19/Non-COVID, and COVID-19/Non-COVID-19 Pneumonia, and COVID-19 severity using CT images	Most of the studies are from the preprint literature. Not considered the demographic and clinical information of the patients	[19]
Wynants et al. & 2020	Diagnosis and Prognosis	Models used for predicting risk of hospital admission, Diagnosis models for detection of COVID-19, Prognosis models for COVID-19 patients	Not specified about the technology used in prediction models for prognosis and diagnosis of COVID-19 Studied have not carried out using X-ray images	[20]
Fierabracci et al. & 2020	Diagnosis	Structure of SARS-CoV-2, Diagnosis, treatment and Vaccine of COVID-19	Not specified the limitations and challenges. Not specified diagnosis of COVID-19 using medical images	[21]
Manigandan et al. & 2020	Diagnosis	Transmission, Diagnostic methods and Clinical Treatment	Not specified the limitations and challenges	[22]
Gola et al. & 2020	Prediction	Study of distinct models used in forecasting, analysis of the methodology and results of these models in forecasting COVID-19 cases during lockdown	Not specified the challenges and limitations of the forecasting models	[23]
Kotwal et al. & 2020	Prediction	Type of mathematical modeling used, Analysis of predicted values using mathematical modeling and actual values in India	Not focused on prediction models used for the state prediction. Not focused on other technologies used in prediction	[24]
Wang et al. & 2020	Drugs used for treatment	Drugs in Clinical trials, Drugs proposed by Computational works, Drugs proposed by In-vitro protein-binding assays	Not focused on the development of peptide treatments	[25]
Rabby et al. & 2020	Drugs used for treatment	Effectiveness of drug against COVID-19	Most of the studies are from single geographical location. Detailed information of laboratory outcomes of suggested drugs is not available in most of the reviews	[26]
Rismanbaf et al. & 2020	Drugs used for treatment	Novel potential COVID-19 therapies	No clinical study has explained the effects of Tocilizumab on COVID-19	[27]
Kaur and Vandana, 2020	Vaccine development	Vaccine production platforms along with their advantages and limitations, list of vaccine candidates available in pipeline, limitations and latest development in the status of promising vaccines	Not specified about ethical implications of the vaccine development, challenges in vaccine development	[28]
Koirala et al.& 2020	Vaccine development	History of vaccines available for coronavirus, vaccine candidates, vaccine production platforms and limitations in the vaccine development	Not specified about ethical implications, vaccine coverage, latest development in the status of vaccines	[29]
Krishna and Lwin, 2020	Social Distancing Measures	Evaluates the effects of social distancing measures for minimizing the transmission of COVID-19	Findings might result in generalization issue if the retrieved studies vary in sample size, quantity and population	[30]
Mbunge et al. & 2020	Social Distancing Measures	challenges in implementing social distancing and self-isolation of workers during COVID-19 pandemic in Africa	Not specified about the ethical utilization of social distancing apps without disrupting the security and privacy of individual	[31]
Howard et al. & 2020	Face mask	Evaluates the effectiveness of mask wearing using an analytical framework	Impact of wearing mask to control dissemination in work place has not been studied in this review	[32]
Paxton et al. & 2020	N95 respiratory mask for COVID-19	Discusses about mask fabrication along with its maintenance, reuse and recycling of existing mask	Not able to perform the filtration efficiency test on a given masks both before and after preservation.	[33]
Jalabneh et al. & 2020	Mobile apps for Contact tracing	Evaluates the effectiveness of mobile apps used for contract tracing in order to control the dissemination of COVID-19 disease.	Not addressed the security and privacy issues that arise in the usage of mobile apps for contact tracing	[34]
Chowdhury et al. & 2020	Contact tracing apps	Discusses about the underlying technologies, protocols and contact tracing apps developed for controlling COVID-19 pandemic	Not addressed proximity measurement issue that arises in the usage of Bluetooth technology	[35]

using medical images, prediction of COVID-19 pandemics, development of drugs and vaccine and prevention measures used in controlling the spread of COVID-19 disease.

3.1. Diagnosis of COVID-19

Diagnosis of COVID-19 disease can be performed either by the direct recognition of viral RNA or by the indirect recognition of the particular antibody responses using etiological tools or by the diagnosis of medical images.

3.1.1. Using etiological tools

To curb the dissemination of current ongoing COVID-19 pandemic, diagnosis of COVID-19 plays a crucial role in the manage-ment of coronavirus infection. Therefore, the procedures such as molecular tests, serology tests, and medical radiographs used for the diagnosis of other viral form of pneumonia are considered as the standard diagnostic procedure of SARS-CoV-2 infection. Several research studies have also been presented on the diagnostic method of COVID-19 infection. A review about the various diagnostic methods, their applicability with present findings, the process of collecting samples and the issues associated in collecting the samples has been reviewed by Mathuria et al. [36]. La et al. [37] have explained about the performance assessment of distinct diagnostic methods including nucleic acid tests, viral antigen test and serological tests in order to produce the information related to the development of algorithmic approaches for the treatment of COVID-19 infection. A review on the latest technologies and

approaches used for the diagnosis of COVID-19 has been presented by Taleghani and Fariborz [12]. In addition, the review also provides a summary of the method, commercial devices and kits developed by the diagnosis of COVID-19 infection by distinct research institutions and companies along with their benefits and challenges. Jing et al. [38] have provided a comprehensive review of distinct molecular approaches such as qRT-PCR, gene sequencing, loop-mediated isothermal amplification (LAMP), nucleic acid mass spectrometry (MS), and gene editing technique based on clustered regularly interspaced short palindromic repeats (CRISPR/Cas13) system along with their advantages and disadvantages has been presented. Further, a review and analysis of causes for false-negative qRT-PCR results and the challenges that arise in enhancing the detection rate of SARS-CoV-2 has been presented. The following Table 3 represents the features, manufacturers of different diagnostic approaches used for the diagnosis of COVID-19 along with their advantages and limitations.

3.1.2. Using medical images

The standard approach used for the identification of COVID-19 is RT-PCR. Due to the limitations of the RT-PCR such as less sensitivity, more time and limited number of available kits, analysis of medical images such as computer tomography and X-ray radiographs of chest are used in the diagnosis of COVID-19 disease because of its fast acquisition nature. Several studies [39–40] reveals the role of imaging in the diagnosis of COVID-19 infection. As COVID-19 infection has similar indications with other types of pneumonia, there is need for the application of technologies in the analysis of medical images to obtain high diagnostic performance. In recent years, the scanning parameters such as scan range and pose and shape of the inmate can be estimated easily using AI-based visual sensors. As optimal screening parameters can be determined using AI-based technologies, it results in producing enhanced quality images. As AI-based technologies results in enhanced quality images, these technologies have been widely used in the inspection of medical images and have attained considerable results in the acquisition, classification, recognition of the medical images and segmentation of medical images [197–200]. Therefore, in present pandemic also AI technologies have been applied in the inspection of COVID infected medical images for achieving high diagnostic performance

Zhang et al. [41] have developed an AI system for the diagnosis of COVID-19 infected patient from other common pneumonia and normal patients by considering large dataset consisting of Computed Tomography images from 3,777 inmates. The suggested AI model assist radiologist and clinical experts in performing quick diagnosis particularly when the healthcare system is overburdened. Further, the proposed AI model also determines clinical markers that correspond with lesion properties of novel coronavirus pneumonia (NCP). Therefore, the clinical markers obtained by the proposed AI model along with the clinical data provides accurate prognosis of COVID-19 disease which may further assist clinical experts in the early management of COVID-19 infection and for the appropriate allocation of healthcare resources. A novel machine learning approach has been developed by Elaziz et al. [42] for the visual diagnosis of chest radiographs as COVID-19 infected and non-COVID-19 X-ray images. The proposed approach utilizes Fractional Multichannel Exponent Moments (FrMEMs) to extort the features from the X-ray images. Then, it uses Manta-Ray Foraging Optimization and differential evolution (MRFODE) algorithm to minimize and discard the insignificant features and to select the most appropriate features from the radiographs. Further, K-Nearest neighbor (KNN) classifier is used to categorize the images as normal and COVID-19 infected images. Moreover, the proposed approach has been evaluated by considering two datasets of X-ray images and the results indicate that the novel machine learning approach has attained an accuracy of 96.09% for the first X-ray dataset and 98.09% for the second dataset. To diagnose novel coronavirus pneumonia from single chest CT image, a simple 2D deep learning structure known as fast-track COVID-19 classification network (FCONet) has been developed by Ko et al. [43]. The proposed model uses one of the four pretrained deep learning approaches such as VGG16, ResNet-50, Inception-v3 and Xception along with transfer learning for the categorization of CT images as COVID, non-COVID and normal images. Further, the model has been evaluated and the empirical results indicate among the pretrained deep learning models ResNet-50 has attained superior performance in terms of 99.58% sensitivity, 100.00% specificity and

Table 3
Features of distinct diagnostic approaches of COVID-19 infection along with their manufacturers, advantages and limitations.

Diagnostic approach	Specimen	Turn Around Time	Advantages	Limitations	Implications
RT-PCR	Collected from nasopharyngeal or oropharyngeal swabs and/or lower respiratory tract	190	Utilized widely, High sensitivity and Specificity	Costly, required qualified technicians, Moderate turnaround time, restrictions on sample transportation	The golden standard approach used in the diagnosis of symptomatic and asymptomatic inmates
RT-LAMP	Taken from nasopharyngeal or oropharyngeal swabs and/or lower respiratory tract	45–60	Less turnaround time, High sensitivity, Less bias in analytical phase	Costly, required qualified technicians, restrictions on sample transportation	Substitute for RT-PCR to reduce the turnaround time of RT-PCR
NP antigen detection test	Collected from nasopharyngeal or oropharyngeal swabs and/or lower respiratory tract	240	Easier collection process	Less sensibility, required qualified technicians, restrictions on sample transportation	It can be utilized in Labs with no equipment for RT-PCR
ELISA	Collected from human serum, plasma, whole blood	240	Less expensive, moderate turnaround time, Easy process of sample collection, Data accepted by *meta*-analysis and cohort data	Required qualified technicians	Second level test in order to confirm Rapid detection test results
CLIA	Collected from human serum, plasma, whole blood	30	High Sensitivity, Helps in early detection of suspicious cases with nucleic acid false negative	Required qualified technicians, data from small cohort	Second level test in order to confirm Rapid detection test results
Rapid Detection Test	Collected from finger prick	10–30	Easy sample collection process	Low specificity and sensitivity	Used for weekly screening in high risk population

99.87% accuracy when compared with the other pretrained deep learning approaches. Furthermore, the proposed model has been evaluated by considering external test data consisting of low-quality CT images and the outcome indicate that ResNet-50 model has attained better detection accuracy of 96.97% in comparison with other pretrained models. To perform segmentation on real world example of COVID-19 CT images, a hybrid swarm intelligence-based (SI) method known as MPAMFO has been developed by Abd Elaziz et al. [44]. The proposed method integrates the characteristics of both marine predators algorithm (MPA) and moth-Flame optimization (MFO). In this approach, the MFO algorithm is used as local search method to prevent the trapping of MPA at local optima. Further, the performance of the model has been evaluated by carrying out two experiments. One experiment is conducted for the segmentation of ten natural grayscale images. While, the other experiment is carried out using real world examples of COVID-19 CT images. The experimental results indicate that the suggested approach attains better performance in comparison with other existing SI-based methods. To obtain both the individual-level classification and lesion segmentation simultaneously, Gao et al. [45] have proposed a dual-branch combination network (DCN) for the diagnosis of COVID-19. To concentrate on the lesion area, the intermediate segmentation results are integrated using lesion attention module. In addition, the transformation from slice-level to individual-level classification was performed by using slice probability mapping method in order to maintain the effect of distinct imaging parameters from individual abilities. Further, the proposed model is evaluated by conducting experiment and the outcomes indicate that the developed DCN model achieves a classification accuracy of 96.74% and 92.87% on internal and external dataset respectively. To segment and quantify the infected area of CT scans into machine-agnostic standard, a pre-processing approach and an accurate segmentation model based on standard embedding space has been suggested by Zhou et al. [46]. In addition, a deep learning algorithm is proposed to resolve the large-scene-small-object problem and further to enhance the segmentation accuracy of the model. To solve the issue of heterogeneity in data and to make the model applicable to any dataset, the pre-processing approach is utilized. The trade-off between the complexity of deep learning model and accuracy of the model is determined by the segmentation model. Furthermore, the extensive experimental outcomes using datasets from multi-country, multi-hospital, and multi-machines describes the superiority of model over other existing models. The other literature reviews on the diagnosis of COVID-19 disease using medical images along with their limitations has been illustrated in Table 4.

3.1.3. Using genetic material

Nowadays, modern technologies like Electron microscopy and next-generation sequencing (NGS) technology are used for the diagnosis of COVID-19 infection [201]. Using these technologies, mutation of the virus can also be assessed. The recognition of genetic material from completely distinct kingdom of organisms and the simultaneous sequencing of thousands to billions of DNA fragments can be done using genomics technology known as NGS [202]. It allows the characterization and analysis of viral genetic material. Presently, the NGS technology is applied in variety of applications such as diagnosis of infectious diseases, outbreak tracking, infection control supervision and mutation and pathogen discovery with different types of biological specimens [203]. Using NGS technology, 380,000 SARS-CoV-2 genome sequences have been shared on the GISAID initiative (global initiative promoting rapid open-access sharing of the genetic sequencing data of influenza viruses and SARS-CoV-2), which provides the way for real-time observation and monitoring of the pandemic [204]. The screening and identification of viral agents without having previous knowledge of the causative agent is considered as the main advantage of the NGS technology [205–206].

Several research works have been carried on the NGS technology to show its efficacy in screening and identification of SARS-CoV-2 viral agents. A systematic analysis of the methodological approaches and currently available platforms for the genome sequencing of SARS-CoV-2 along with repositories and databases that paves way to SARS-CoV-2 genomic data and associated metadata has been presented by Chiara et al. [207]. To provide high-throughput testing of COVID-19, a novel approach that makes use of isothermal amplification and next-generation sequencing has been suggested by Huang and Zhao [208]. Using the proposed approach, thousands of specimens can be easily diagnosed within 1–2 days at lower operating cost. Moreover, it provides fast and reliable diagnosis by allowing patients to collect process and mail their own samples. A multiplexed, extensible, readily automated platform for SARS-CoV-2 known as "Systematic Parallel Analysis of RNA coupled to Sequencing for Covid-19 screening" (C19-SPAR-Seq) has been proposed by Aynaud et al. [209] for interpreting the samples of tens of thousands of patients in a single run. In addition, a control-based Precision-Recall and Receiver Operator Characteristics (coPR) analysis has been employed for addressing the output required by clinical diagnostic. The proposed C19-SPAR-Seq combined with coPR obtained 100% specificity and 91% sensitivity on low viral load samples and attained sensitivity greater than 95% on samples of high viral load. For detecting the high throughput and genetic epidemiology of SARS-CoV-2, an approach known as COVIDSeq NGS protocol has been proposed by Bhoyar et al. [210]. Further, the proposed approach has been applied on a total of 1536 samples. From the analysis, a high similarity among the technical duplicates and the interpretations of SARs-CoV-2 using COVIDSeq and RT-PCR has been observed. Moreover, an in-depth analysis confesses that total of 6 samples that were detected as negative in RT-PCR were identified as SARS-CoV-2 with high confidence using COVIDSeq approach. Moreover, the COVIDSeq approach also identified SARS-CoV-2 in 21 samples of inconclusive samples and 16 samples of pan-sarbeco positive samples. To detect pathogen directly from clinical specimen, an approach known as Metagenomic next-generation sequencing (mNGS) has been developed by Mostafa et al. [211]. In addition, the proposed approach also presents important information on the microbiome composition and revealed information about coinfections that are linked with the progression of disease. The performance has been evaluated by applying the approach on Oxford Nanopore long-read third-generation metatranscriptomic and metagenomic sequencing. Further, Nasopharyngeal (NP) swab samples collected from 50 patients were analyzed using CosmosID bioinformatics platform. Form the analysis, it was observed that their proposed approach identified SARS-CoV-2 in 77.5% of the samples identified as positive using RT-PCR. Moreover, approach also identified 12.5% bacterial or viral coinfections in the positive specimens of SARS-CoV-2. The analysis also helpful in identifying the decrease in microbial diversity ((Shannon diversity index, $P = 0.0082$; Simpson diversity index, $P = 0.018$; Chao richness estimate, $P = 0.0097$) and differences in microbial communities associated with disease severity ($P = 0.022$) among confirmed COVID-19 inmates. From the literature review, it was observed that large-scale monitoring and reliable diagnosis of SARS-CoV-2 within short time and other pathogens, diagnosis of coinfections associated with SARS-CoV-2 and analysis of respiratory biome can be efficiently performed using NGS technology.

3.2. Prediction of COVID-19 epidemics and transmission

As the current COVID-19 infection has rapidly disseminated over the world, it is essential to develop a procedure to determine

Table 4

Application of AI technologies in the diagnosis of COVID-19.

Author & year	AI method	Functionality	Performance of the Model	Limitations	Ref
Islam et al. & 2020	CNN + LSTM	Detection of COVID-19 using 4575 X-ray images	Obtains 99.5% accuracy	Focuses only on the posterior-anterior views. So, cannot differentiate anterior-posterior and lateral views. COVID-19 images consisting of symptoms of multiple diseases cannot be classified efficiently. No involvement of radiologist	[47]
Heidari et al. & 2020	Deep Learning based CAD scheme	Detection of COVID-19 pneumonia from 8474 X-ray images	Achieves an overall accuracy of 94.5%	Evaluates only two image processing techniques to yield filtered images which may not be considered as optimal methods. Need to develop new image processing and segmentation algorithms to discard diaphragm and other areas outside the lung region.	[48]
Rao et al. & 2020	Machine Learning algorithm	Detection of COVID-19 through the mobile phone Survey	–	Survey does not include asymptomatic patients	[49]
Mei et al. & 2020	CNN + Multi-layer perceptron (MLP) model	Rapid diagnosis of inmates with COVID-19 infection from CT images of 279 patients	Results in an area under the curve (AUC) of 0.92	Considers small sample dataset which results in the issue of generalizability of the model. Focuses only on COVID-19 positive cases	[50]
Li et al. & 2020	Deep Learning model	Detection of COVID-19 from 4356 chest CT images	Achieves an AUC of 0.9	Study does not consider the comparison with other viral pneumonia. Does not find the severity of the COVID-19 from CT Images. Overlap in the chest CT images identification with pneumonia. Lack of lack of transparency and interpretability in image visualization process	[51]
Zheng et al. & 2020	DeCoVNet	Detection of COVID-19 from 630 Chest CT images	Obtains an accuracy of 90.1%	Temporal information was not utilized by UNet model. Imperfect ground truths were used in model training which can be further enhanced by 3D segmentation. Data used in training model is from single source. No cross-center validations were done.	[52]
Abraham & Madhu, 2020	Multi-CNN and Bayesnet classifier	Automated detection of COVID-19 infection from two datasets consisting of 950 and 78 X-ray images	Results in accuracy of 91.16% on 950 X-ray images and accuracy of 97.44% on 78 X-ray images	The model is not tested for multi-class classification. Does not accomplish segmentation of the infected area. Multi-CNN have not been investigated in the study	[53]
Fan et al. & 2020	Inf-Net	Determines infected lung regions from 638 Slices of real CT volumes	Attains Dice similarity = 0.597 and specificity = 0.977	The two-step strategy utilized to obtain multi-class infection labeling generate sub-optimal learning performance. Does not contain COVID detection module.	[54]
Pu et al. & 2020	Computer vision and deep learning technology	Identify, quantify and monitor advancement of pneumonia associated with two datasets consisting of 125 Chest CT and 72 serial chest CT scans	Results in dice coefficient of 81%, sensitivity of 95% and specificity of 84%	The algorithm cannot detect Ground Glass Opacities (GGOs) having very low density. Cannot distinguish the pneumonia regions associated with COVID-19 from other abnormalities.	[55]
Selvaraj et al. & 2020	Deep Neural network model	Detect and segment COVID-19 infection from axial view of 80 CT images	Results in specificity of 0.942, sensitivity of 0.701and MAE of 0.082	Cannot detect GGO from poor contrast CT images.	[56]

(AUC is Area under the receiver operating characteristic (ROC) curve, MAE is Mean Absolute Error).

the number of probably infected people on a regular basis to assist the government and health policy makers to take necessary actions in controlling the spread of disease and proper allocation of the resources.

3.2.1. Application of mathematical and statistical models in the prediction of COVID-19

From the last few pandemics, distinct mathematical and statistical models have been extensively utilized in the determination of human loss and also in the estimation death count until a particular period or end of the pandemic. As these models results in better predictions, the present pandemic is also demanding the applicability of these models in the prediction of epidemic and transmission. The analysis is performed by accessing data from authorized sources, search engines and mobile phone data. A mathematical

model known as SAIU (susceptible (S)-asymptomatic (A)-reported symptomatic infectious (I)-unreported symptomatic infectious (U)) model has been developed by Samui et al. [57] to inhibit and handle the transmission dynamics of coronavirus pandemic in India. Initially, basic reproduction number R_0 is computed which can be further utilized to investigate the predictions and simulations of the model. Then the local and global stability analysis for the infection free equilibrium point E_0 and endemic equilibrium point E_* corresponding to R_0 has been performed. Further, sensitivity analysis has been done to decide the significance of the model parameters in disease transmission. To find the estimated model parameters, sensitivity indices of R_0 has been calculated. Based on the estimated data, the SAIU mathematical model predicts that there will be highest peak around 60 days and after that the curve will be flattened but the pandemic will

continue for long period. The comparative analysis of mathematical and statistical models in the prediction of COVID-19 epidemics and transmission dynamic has been illustrated in Table 5.

3.2.2. Application of AI technologies in the prediction of COVID-19

Although mathematical and statistical models have been used in the prediction of transmission dynamics, allotment of hospital resources, evaluation of impact of social distancing, travelling restrictions, these models require large number of parameters and relies on assumptions. To overcome these limitations, AI technology has been used in the prediction of COVID-19 dynamics and transmission analysis. To forecast the number of confirmed cases, recovered cases and to predict the mortality rate in Saudi Arabia, a deep learning based LSTM model has been proposed by Elsheikh et al. [66]. Initially, the model determines the optimal value of the parameters that are utilized in enhancing the forecasting accuracy of the model. The efficacy of the model has been assessed using evaluation metrics such as RMSE (Root mean Square Error), MAE (Mean Absolute Error), R2 (coefficient of determination), overall index, coefficient of variation and residual mass and efficiency coefficient. Then, the performance of the proposed LSTM model has been compared with Autoregressive Integrated Moving Average (ARIMA) and Nonlinear Autoregressive Artificial Neural Networks (NARANN) and the results reveal that LSTM results in better forecasting accuracy when compared with other models. Further, the suggested LSTM model has also been used to forecast the total number of confirmed positive cases in Brazil, India, Saudi Arabia, South Africa, Spain, and USA. The results obtained using

suggested LSTM model may assist the policy makers in implementing proper plans for organizing Haji and for deciding the closure period of schools and universities in Saudi Arabia. The following Table 6 represents the application of AI technologies in the prediction of COVID-19 epidemics and transmission analysis.

3.3. Drug discovery and vaccine development

The massive outbreak of the COVID-19 has prompted various scientists, researchers, laboratories, and organizations around the world to conduct large scale research to develop vaccines and other treatment strategies. AI technologies play a vital role in the development of drugs and vaccine which aids in combating COVID-19 pandemic. In the COVID-19 drug development, AI technologies are basically used for examining the interactions between existing drugs and protein targets of COVID-19. Moreover, these technologies are also used to discover the new drug candidates for COVID-19 by formulating new molecular structures that have inhibitory consequences on proteases at molecular level. An end-to-end architecture known as CogMol (Controlled Generation of Molecules) has been developed by Chenthamarakshan et al. [75] for developing new drug-like small molecules with high target specificity and selectivity. Both the SMILES Variational Autoencoder (VAE) and an efficient multi-attribute controlled sampling scheme are incorporated in the proposed model. The proposed model is evaluated using three target proteins of SARS-CoV-2 and the results indicate that the generated candidates are unique at both molecular and chemical levels. A comprehensive study on

Table 5
Application of mathematical models in the prediction of COVID-19 epidemics and transmission dynamics.

Author & Year	Model	Type of Data	Functionality	Results	Limitation	Ref
Alzahrani et al. & 2020	ARIMA (Autoregressive Integrated Moving Average)	Time series data	To predict the expected daily number of COVID-19 cases in next four weeks in Saudi Arabia	Cases may reach to7668 new cases/day and approximately 127,129 cumulative daily cases in next four weeks	If the model contains high non linearity, then the accuracy may be reduced as ARIMA is a linear model	[58]
Ribeiro et al. &2020	Regression models	Time series data	Short term forecasting of cumulative confirmed cases	Results in sMAPE value in the range between 0.87% and 3.51%, 1.02%–5.63%, and 0.95%–6.90% for one, three and six days respectively	The diversity of exogenous factors that can affect the daily cases of COVID-19	[59]
Rostami-Tabar et al. & 2020	Multiple Linear regression with Call data	Phone call data	For predicting daily COVID-19 cases	Achieves RMSE of 178.06	Study does not include hospital information such as COVID-19 admission and bed occupancy	[60]
Wang & Nao	Partial Differential Equation model	Google Community mobility reports	To predict COVID-19 cases in Arizona	Accuracy = 94%	Google Community Mobility data is not available at the zip code level	[61]
Yuan et al. & 2020	Linear model	Google Trends data	To predict COVID-19 daily new cases and new deaths in the USA	Pearson's r of daily cases is 0.978, 0.978 and 0.979 for search interest of COVID, COVID Pneumonia and COVID heart	Retrospective nature of the modeling part is the limitation of the study	[62]
Singh et al. & 2020	Holts Winter Model	Time Series data	To predict the COVID-19 confirmed cases, active cases and deaths in India	MAPE of Confirmed cases = 11.2298%, Active cases = 16.5113%, Deaths = 13.2542	Does not include epidemiological knowledge	[63]
Malavika et al. & 2020	Logistic growth curve mode + Susceptible Infection and Recover (SIR) model + Time Interrupted Regression model	Time series data	Predicts the COVID-19 new cases and maximum number of active cases. Also evaluates the impact of lockdown	The maximum number of predicted cases by May 18, 2020 is 57,449.	Issues in testing strategies and asymptomatic cases may result in uncertainty.	[64]
Zhao et al. & 2020	Multivariable regression model	Clinical data	Predicts mortality rate and ICU admissions	AUC of ICU admission = 0.74, AUC of mortality rate = 0.83	As the study is from single institution results in issue of generalizability.	[65]

(sMAPE is Symmetric mean absolute percentage error, RMSE is Root Mean Square Error.).

Table 6
Application of AI technologies in the prediction of COVID-19 epidemics and transmission analysis.

Author & Year	Model	Type of Data	Functionality	Results	Limitation	Ref
Chimmula et al. & 2020	LSTM Network (Long Short Term Memory)	Time series data	Prediction of COVID-19 transmission dynamics in Canada	For short-term predictions in Canada RMSE = 34.83 Accuracy = 93.4% For short-term predictions in Canada RMSE = 45.70 Accuracy = 92.6%	Does not include patients who are on incubation period or not tested	[67]
Dhamodharavadhani et al. & 2020	Statistical Neural Network (SNN) models	Time series data	Prediction of mortality rate in India	For dataset1 RMSE = 8.528095 For dataset2 RMSE = 7.898071	Does not consider demographical and topographical components related with the spread of COVID-19 Hybrid SNN-NAR-NN model is suitable only for short-term prediction of mortality rate	[68]
Yan et al. & 2020	XGBoost machine learning-based model	Clinical Data	Prediction of mortality rate	Accuracy = 90%	The study is restricted to clinical settings because results may alter based on the quality and size of the dataset	[69]
Singh et al. & 2020	Least square support vector machine (LS-SVM)	Time series data	Forecasting of daily confirmed cases of COVID-19 in most affected five countries of world	Accuracy = 99%	The capability and linear dependencies of the model can be checked only if further modeling of data series is done	[70]
Nkwayep et al. & 2020	Ensemble Kalman filter	Time series data	Short-term forecast of COVID-19 in Cameroon	Basic Reproduction number R_0 = 2.9495	Generalization of result is based on small dataset	[71]
Pinter et al. & 2020	Multi-layered perceptron-imperialist competitive algorithm (MLP-ICA	Time series data	Predict the COVID-19 outbreak in China	RMSE of total cases = 167.88, RMSE of total mortality rate = 8.32	Changes in prevention measures results in change in the accuracy of the model	[72]
Qin et al. & 2020	subset selection method	Social Media search Index data	To predict number of COVID-19 cased	RMSE = 51.6671	other respiratory diseases with similar symptoms are considered as the bias in the prediction model	[73]
Ayyoubzadeh et al.	LSTM model	Google Trends data	To estimate the number of positive cases in Iran	RMSE of LSTM = 27.187	Limited access to google search data. Limited amount of training data	[74]

the application of computational intelligence along with the knowledge of immunoinformatics, structural and system biology for the design and development of COVID-19 vaccine has been presented by Bharadwaj et al. [76]. Further, analysis on the COVID-19 drug discovery and vaccine development has been represented in Table 7.

3.4. Prevention of COVID-19

Since the beginning of the outbreak, the novel coronavirus has caused a serious threat to the health of the people all over the world. With the growing trend of patients, several researchers and health organizations are uninterruptedly working to develop vaccine or appropriate medication for the treatment of the COVID-19 disease. Due to limited number of medical facilities, unavailability of specific treatment to cure the COVID-19 disease and as the vaccine development process is under trails, the government of various countries have taken the alternative precautions such as social distancing, contact tracing, wearing mask etc., to inhibit the spread of the COVID-19 disease.

3.4.1. Prevention of COVID-19 through social distancing
Social distancing is one of the solutions suggested by the WHO that aims in minimizing the closeness of people to inhibit the extensive spread of COVID-19 disease in public places. After declaring COVID-19 as airborne disease by the WHO on July 8, 2020, social distancing is considered as the most essential and the best way to stop the spread of the COVID-19 disease [87]. Therefore, the governments have tried to enforce distinct social

distancing practices such as travelling restrictions, border restrictions, closing of schools, workplaces, gyms, shopping malls etc., and an adequate social distancing space among individuals to inhibit the dissemination of virus. As per the guidelines of the WHO, the governments and health authorities of distinct countries declared 6 feet of distance as sufficient social distancing space between the individuals [88]. Anyhow, controlling the amount of infection dissemination is not an easy task, as people need to go out for performing essential needs. Therefore, intelligent computing techniques have been developed to assist the healthcare system and government in coping up with the challenges that arise in the implementation of social distancing practices. A hybrid model based on Computer Vision and YOLOv4-based Deep Neural Network (DNN) has been suggested by Rezaei and Mohsen [89]. The proposed approach is used for the automatic identification of the crowded people through CCTV security cameras in indoor and outdoor places. The inverse perspective mapping (IPM) technique and SORT tracking algorithm along with the DNN model is used for the identification of people and monitoring of social distancing at crowded places. Further, the developed model has been conducted in challenging conditions with mean average precision and real time speed of 99.8% and 24.1 fps respectively using Microsoft Common Objects in Context (MS COCO) and Google Open Image datasets. Moreover, an online infection system is also provided by the developed model through the statistical analysis of spatio-temporal data from people moving paths and rate of violating the social distancing measure. A vision-based social distancing model has been presented by Yang et al. [90]. The proposed model utilizes monocular camera for identifying the individuals in region

Table 7
Other studies on the development of COVID-19 drugs and vaccines.

Strategy	Author & year	Approach	Application	Limitations	Ref
Drug discovery	Zeng et al. & 2020	an integrative network-based deep-learning methodology known as CoV-KGE	Used to identify 41 repurposable drug candidates	Not considered the confidence values of the relation between entities. Noise generated may affect the performance of the system	[77]
	Hooshmand et al. & 2020	Multimodal Restricted Boltzmann Machine approach (MM-RBM)	Used for clustering two types of drugs. Used in detecting promising solutions for COVID-19 with less side effects	Not performed in vitro or in vivo tests	[78]
	Acharya et al. & 2020	supercomputer-based virtual high-throughput screening ensemble-docking pipeline	perform exhaustive docking of one billion compounds in less than 24 h	Not incorporated AI approaches in clustering MD trajectories and rescoring ligand ranking	[79]
	Abdel-Basset et al. &2020	heterogeneous graph attention (HGAT) model	for predicting the affinity scores of drugs against SARS-CoV-2 amino acid sequences	Not shown the semantic representation of input sequences. Requires large time for execution	[80]
	Beck et al. & 2020	Molecule Transformer-Drug Target Interaction (MT-DTI)	To predict binding affinity between drugs and protein targets	Not performed in vitro or in vivo tests	[81]
	Hofmarcher et al. & 2020	a deep neural network based ChemAI	predict inhibitory effects of molecules on SARS-CoV-2 proteases	Considered small amount of data	[82]
Vaccine Development	Ong et al. & 2020	Vaxign reverse vaccinology tool and Vaxign-ML machine learning tool	For predicting COVID-19 vaccine candidates	–	[83]
	Ward et al. & 2020	Online immuno-analytics	To instruct control activities in a post-vaccine surveillance setting	–	[84]
	Abdelmageed et al. & 2020	Immune-informatics approach	To design a multiepitope peptide vaccine for COVID-19	–	[85]
	Fleri et al. & 2020	Immune Epitope Database and Analysis Resource (IEDB)	Used in epitope prediction and vaccine design	–	[86]

of interest (ROI). In addition, the proposed model also calculates the interpersonal distance without recording the data and instructs the mob if any violation of social distancing is identified by issuing a non-intrusive audio-visual indication in real time. Moreover, the model uses social density metrics to alert the people not to enter the ROI if density is larger than the social density metrics value. For the emergency management and for implementing structural and environmental monitoring, an IoT system that makes use of IoT-WSN (wireless sensor network) and shortest path finding and neural network algorithms has been suggested by Fedele et al. [98]. The proposed framework makes use of sensors, cameras and Near Field Communication (NFC) technology for gathering useful information in order to acquire safe path advices and social distancing alarm for users and platform managers. In addition, raw data has been forwarded to platform dashboards for the online monitoring of structural and environmental conditions. An automated drone that makes use of yoloV3 algorithm for detecting whether public is maintaining social distance and wearing mask or not has been proposed by Ramadass et al. [100]. In addition, the developed approach also provides mask to the individuals who are not wearing mask and describes the significance of wearing mask and maintaining social distance to public. To monitor the social distancing advices by the public, an innovative solution known as MySD (My Safe Distance) that makes use of different modules such as Bluetooth Distance tracker, GPS module, Google Maps API and COVID-19 Zone indicator has been developed by Rusli et al. [102]. To determine the distance between two Bluetooth transceivers, the MySD makes use of distance estimation model. Further, MySD makes use of google map API and GPS information to determine the location of the user. By using this information, MySD creates invisible safe zone surrounding which helps in reducing the possibility of getting infected with COVID-19 infection. The application of distinct technologies in the prevention of COVID-19 through social distancing measures has been represented in Table 8.

3.4.2. Prevention of COVID-19 through contact tracing

The process of identifying individuals who have contact with the COVID-19 infected people is known as contact tracing. The contact tracing prevention mechanism helps in minimizing the spread of the COVID-19 infection. According to the guidelines of the WHO [103], the contact tracing process involves three steps i) identification of the persons who has contact with infected person. ii) recording the details of those individuals iii) testing those people as early as possible. To furnish the real-time information to Centers for Disease Control and Prevention (CDCs), a Software-Defined Networking Controller-centric global public platform has been proposed by Jung et al. [104] for monitoring and tracking the COVID-19 infected people. The CDC maintains the list of COVID-19 infected people and installs virtual Internet of Things (vIoT) nodes in the smartphones in the form of apps. The proposed platform design assures both confidentiality and authentication services. Further, the proposed platform design is also used for minimizing the Query/Reply latency when the platform supports large number of world-wide CDCs. A novel contact tracing model based on IoT and blockchain technology has been proposed by Garg et al. [105] to capture information on movements and contacts of objects. By using proof-of-concept RFID transceivers and storing the information on blockchain technology, the proposed model tracks the moving objects and preservers the owner's privacy. The proposed model permits moving objects to receive or send notifications when they are close to a probable or confirmed diseased case, or flagged place or object and also assist in identifying the super spreading objects or persons. To trace the human contact within indoor trajectories, a graph-based semantic indoor trajectory data model has been proposed by Ojagh et al. [109]. For the semantic partitioning of raw indoor movement trajectories and hierarchical illustrations of cell spaces in a building, the proposed model incorporates OGC (Open Geospatial Consortium) IndoorGML standard and multi-layer space model. Further, the proposed model makes use of three temporal, structural and

Table 8
Analysis of distinct technologies in the prevention of COVID-19 through social distancing measures.

Author & year	Technology	Focused Area	Limitations	Ref
Yang et al. & 2020	AI technology	Social distancing detection and warning system	Pedestrians were not considered	[90]
Soures et al. & 2020	Hybrid Neural Network model	Impact of social distancing measures in controlling COVID-19 infection	Rapid changes in the dataset may affect the results	[91]
Broniec et al. & 2020	AI tool (VERA)	Effect of social distancing measures to control COVID-19 infection	Supports only conceptual modelling	[92]
Punn et al. & 2020	Yolo V3 and Deepsort techniques	Monitoring of Social distance	Privacy and individual rights have not been addressed	[93]
Ahmed et al. & 2020	Deep Learning based Platform	Tracking of Social distancing	Not implemented in indoor and outdoor environment	[94]
Fazio et al. & 2020	IoT-based Bluetooth Low Energy (BLE)	Tackling social distancing measures using Proximity-based indoor navigation system	Algorithms not used for detecting best navigation path	[95]
Alrashidi et al. & 2020	Intelligent IoT system	To control the locations and movement in Indoor Spaces	The constraint of existing obstacles is not explored	[96]
Nadikattu et al. & 2020	Novel smart device	Senses distance between individuals and triggers alarm when the person in the range is having symptoms	Accuracy of system can be further increased by increasing the design of the sensor	[97]
Fedele et al. & 2020	IoT -WSN	Monitoring social distancing and Emergency management	Not implemented using low computational devices such as microcontrollers	[98]
Visal et al. & 2020	OpenCV + Deep Learning + Drones	Monitoring of social distancing	Controlling large mob is not an easy task	[99]
Ramadass et al. & 2020	Automated Drone	Controlling social distancing in public places	Privacy of the individual is not addressed	[100]
Garg et al. & 2020	Block-chain based system	For implementing social distancing for prolonged period	Depends on participants possessing and operating a smartphone	[101]
Rusli et al. & 2020	GPS technology based MySD	Monitors the distance between individuals and alerts signal	Depends on the participants usage of MySD	[102]

circumstantial hierarchical structures to provide various granularity levels for trajectory representation of data. The following Table 9 represents the analysis of COVID-19 contact tracing using different technologies.

3.4.3. Prevention of COVID-19 through face mask

As COVID-19 infection is disseminated through airdrops and close contact, Governments have implemented new rules for public to wear face masks. The main objective of wearing mask is to minimize the dissemination rate. A comprehensive review on wearing in controlling the spread rate of coronavirus infection, technical details of manufacturing commercial and home-made mask and the recent developments in mask engineering and materials has been performed by Chua et al. [110]. A deep learning based model known as Facemasknet has been developed by Inamdar and Ninad [111] for the identification of persons wearing mask, not wearing mask and improperly worn mask. The proposed approach works on both still images and live video streams. To detect face mask, a novel hybrid based on deep and conventional machine learning approaches has been presented by Loey et al. [112]. The proposed model contains two components. The first component consists of Resnet50 for extracting features, while the second component makes use of machine learning approaches such as decision trees, support vector machine and ensemble algorithms to classify the mechanism of face masks. To detect the ser-

vice stage of mask being used, a detection model depending on mobile microscope has been presented by Chen et al. [116]. Initially, the proposed model extracts the four features such as contrast, correlation, energy and homogeneity from the microphotos of face masks by utilizing gray level co-occurrence matrixes (GLCMs). Afterwards, the K Nearest Neighbor (KNN) algorithm is enforced to identify the service stage of the mask being utilized. The empirical results reveal that the proposed model attains an accuracy of 98.6% in the detection of facemask. The analysis of different technologies used in the detection of face mask has been described in Table 10.

4. Critical investigation

A systematic review of articles related to combating COVID-19 has been carried out in this study. From the analysis, it is observed that the strategies such as diagnosis of COVID-19 using medical images, prediction of COVID-19 using forecasting models, development of drugs and vaccine in the treatment of COVID-19 and prevention of COVID-19 using social distancing measures, face mask and contact tracing have been used in controlling and management of the COVID-19 pandemic. In this section, a systematic analysis of the type of data and technologies used in combating COVID-19 has been presented. Further, it also presents a graphical analysis of

Table 9
Analysis of COVID-19 contact tracing using distinct technologies.

Author & year	Technology	Performance of the model	Limitations	Ref
Garg et al. & 2020	IoT and Blockchain technology	To deploy prototype, average cost =$1.95 To call functions, average cost =$0.34	not implemented the concept of security	[105]
Roy et al. & 2020	IoT technology	Efficiently tracks the infected individual and also used for tracing back all exposed people	Limited to simulation-based experiments only	[106]
Hu and Peng, 2020	IoT technology	Effectively tracks the infected individual even in the presence of lockdown measures.	confined to simulation-based experiments only	[107]
Polenta et al. & 2020	BubbleBox	Maximizes the coverage area of contact tracing	Not assessed the acceptability of the wristband among the users	[108]
Ojagh et al. & 2020	Graph-based data model	Average execution time of person-to-place contact tracing enhances by 58.3%.	Focused only on indoor environments	[109]

Table 10
Analysis of technologies used in the detection of face mask.

Author & year	Technology	Performance of the model	Limitations	Ref
Loey et al. & 2020	Hybrid Deep Transfer learning model	For Real-World Masked Face Dataset (RMFD), accuracy = 99.64%, for Simulated Masked Face Dataset (SMFD), accuracy = 99.49%, for Labeled Faces in the Wild (LFW) accuracy = 100%	conventional machine learning methods also attains high accuracy	[112]
Loey et al.& 2020	ResNet-50 + YoloV2	Precision percentage of adam optimizer = 81%	Cannot detect face mask from images and videos	[113]
Chowdary et al. & 2020	Inception V3	Accuracy = 100%	–	[114]
Militante et al. & 2020	VGG16 model with alarm system	Accuracy = 96%	Not compared with other pretrained models to show the efficiency of the system	[115]
Chen et al. & 2020	Service stage based on Mobile phone	Precision = 82.87%	Not considered the conditions that affect the usage life of face mask	[116]
Yadav et al. & 2020	Computer vision + MobileNet V2	Precision score = 91.7%	–	[117]
Mundial et al. & 2020	Machine Learning approach	Accuracy = 97%	Does not accomplish registration of masked face	[118]

number of articles published in COVID-19 research using type of data, technology, strategy used in combating COVID-19 and distinct approaches used in prediction of COVID-19.
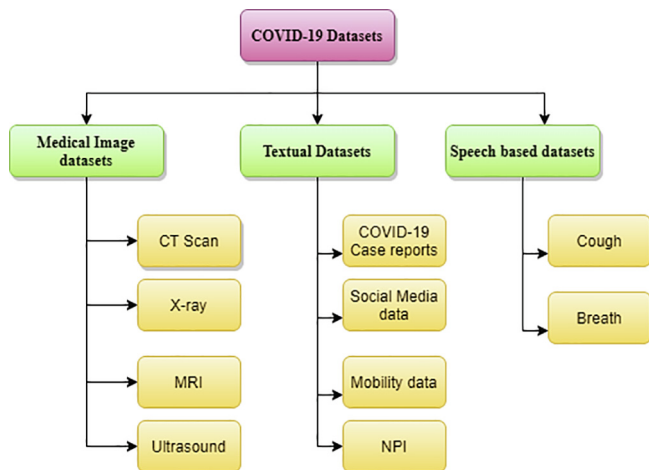
Fig. 2. COVID-19 datasets.

4.1. Type of data utilized in the research of COVID-19

The datasets utilized in the diagnosis, prediction and prevention of COVID-19 infection are basically categorized as medical image datasets, textual datasets and Speech based datasets as shown in Fig. 2. The applications of COVID-19 dataset are depicted in Fig. 3. The medical image datasets such as chest CT, X-ray, MRI and ultrasound radiographs are basically used in the automated diagnosis, segmentation and augmentation of COVID-19. The COVID-19 textual data can be used for forecasting and visualizing of COVID-19 cases, studying the impact of mobility and non-pharmaceutical interventions (NPI) on the COVID- 19 cases and for estimating the transmission analysis at regional level. Further, the speech-based dataset that includes breath and cough signals are used in the diagnosis and prediction of COVID-19 severity.

The following Table 11 represents the comparative analysis of medical, textual and speech-based datasets in terms of application, datatype and method.

4.1.1. Challenges of COVID-19 dataset

Due to the rapid spread of COVID-19 infection, the availability and openness of data is considered as the key barrier in the COVID-19 research. The real-world applications will be possible only with the availability of more open source data. The following are some of the challenges of COVID-19 datasets that needs to be addressed for further enhancing the COVID-19 research.
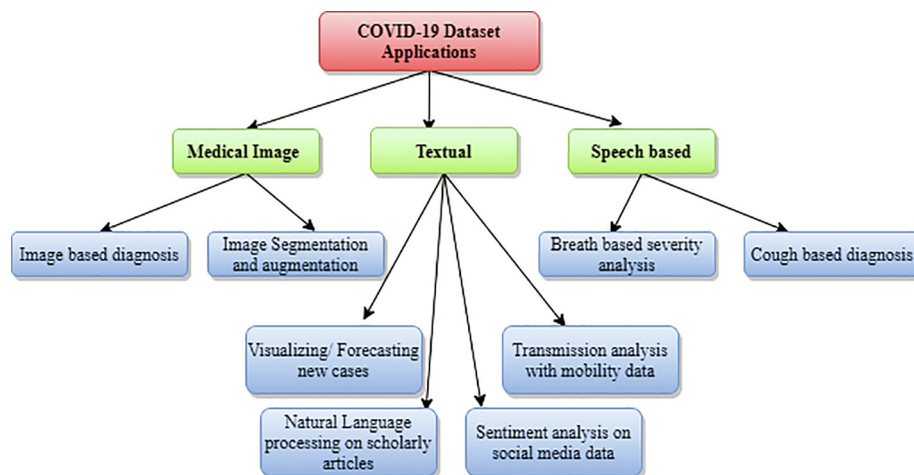

Fig. 3. COVID-19 dataset applications.

Table 11
Analysis of datasets used in COVID-19 research.

Dataset	Datatype	Application	Method	Study & Ref
Medical image	X-ray & CT CT X-ray	COVID-19 Diagnosis	Deep CNN and Transfer learning	Cohen et al. [119] Zhao et al. [120]. Wang et al. [121] Hemdan et al. [122], Apostolopoulos and Mpesiana [123]
	X-ray Ultrasound	COVID-19 Diagnosis	CNN	Narin et al. [124], Chowdhury et al. [125] Born et al. [126]
	X-ray	COVID-19 Diagnosis	CNN + SVM	Sethy and Behera [127], Hussain and Khan [128]
	CT	COVID-19 Segmentation	CNN	Shan + et al. [129], Jun et al. [130], Bai et al. [131], Pandey et al. [132]
Textual data	COVID-19-cases	Community transmission	Expectation-maximization Maximum likelihood fitting and the Akaike information criterion Bayesian approach	Tindale et al. [133] Du et al. [134] Nishiura et al. [135]
	COVID-19 statistics	COVID-19 visual Analysis COVID-19 spread	Exploratory data analysis ARIMA	Dey et al. [136] Benvenuto et al. [137]
	Epidemiological data set	Transmission analysis	Statistical	Kraemer et al. [138], Anzai et al. [139]
	Tweets	Social dynamics data Perception and policies	Statistical analysis Proposed NLP, data mining	Banda et al. [140] Lopez et al. [141]
	Mobility	Predicting COVID-19 COVID-19 Forecasting and Management	Partial differential equation –	Wang et al. [142] Ilin et al. [143]
	NPI	Investigate NPI stringency	–	Hale et al. [144]
Speech based	Breath samples Voice data	Lung disease classification Cough based COVID-19 diagnosis	Stacked AutoEncoders, LSTM & CNN Deep and ML classifiers	Trivedy et al. [145] Imran et al. [146]

- Most of the data and code utilized for the analysis of COVID-19 infection is closed source data. Therefore, more efforts to augment existing data with clinical data and self-testing applications such as breath and cough data are needed for the efficient COVID-19 analysis.
- Another key challenge is the amalgamation of the COVID-19 data sets. Therefore, standards and protocols together with international associations are needed for the amalgamation of datasets.
- As most of the data comes from China and European countries, it may cause selection bias when utilized same data in the analysis of COVID-19 in other countries.
- Most of the studies [29,30] reveal that RT-PCR is the primary approach of diagnosis and medical imaging remains as secondary diagnosis approach due to the limited availability of RT-PCR kits. Therefore, further research is required to establish a relation between RT-PCR test and medical radiographs.
- As large datasets are required to develop more accurate models, collaboration and labeling of large datasets is necessary for the diagnosis of COVID-19
- As only one speech-based dataset is available for the diagnosis of COVID-19, only limited research has been performed. Therefore, there is need for the collaboration of more speech-based dataset to further enhance the research.
- The important issue in the textual data is the timeliness of the research, as most of the social media data collected for analysis becomes outdated very fastly.

4.1.2. Distribution of articles in COVID-19 research based on type of COVID-19 data

The following Fig. 4 depicts the distribution of articles based on type of COVID-19 dataset. From the figure, it is noted that majority of the research i.e., 68.3% has been performed using medical data. Next, 17.1% of the research has been carried using textual data. Only 14.5% of research has been carried using speech-based dataset. Among the medical data, majority of the research i.e., 35.8%
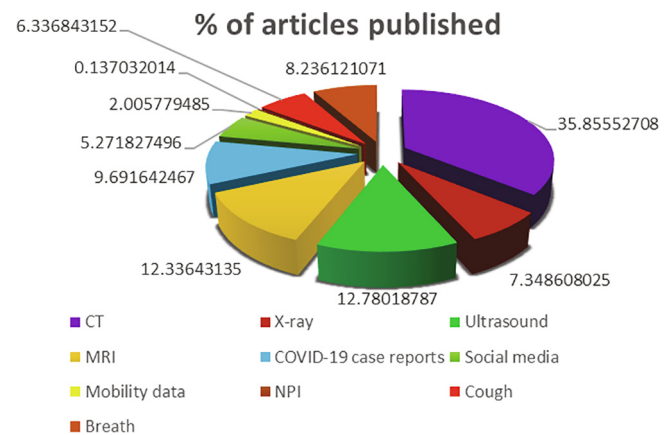

Fig. 4. Distribution of articles based on type of COVID-19 dataset.

of work has been carried using CT radiographs. Using textual data, majority of the research has been done using COVID-19 case reports i.e., 9.69%. while less research has been carried using NPI dataset i.e., 0.13%. In speech-based dataset, 7.3% of work has been performed using breath signals.

4.2. Comparative analysis of emerging technologies used in combating COVID-19

Based on the systematic review of literature, the technologies used in combating COVID-19 has been depicted in Fig. 5 and the comparative analysis of emerging technologies along with their application and challenges has been describe in Table 12.

4.2.1. Distribution of articles in COVID-19 research based on the technology

The distribution of articles based on the type of technology has been depicted in the Fig. 6. It has been observed from the figure
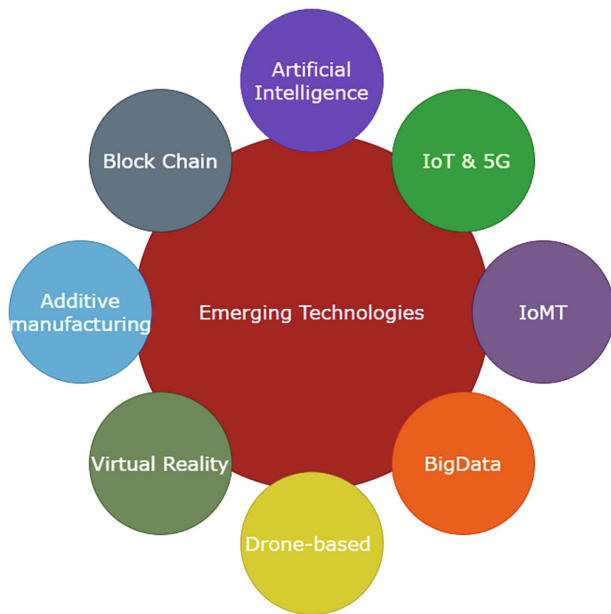
Fig. 5. Emerging technologies in combating COVID-19.

that 46.54% of research in combating COVID-19 has been performed using the AI technology. Next, majority of the work has been published using the technology of Bigdata. Due to the limitations such as high cost, privacy and security issues, less work has been accomplished using other technologies such as virtual reality, IoT, 5G, drone-based, additive manufacturing, blockchain and IoMT technology.

4.3. Efficiency of diagnosis models

It has been observed from the systematic review of strategies used in battling COVID-19 pandemic that majority of the diagnosis models using medical images have been developed using the machine learning and deep learning approaches. Among the deep learning approaches, the CNN approach that has the capability of extracting features automatically has been widely used in the diagnosis of COVID-19 pandemic. In addition to the CNN approach, distinct pretrained network models have also been successfully utilized in the segmentation, feature extraction and categorization of COVID-19 medical images. Among the pretrained network models, it is observed that DenseNet121, ResNet50, ShuffleNet have been successfully utilized in the classification of COVID-19 medical images. For segmentation of the COVID-19 images, UNet++ framework produces successful results. Besides deep learning approaches, some researches have applied machine learning approaches to extract the features from the results. As machine learning approaches produces high recognition accuracy, it results in the advantage by means of learning speed. The following Table 13 illustrates the analysis of different deep learning approaches used in the diagnosis of COVID-19 medical images.

Figs. 7 and 8 depict the performance analysis of distinct customized and pre-trained DL approaches used in the detection of COVID-from CT and X-ray images.

4.3.1. Distribution of articles in COVID-19 research based on the strategies used in battling COVID-19 pandemic

The distribution of articles in COVID-19 research based on the strategies used in controlling the spread of COVID-19 pandemic has been depicted in Fig. 9. From the figure, it is noticed that 41.4% work in controlling the spread of COVID-19 pandemic has

been carried out in the diagnosis of COVID-19 using medical radiographs. After the strategy diagnosis of medical images, 39.8% research has been carried using the prediction models which results in the forecasting of transmission analysis and COVID-19 cases. Less research work has been carried out in the development of drug and vaccine and preventive measures used in inhibiting the dissemination of infection.

4.3.2. Challenges of deep learning approaches in the diagnosis of COVID-19 medical radiographs

There are many challenges that arise in the application of deep learning approaches in the detection of novel coronavirus from the medical images which need to be addressed to further develop more robust models. Basically, the deep learning approaches requires large amount of data to develop potential systems for the detection of novel coronavirus. As COVID-19 research is the latest research, only limited size datasets are available. Therefore, the major challenge in the development of robust diagnosis models is the lack of standard datasets. Though large number of diagnosis models is developed, it is difficult to judge which models results in better results. This is mainly due to the fact that most of the models used data from internet sources which consist noisy, ambiguous and unreliable labels. Most of the developed models have not considered the demographic and clinical information of the inmates to determine the efficiency of the models. Another challenge observed in the deep learning-based diagnosis models is the lack of confidence interval.

4.3.2.1. Case study on the impact of data on the efficiency of diagnosis of medical radiographs using deep learning approaches. In this section, how the nature of the data affects the efficacy of the diagnosis models has been presented. The overall framework of the proposed models in case study A and B are depicted in the Fig. 10 and the list of parameters used in training phase of the proposed model is represented in Table 14.

Case study A (considering online data): In this cases study, the medical image dataset consisting of 1252 Covid-19 images and 1240 Non-Covid-19 images is considered from Kaggle [194]. Then the pretrained models such as VGG16, DenseNet121, MobileNetV2, Xception and Inception V3 has been evaluated on the considered dataset with le-3 learning rate, 32 batch size, binary cross entropy as loss function. The models have been evaluated for 30 epochs and the best scores of the models has been analyzed using the evaluation metrics such as accuracy, sensitivity, and specificity. The following Fig. 11a–c represents the comparative analysis of the evaluation metrics used in determining the effectiveness of the pretrained models and Fig. 11d and 11e represents the loss and accuracy curve of VGG16 model [195].

Case study B (Considering original medical data from Hospital): In this cases study, the medical image dataset consisting of 600 Covid-19 images and 600 Non-Covid-19 images is considered from Govt Hospital of Tekkali. Then the pretrained models such as VGG16, DenseNet121, MobileNetV2, Xception and Inception V3 has been evaluated on the considered dataset with le-3 learning rate, 32 batch size, binary cross entropy as loss function. The models have been evaluated for 30 epochs and the best scores of the models has been analyzed using the evaluation metrics such as accuracy, sensitivity and specificity. The following Fig. 12a–c represents the comparative analysis of the evaluation metrics used in determining the effectiveness of the pretrained models and Fig. 12d and e represents the loss and accuracy curve of VGG16 model.

From the case studies, it can be observed that the performances of the models such as VGG16, DenseNet121, MobileNetV2, Xception and InceptionV3 has been enhanced in terms of accuracy,

Table 12

Comparative analysis of emerging technologies used in combating COVID-19 disease.

Technology	Description of technology	Application of technology	Challenges
Artificial Intelligence	AI is a robust mechanism that enables the computers to learn and think [6].	Detection of COVID-19 from medical radiographs. Segmentation and quantitative assessment of COVID-19 medical images Tracking and predicting of COVID-19 cases and transmission	Limited access to COVID-19 data. Unable to detect COVID-19 individuals having asymptomatic condition.
IoT & 5G	The IoT is defined as the establishment of connection between services and semantics through wireless protocols and the support for global mobile networks is provided by 5G technology [6]	Monitoring of patients in quarantine and isolation from remote area Collecting of COVID-19 symptoms from remote locations and providing online consultancy Tracking of quarantined individuals	Use of IoT results in privacy issue of the patient. Implementation of 5G technology requires large amount of capital. In developing countries, deployment of IoT and 5G technology might be expensive
IoMT	The IoMT, also known as the healthcare IoT, is defined as the integration of medical devices and software applications for providing extensive healthcare services [147]	Monitoring of patients in quarantine and isolation from remote area Providing online consultation by collecting symptoms of suspected and infected patients from remote locations Provides additional health services that can be easily combined with IoMT platforms such as counseling service Amalgamation of electronic records of COVID-19 suspected/infected patients as they travel from one country to another	Results in privacy and security issue of the individuals. Requires data interoperability and standardization of COVID-19 datasets.
BigData	Bigdata is a discipline that analyzes and extracts information and features from large and complex data that cannot be traditionally processed with application software [148].	Used for storing and processing large amount of data to track COVID-19 cases. Provides real-time access to researchers and epidemiologist for doing research on COVID-19 data	Results in security and privacy issues
Drone-based technology and autonomous robots	Drone technology is like a flying robot controlled by a software application. Both drone and autonomous robots perform specific responsibilities without human intervention [6].	For controlling social distancing in crowd places. For delivering medication to COVID-19 infected patients. For collecting samples from COVID-19 infected patients.	No clear regulations and policies on the utilization of drones in healthcare system are issued by the WHO Results in privacy issue of individuals.
Blockchain technology	Blockchain is defined as a transaction record among two parties [6].	Ensures delivery of medication to COVID-19 patients Provides knowledge of self-testing for COVID-19 infected patients.	Results in scalability problem. Lack of knowledge about the integration of blockchain technology in healthcare system
Virtual reality	Virtual reality is a technology used to create a simulated real time environment [148].	Supports training of healthcare professionals. Provides awareness about COVID-19 transmission, preventive measure and symptoms of COVID-19 infection Supports treatment for psychological problems	Cost is high. Less number of experts are available to configure virtual reality systems.
Additive Manufacturing	Additive manufacturing is an emerging field that assist in the design of medical equipment which can supply needed materials at lower costs [148].	3D printing is used for the production of mask and personal protective Noncontact 3D scanning assist in the thoracic chest scanning of COVID-19 infected individuals.	Cost is high and results in scalability problem

sensitivity, and specificity when considered the original medical radiographs.

4.4. Efficiency of prediction models

Since the surge of the COVID-19 outbreak, the number of cases is increasing exponentially all over the world. Therefore, large number of prediction models [166–169] has been developed by several researchers and modeling groups across the world using the concept of mathematical, statistical and intelligent computing approaches. Basically, these models are used to forecast the COVID-19 trends across the world such as mortality rate, infected cases, effect of social distancing measures, resource allocation at hospitals, impact of travelling restrictions and so on which may further help the government and healthcare sector to take appropriate actions for controlling and managing the COVID-19 pan-

demic. These models have exhibited a lot of deviations in the predictions. This is mainly due to the uncertainty of data. The lack of reliable data because of the frequent partition of data over distinct geographical areas and availability of small amount of information at the beginning stage of pandemic is one of the reasons for failure of forecasting models. Most of the prediction models assume homogeneity. That means the models assume that all people have equal chance of infecting other people. Therefore, making wrong assumptions in modelling is another reason for the failure of the models. Most of the prediction models forecasted the predictions by considering only confirmed cases. Not considering the asymptomatic inmate's data in modelling is another reason for the failure of the model. The prediction models used for forecasting mortality rate have considered only the number of deaths. These models have not considered other factors like age and comorbidities. Therefore, lack of inclusion of epidemiological features is
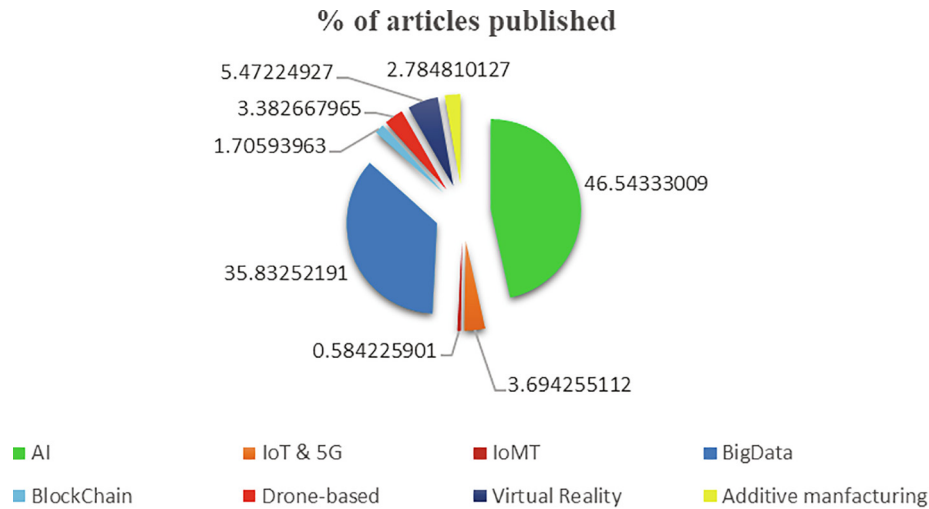
% of articles published

5.47224927
2.784810127
3.382667965
1.70593963
46.54333009
35.83252191
0.584225901
3.694255112

- ■ AI
- ■ IoT & 5G
- ■ IoMT
- ■ BigData
- ■ BlockChain
- ■ Drone-based
- ■ Virtual Reality
- ■ Additive manfacturing

Fig. 6. Distribution of articles based on technology.

considered as another drawback for the failure of prediction models. Most of the models are stochastic in nature. These models require large number of iterations which may result in different estimates. So, lack of determinacy is another reason for the variations in the prediction results. As majority of the models have not appeared in the peer-literature review, lack of transparency is another drawback in the failure of prediction models. These reasons need to be addressed in future for the development of accurate prediction models.

4.4.1. Contribution of distinct approaches in the prediction of COVID-19 pandemic

From the start of the pandemic, several approaches such as mathematical, statistical, machine and deep learning have been used in the development of COVID-19 prediction models by various researchers and modeling groups. The following Fig. 13 depicts the contribution of different approaches in the development of COVID-19 prediction models. From the figure, it is evident that 40.8% of prediction models have been developed using machine learning approaches. After machine learning approaches, majority of the prediction models has been developed using deep learning approaches i.e., 29.9%. Next, mathematical models and statistical approaches have contributed 19.9% and 9.3% respectively in the development of COVID-19 prediction models.

4.5. Usage statistics of COVID-19 contact tracing apps

The following Fig. 14 shows the usage statistics of distinct COVID-19 contact tracing apps as of October 30, 2020 [170]. The Ehteraz app developed by Qatar has the maximum penetration rate of 91%. The TraceTogether, COVIDSafe and Smittestopp developed by Singapore, Australia and Norway have better penetration rate due to its smaller population. Even though Arogya Setu app developed by India is the most downloaded app, it ranks 15th position because of its dense population.

4.6. Analysis of the distinct vaccine production platforms used in COVID-19 vaccine development

Many efforts have been made towards the vaccine development for COVID-19 in order to control the pandemic. The following Table 15 describes the distinct vaccine production platforms used in the development of COVID-19 along with their limitations and advantages [28]. Fig. 15 displays the statistics of different COVID-19 vaccines under research [28].

5. Future research issues and challenges

In this section, we outline some cross cutting challenges and future issues in combating Covid-19 using intelligent approaches.

5.1. Limitations in data

The models developed for combating COVID-19 using intelligent approaches produces accurate results if they utilize abundant and high-fidelity data. It is evident from the study, that most of the use cases specified above are not making use of extensive labelled datasets. Even though some public datasets are available for medical radiographs diagnosis, the size of these datasets are small when compared with the requirements of the intelligent approaches. This is mainly due to the segregation of data at national, regional and hospital level. Therefore, the key challenge is to develop a common platform for the researchers for sharing and accessing the data across nations, regions and hospital levels. It is also essential to establish the standards while collecting data from different sources. In addition, most of these datasets suffer from noise. So, noise reduction is another key challenge in the successful implementation of models developed using intelligent approaches. Moreover, most of the works considered only few parameters such as lockdown policy, weather etc. in estimating the transmission rate of COVID-19 epidemiology. Therefore, a comprehensive study considering all the parameters that influence the reproductive rate should be performed to produce more accurate prediction models of epidemiology.

5.2. Need for accuracy of results and transparency of information

As most of the studies are performed using quickly produced datasets, there is chance of existing hidden risk in all the scientific works done in combating COVID-19. The presence of hidden risk may result in biases in the outcomes of the research which may affect the policies used in battling the Covid-19 infection. Therefore, the key challenge in the accuracy of prediction is to determine the uncertainty of conclusions and to provide reproducible conclusions.

To make accurate predictions and to take correct actions, it is essential to produce quality and relevant data to the public.

Table 13
Comparative analysis of different deep learning approaches used in the diagnosis of COVID-19 medical images.

| Author & Ref	Approach	Type of image	Number of Images	Task (Type)	Partitioning ratio	Performance
Jin et al. [149]	ResNet152	CT	COVID-19 positive = 496, COVID-19 negative = 1385	Classification	Random partition	Accuracy = 94.98, Sensitivity = 94.06, Specificity = 95.47, Precision = 91.53, F1-Score = 92.78, AUC = 97.91
Li et al. [150]	ResNet50	CT	COVID-19 = 1296, CAP = 1735, non-pneumonia = 1325	Classification	Training = 90, Testing = 10%	Sensitivity = 90, Specificity = 96, AUC = 96
Yousefzadeh et al. [151]	Ai-corona	CT	COVID-19 = 706, non-COVID-19 = 1418	Classification	Training = 80% Validation = 20%	Accuracy = 96.4, Sensitivity = 92.4, Specificity = 98.3, F1-Score = 95.3, AUC = 98.9, Kappa = 91.7
Chen [152]	U-Net++	CT	46,096	Segmentation	Random partition	Accuracy = 95.24%, Sensitivity = 100%, Specificity = 93.55%
Ardakani et al. [153]	AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101, Xception	CT	COVID-19 = 510, non-COVID-19 = 510	Classification	Training = 80% Validation = 20%	Accuracy = 99.51, Sensitivity = 100, Specificity = 99.02, Precision = 99.27, AUC = 99.4,
Cifci [154]	AlexNet, Inception-V4	CT	5800	Classification	Training = 80%, Validation = 20%	Accuracy = 94.74, Sensitivity = 87.37, Specificity = 87.45
Loey et al. [155]	GAN, Alexnet, Googlenet, Resnet18	X-ray	COVID = 69, normal = 79, pneumonia_bac = 79, pneumonia_vir = 79	Classification	Training = 80%, Testing = 10%, Validation = 10%	Accuracy = 100, Sensitivity = 100, Precision = 100, F1-Score = 100
Gozes [156]	U-Net, ResNet	CT	157 patients	Segmentation	Random partition	AUC = 99.6%, Sensitivity = 98.2%, Specificity = 92.2%
Ozcan [157]	GoogleNet, ResNet18, ResNet50	X-ray	COVID-19 = 131, bacteria = 242, normal = 200, virus = 148	Classification	Training = 50%, Testing = 30%, Validation = 20%	Accuracy = 97.69, Sensitivity = 97.26, Specificity = 97.90, Precision = 95.95, F1-Score = 96.60
Apostolopoulos and Mpesiana [123]	VGG19, MobileNetv2, Inception, Xception, Inception-ResNetv2	X-ray	COVID-19 = 224, pneumonia = 714, normal = 504	Classification	10-fold cross-validation	Accuracy = 96.78, Sensitivity = 98.66, Specificity = 96.46
Minaee et al. [158]	ResNet18, ResNet50, SqueezeNet, DenseNet-121	X-ray	COVID-19 = 71, non-COVID = 5000	Classification	Training = 40% Testing = 60%	Sensitivity = 100, Specificity = 95.6, AUC = 99.6
Bukharia et al. [159]	ResNet50	X-ray	COVID-19 = 89, normal = 93, pneumonia = 96	Classification	Training = 80% Testing = 20%	Accuracy = 98.18, Sensitivity = 98.24, Precision = 98.14, F1-Score = 98.19
Farid et al. [160]	CNN	CT	COVID-19 = 51, SARS = 51	Classification	10-fold cross-validation	Accuracy = 94.11, Precision = 99.4, F1-Score = 94, AUC = 99.4
Singh et al. [161]	MODE-CNN	CT	COVID-19 positive = 75, COVID-19 negative = 75	Classification	Various proportions of training and testing dataset	Accuracy = 93.25, Sensitivity = 90.70, Specificity = 90.72, F1-Score = 89.96, Kappa = 90.60
Elghamrawy and Hassanien [162]	WOA-CNN	CT	COVID-19 = 432, viral pneumonias = 151	Classification	Training = 65%, Testing = 35%	Accuracy = 96.40, Sensitivity = 97.25, Precision = 97.3
Khan et al. [163]	CoroNet (CNN)	X-ray	COVID-19 = 284, normal = 310, pneumonia bacterial = 330, pneumonia viral = 327	Classification	Training = 80%, Validation = 20%	Accuracy = 89.5, Sensitivity = 100, Precision = 97, F1-Score = 98
Rahimzadeh and Attar [164]	Concatenated CNN	X-ray	COVID-19 = 180, pneumonia = 6054, normal = 8851	Classification	5-fold cross-validation	Accuracy = 99.50, Sensitivity = 80.53, Specificity = 99.56, Precision = 35.27
Mukherjee et al. [165]	Shallow CNN	X-ray	COVID-19 = 130, non-COVID = 130	Classification	5-fold cross-validation	Accuracy = 96.92, Sensitivity = 94.20, Specificity = 100, Precision = 100, F1-Score = 97.01, AUC = 99.22
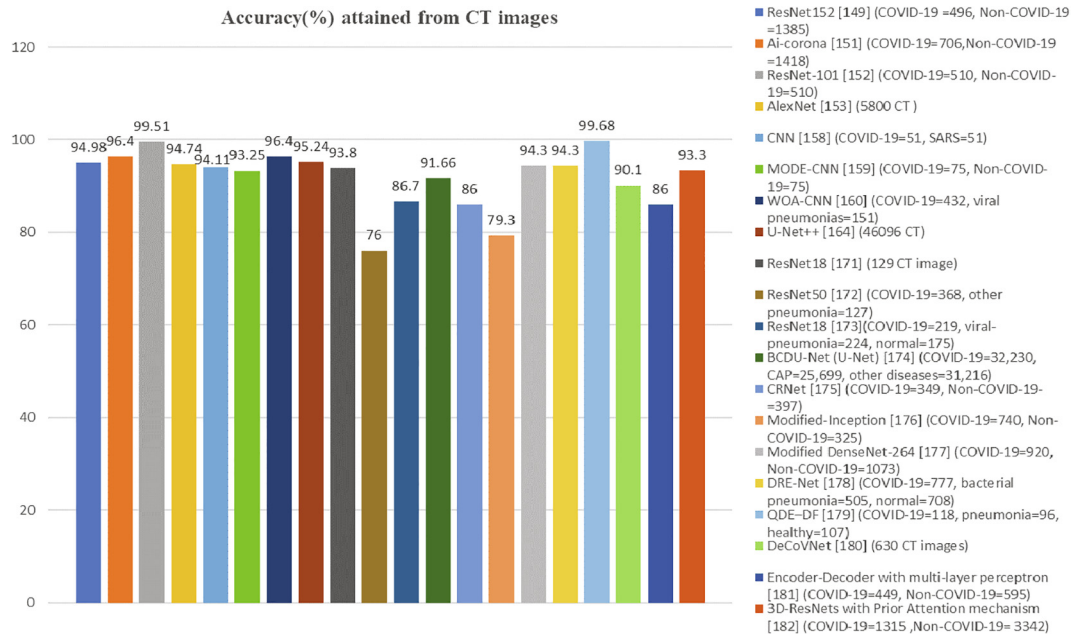
Fig. 7. Analysis of Accuracy (%) attained from CT images using distinct DL approaches.
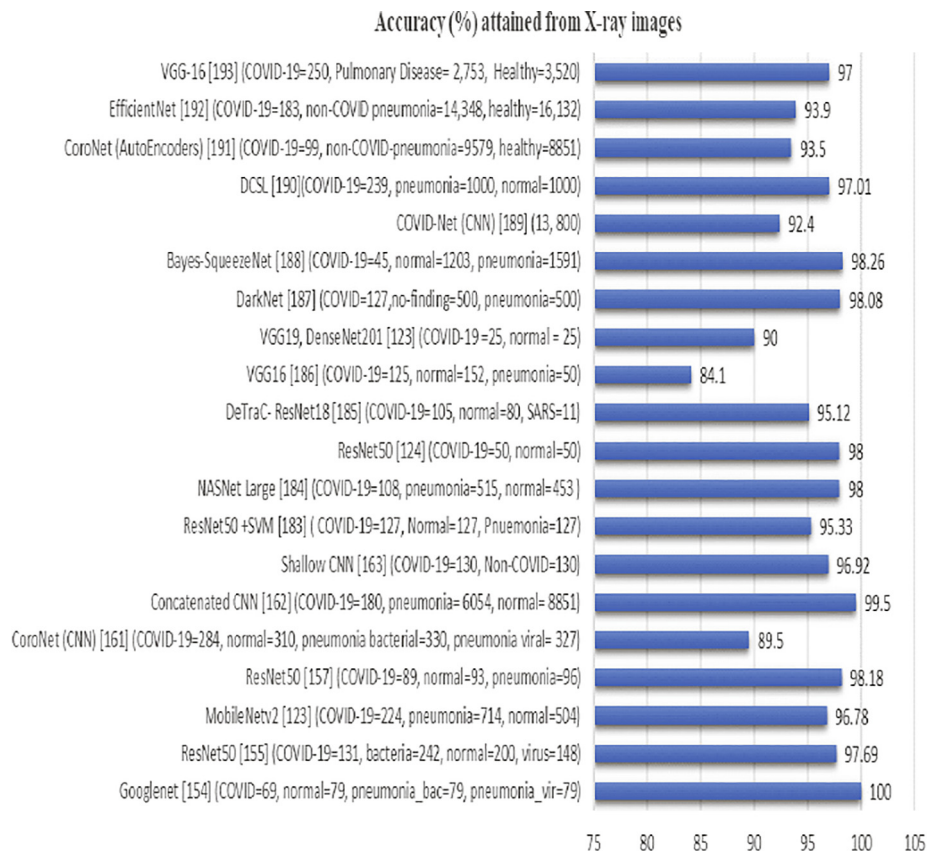

Fig. 8. Analysis of Accuracy (%) attained from X-ray images using distinct DL approaches.

However, the data collected from the social media and crowd-sourcing remains a challenge because of the lack of standards and guidelines in uploading the data from these sources. Therefore, the key challenge is to provide transparent information to the public by uploading quality and appropriate information in the social media.

5.3. Need of developing symptom based intelligent systems.

As the characteristics of coughing are different from the characteristics of other pneumonia, it can be considered as one of the symptoms in accurately determining the Covid-19 infection patients. Therefore, there is need to carry out more research using
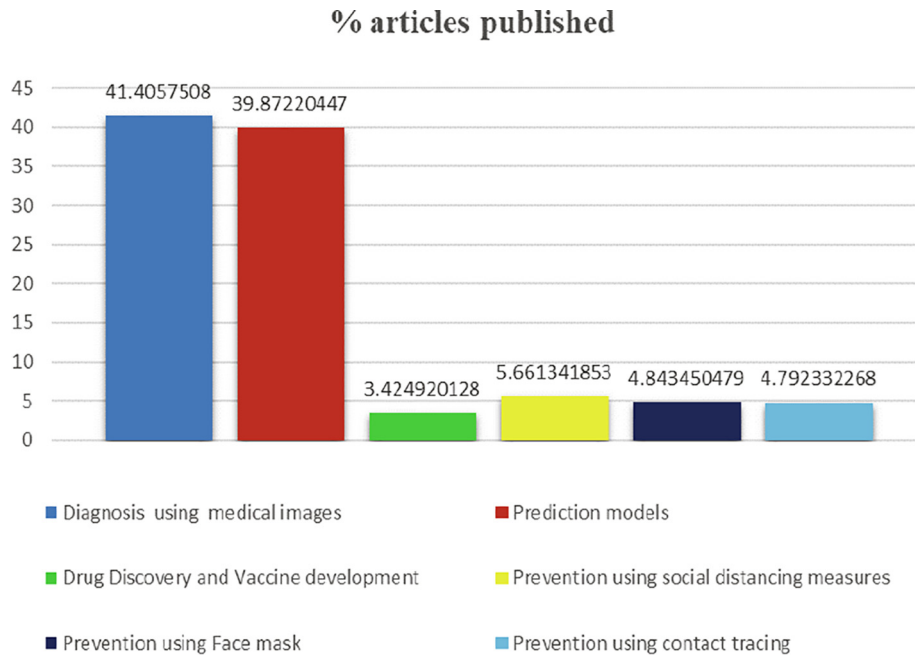
Fig. 9. Distribution of articles based on strategies used in combating COVID-19.
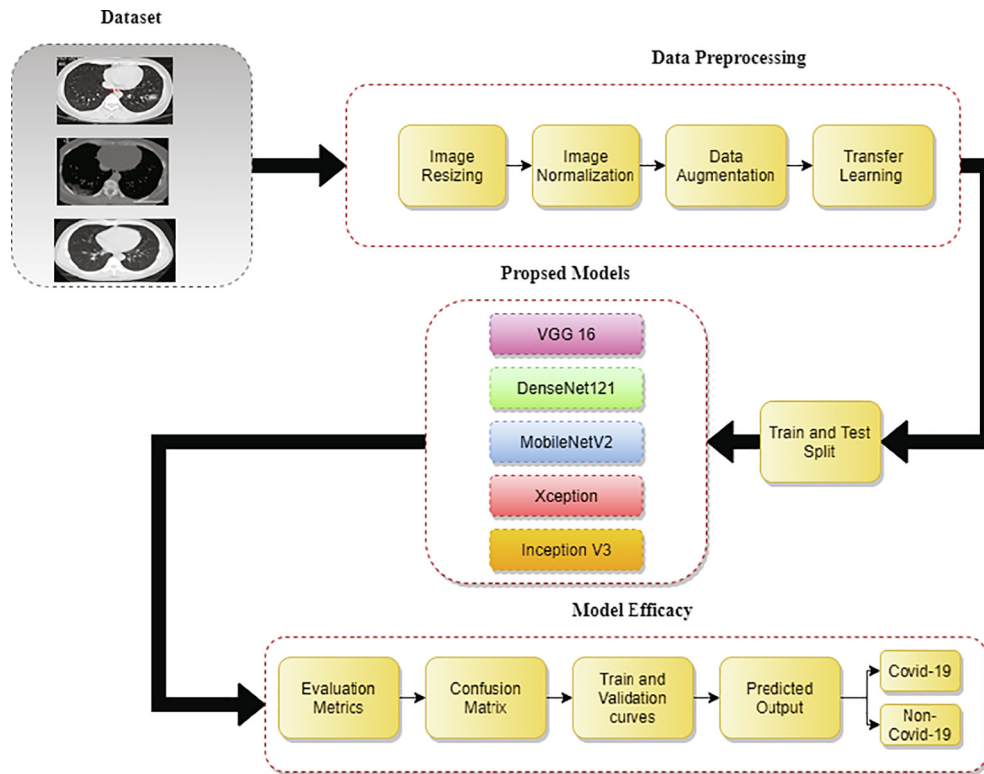
Fig. 10. Overall framework of the proposed models.

coughing signals to develop accurate models for the detection of Covid-19 infection.

It is observed from the studies that the majority of the work has been accomplished by considering the characteristics of Covid-19 and other pneumonia infection from medical images. These studies have not considered factors like age, gender and comorbidities. Therefore, amalgamation of demographic and clinical characteristics along with the diagnosis of medical images results in the

development of accurate models for the detection of Covid-19 infection.

5.4. Necessity of developing advanced intelligent approaches

The devices such as smart watches and wearable devices can be used to collect the travelling history or measure the symptoms of people. This data can be further used by the AI systems to provide

Table 14
Parameters used for Training model.

Training Parameters	VGG16	DenseNet121	MobileNetV2	Xception	InceptionV3
Learning rate	le-3	le-3	le-3	le-3	le-3
Batch Size	32	32	32	32	32
Loss Function	Binary Cross-entropy	Binary Cross-entropy	Binary Cross-entropy	Binary Cross-entropy	Binary Cross-entropy
Epochs	30	30	30	30	30
Horizontal Flipping	True	True	True	True	True
Vertical Flipping	False	False	False	False	False
width_shift_range	0.2	0.2	0.2	0.2	0.2
height_shift_range	0.2	0.2	0.2	0.2	0.2
Rescaling	1/255	1/255	1/255	1/255	1/255
Rotation range	15	15	15	15	15
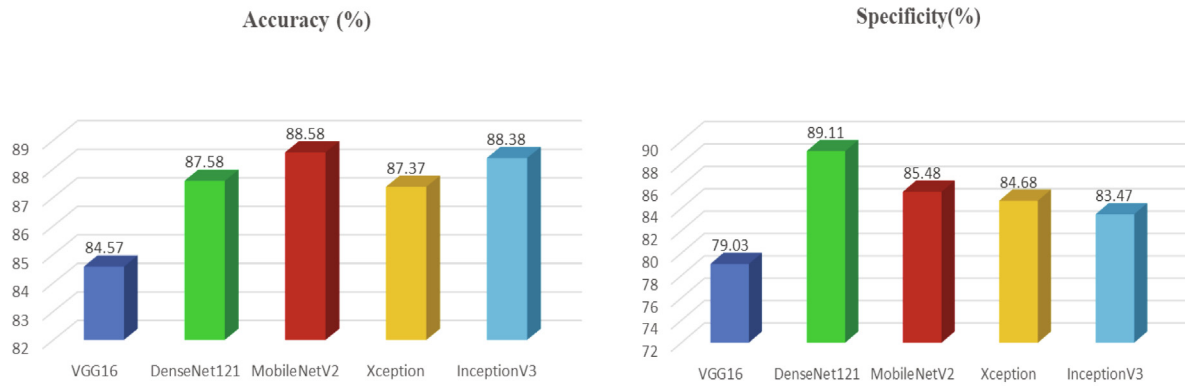
(a) Accuracy

(b) Specificity
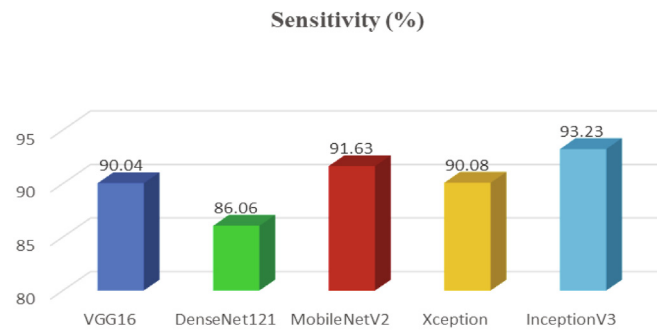
(c) Sensitivity
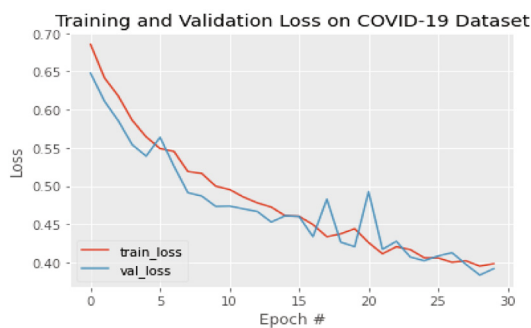
(d) Loss curve of VGG16
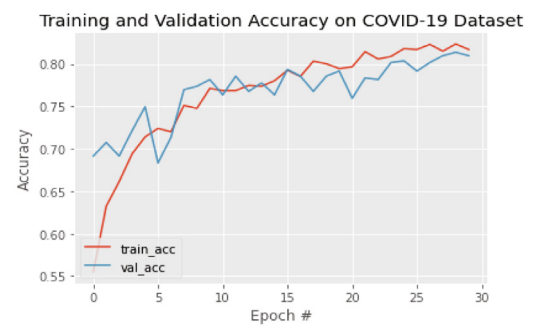
(e) Accuracy curve of VGG16

Fig. 11. Comparative analysis of evaluation metrics of distinct pretrained models for online data.

(a) Accuracy

(b) Specificity

(c) Sensitivity

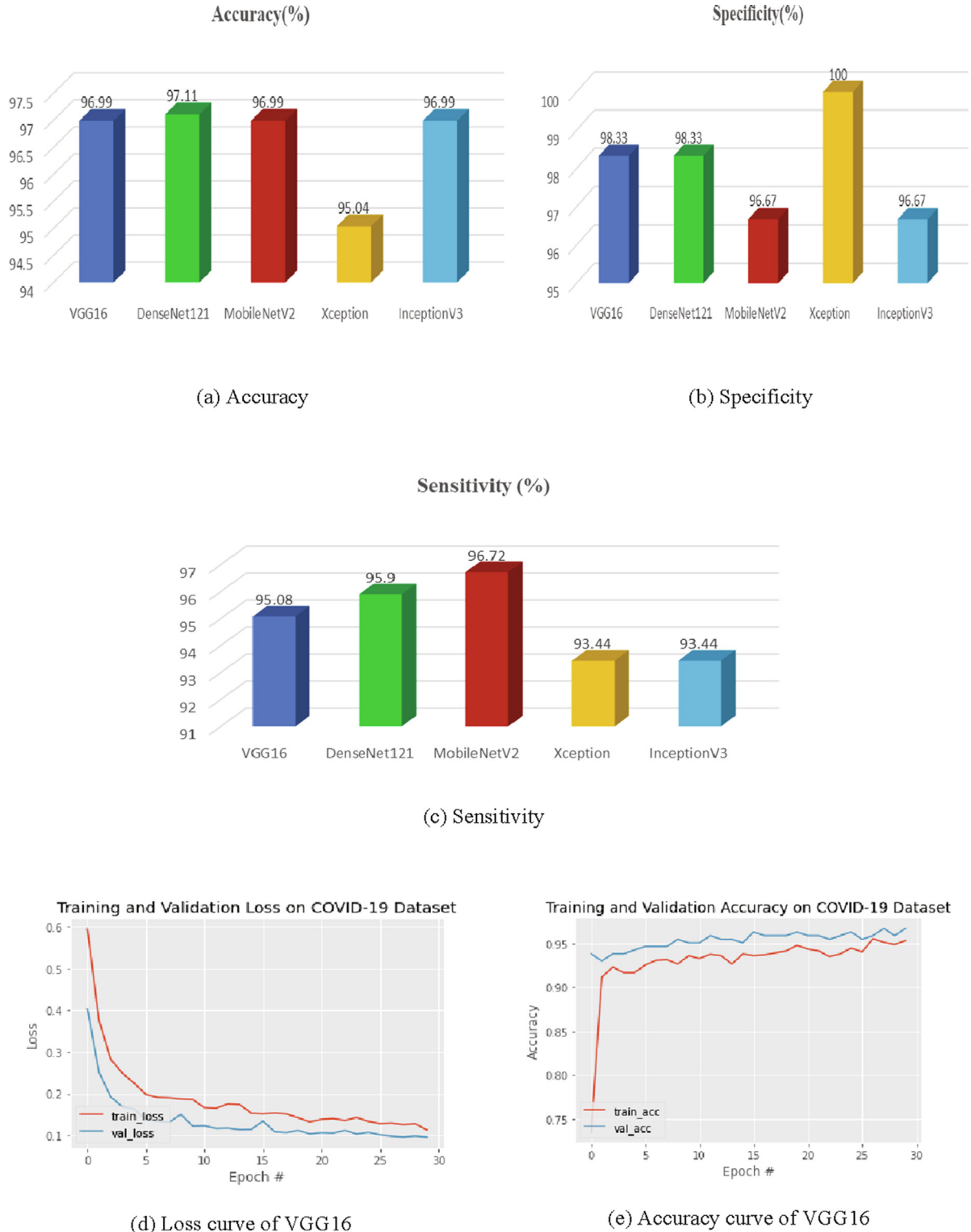(d) Loss curve of VGG16

(e) Accuracy curve of VGG16

Fig. 12. Comparative analysis of evaluation metrics of distinct pretrained models for original medical data.

diagnosis or clinical advices to the people and to provide early instructions to the people regarding quarantine and social distancing. The development of these systems should consider factors such as low cost, usage of limited network resources, accessibility to illiterate and disability people, multi-language support for its successful implementation in combating Covid-19 infection. Therefore, the key challenge that arises in the development of

these technologies is the successful deployment in economically developing countries.

Moreover, the other diagnosis approaches such as magnetic resonance imaging (MRI) and ultrasound scans have limited usage. Even though the ultrasound scans have benefits such as easy usage, less radiation and low cost when compared with the CT scans, very limited work [126] has been done using ultrasound scans. Simi-
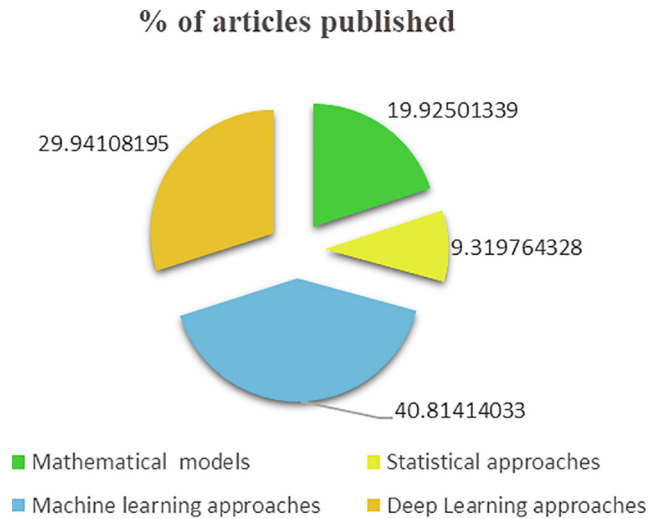
% of articles published

Fig. 13. Contribution of distinct approaches in COVID-19 prediction.

larly, MRI is identified as the reliable imaging modality technique as it uses non-invasive technique. Though MRI results in high resolution images, very limited work has been accomplished using MRI [196]. This is mainly due to unavailability of adequate training dataset. Therefore, the challenge is to develop adequate labelled datasets for the deployment of these approaches in battling Covid-19 infection.

6. Conclusion

While the world continues to grab with the impact of COVID-19, the researchers and technocrats have always been dynamic in addressing the challenging issues emerging in COVID-19. As the infection is spreading expeditiously across the world, there is a need of developing more efficient strategies which may assist the government and healthcare sector in curbing the spread of the present pandemic. Therefore, this paper presents a comprehensive review of the ongoing works in the diagnosis, prediction, drug and vaccine development and preventive measures used in combating the current paper. Initially, the paper presents an in-depth analysis of different strategies used in controlling the spread of the pandemic along with their applications and limitations. It also focuses on different technologies used in combating the COVID-19 pandemic. Following this, the analysis is extended by making a critical analysis on the distinct type of data, emerging technologies, approaches used in diagnosis and prediction models, statistics of contact tracing apps and vaccine production platforms used in combating COVID-19. It also highlights the challenges and pitfalls observed in the reviewed works. Despite of all the significant development in the strategies used for combating present pandemic, the performance of the approaches is not yet stable due to the unavailability of enough COVID-19 datasets and inconsistent datasets. Furthermore, most of the ongoing work has not guaranteed the security and privacy of the health information of the public. Therefore, further research is still needed for the development of efficient strategies in battling COVID-19 pandemic.
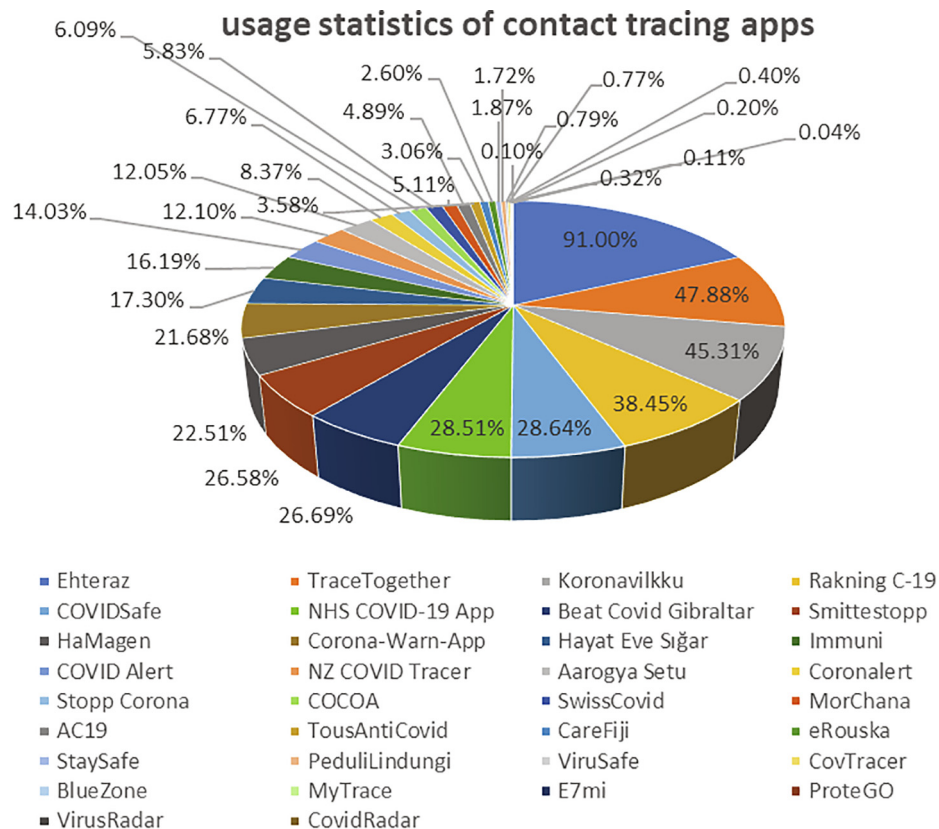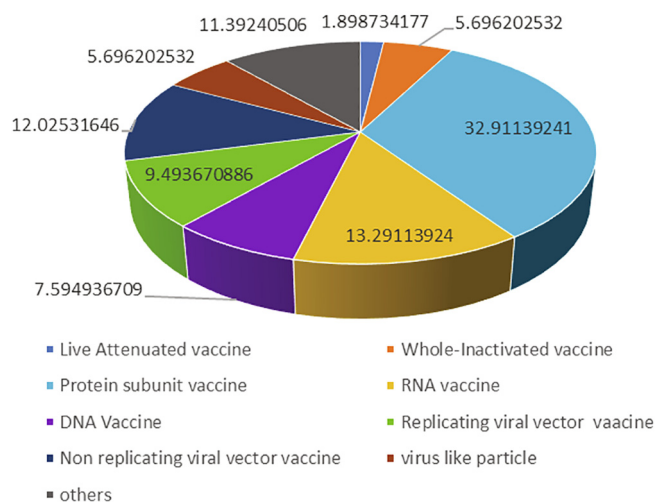

Fig. 14. Usage statistics of distinct COVID-19 contact tracing apps.

Table 15
Analysis of vaccine production platforms used in COVID-19 vaccine development.

Vaccine platform	Vaccine candidate	Advantages	Limitations
Live Attenuated Vaccine	Preclinical stage	Capable of simulating the immune system by inducing the toll-like receptors (TLRs). It is capable of developing from 'cold adapted' virus strains and reverse genetics.	Results in recombinants post vaccination due to nucleotide substitution during viral replication
Whole-Inactivated Virus Vaccine	PiCoVacc	Consist of pre-existing technology and infrastructure needed for its development. Already tested for SARS-CoV and other type of diseases. Immunogenicity can be enhanced by using with adjuvants	Not handled large number of viruses. Not maintained integrity of immunogenicity particles
Protein subunit vaccine	NVX-CoV2373	Safer vaccine with less side effects	Does not have memory for future responses
Virus vector based vaccine	AZD1222, Ad5-nCoV	Contains vigorous immune response. Has been extensively utilized for MERS-CoV Does not handle any infectious particle	Integration of viral genome in host genome may result in cancer
RNA vaccine	mRNA-1273, BNT162	Avoids the risk of amalgamation into the host genome due to the occurrence of translation in the cytosol of host cell	Various safety issues have been reported because of reactogenicity
DNA Vaccine	INO-4800	Does not need to handle any infectious particle. It is temperature stable and cold-chain free	Results in abnormalities because of the insertion of foreign genome in human genome.

statistics of distinct vaccines under research (%)

- Live Attenuated vaccine
- Whole-Inactivated vaccine
- Protein subunit vaccine
- RNA vaccine
- DNA Vaccine
- Replicating viral vector vaacine
- Non replicating viral vector vaccine
- virus like particle
- others

11.39240506   1.898734177   5.696202532
5.696202532
12.02531646
9.493670886
7.594936709
32.91139241
13.29113924

Fig. 15. Statistics of distinct vaccines under research.

Author contributions

Weiping Ding, Janmenjoy Nayak, H. Swapnarekha, contributed the central idea, analyzed most of the data, and wrote and revised this paper. Ajith Abraham, Bighnaraj Naik, and Danilo Pelusi contributed to refining the ideas, carrying out additional analyses and revising this paper.

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.

Acknowledgements

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