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Intelligent Internet of Things and Advanced Machine Learning Techniques for COVID-19

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Abstract

INTRODUCTION: Coronavirus disease (COVID-19) has recently emerged around the world. The beginning of the disease was in the Chinese city of Wuhan and then it has been spread and became a global epidemic. An early diagnosis of COVID-19 disease is absolutely necessary to control the epidemic.

OBJECTIVES: The aim of this paper is to present a review of the contribution of machine learning (ML) and IoT to confront the epidemic.

METHODS: Diagnosis using real-time reverse transcriptase-polymerase chain reaction (RT-PCR) is a definite diagnosis, but this method takes time, while a diagnosis using a computed tomography (CT) scan is a faster approach to diagnosis. However, a large number of patients need a CT scan, which puts a lot of pressure on the radiologist so visual fatigue may lead to diagnostic errors so there is an urgent need for additional solutions. Artificial intelligence (AI) is an efficient tool to combat COVID-19 disease. Computer scientists have been developing many systems to handle this epidemic.

RESULTS: It was found that ML is an efficient and powerful AI technology that can be used for trustworthy COVID-19 detecting and diagnosis from X-ray and CT images and it can be a potential method for diagnosis in the radiology department. In addition, ML can be used in segmentation, prediction purposes for COVID-19. Furthermore, ML can effectively support drug discovery procedure and can reduce clinical failures.

CONCLUSION: IoT has a significant role in monitoring an individual's health and COVID-19 diagnosis. This paper also highlights the challenges of employing ML and intelligent IoT for fighting COVID-19.

Keywords: Machine learning; Coronavirus; Artificial Intelligence; Internet of Things.

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1. Introduction

This Coronavirus is a novel virus that causes COVID-19 disease. It is also called SARS-CoV-2 [9]. The disease has first appeared in Wuhan, China, in December 2019 and has spread worldwide [5]. COVID-19 disease outbreak has led to the declaration of a global health emergency [17]. Countries with a large number of infected people are the USA, Spain, Italy, the U.K., and France. Old people and people with weak immunity system are the most affected people [9]. It is expected to be a seasonal disease after the current pandemic [4]. As new cases are announced daily around the world [18]. The spread of the virus has led to a state of anxiety and panic around the world, prompting countries to decide to either totally or partially lockdown [7]. Non-pharmaceutical interventions

(NPIs) such as social distance, school closure, and voluntary quarantine are very significant to decrease disease spread [9,43]. However, these strategies harm the daily routine, economy, business, and the education system. Owing to the closures of schools, colleges, and universities, it is likely that the trend will be e-Learning in many countries of the world. However, there are many challenges to implement this, including the lack of training of faculty members on methods of education using the Internet as they are accustomed to traditional methods. Also, it is very difficult to apply this method in remote areas due to the lack of availability or weakness of the Internet. Besides, e-learning has the drawback of the lack of students' commitment to study. Thus, this epidemic harms students and teachers [42,43,45,46]. So, parents should help their children to learn their lessons remotely to active, and mentally stimulated during the period of quarantine [46]. Moreover, there is a negative effect of quarantine on mental health involving psychological and emotional issues [44]. The common respiratory symptoms of this disease are fever, cough, and breathing difficulties [21]. At the beginning of the infection, symptoms of acute respiratory infection occur and patients may reach the advanced stage rapidly and develop acute respiratory distress syndrome (ARDS) [10]. The early classification of the novel COVID-19 is necessary to treat and control the disease [6]. The laboratory test has drawbacks such as the need for a long time and high cost. It also has been found that RT-PCR detection of viral RNA from sputum or nasopharyngeal swab possesses a relatively low positive rate in the early stage to detect COVID-19 [15]. Diagnosis using CT is a rapid approach but the performance of doctors to diagnose the disease using this approach is moderate. Also, this process is a waste of time, especially when there are many patients. So, there is a need to find additional solutions to help them in the diagnosis [3,8]. AI plays a major role in identifying early infection with coronavirus, and it also assists in tracking the status of infected people. Also, it assists to ease research related to this virus by analyzing available data. Healthcare organizations need decision-making techniques to deal with this virus and assist them to get suitable suggestions in real-time to prevent its spread. AI works in an effective way to imitate human intelligence. It is also useful for understanding and proposing the enhancement of a vaccine for COVID-19 [1]. In the current situation, all countries are looking for practical and inexpensive solutions to help them cope with this disease [2]. With the help of AI capabilities, computer scientists have been able to identify the disease early by analyzing medical image data [8,54]. ML has the advantage of having the capability to solve complex issues effectively [18]. IoT employs several connected devices to create an intelligent network for a suitable health management system. It is used to track the diseases to enhance the safety of the patient. It automatically collects the medical data of the patient without any human contact [2]. Infrared thermometers are used in all public places to measure body temperature. The drawback of this method is the possibility of the virus spreading from the infected person to the person who performs the screening procedure. So, there is an urgent need for alternative methods with less human interactions [17].

The paper aims to provide researchers a review of advanced solutions that can be used to assist in combating COVID-19 disease.

The major contributions of the paper are as follows:

- It reviews the work that has been done using machine learning for COVID-19 diagnosis, segmentation, and prediction
- It presents the applications of IoT for COVID-19.
- It highlights the role of AI for IoT based COVID-19 monitoring strategies.
- This work will empower the researchers to further work on evolving additional solutions to combat COVID-19.

2. Related Work

In [53], the effect of covid-19 on kidney and failure of acute renal has been investigated. The results exhibited that the SARS-CoV-2 NP antigen has been accumulated in kidney tubules. Also, viruses- like particles were visible in the kidneys.

In [55], the relation between chest CT results and clinical conditions of COVID-19 pneumonia has been studied. It was found that most patients with confirmed COVID-19 pneumonia have ground-glass opacities (GGO) or mixed GGO and vascular enlargement in the lesion. Thus, CT images can assist in the evaluation process of the severity of COVID-19 disease.

ML can play an effective role in the healthcare field [63]. In [63], deep learning (DL) based system was proposed for detecting Lung abnormalities from X-ray images and CT scans with high accuracy.

IoT is a network of devices that can interact and share data. IoT has many applications such as smart parking, smart building, smart parking, smart agriculture, and smart healthcare [61].In [62], an IoT system was proposed to monitor the levels of blood glucose. This system can help in preventing any complications for elderly individuals.

3. Methods

Various academic digital databases have been studied and analyzed which includes ScienceDirect, IEEEXplore, Google Scholar, and PubMed. Different keywords that are related to using ML and IoT for COVID-19 was used.

4. Discussion and Results

COVID-19 is considered a global crisis. Owing to the severe situation and the need for new technologies that can help in combating this epidemic. This paper introduces a review of ML and IoT applications that can be used to combat this epidemic. In particular, it highlights emerging applications of ML for combating COVID-19 such as detecting and diagnosis, predicting, segmentation, and drug discovery. It also highlights the Challenges of using ML for COVID-19 and discusses the role of AI for IoT based COVID-19 monitoring strategies. Furthermore, it highlights the application of IoT for monitoring an individual's health and COVID-19 diagnosis. Also, it discusses the challenges of utilizing IoT in healthcare.

4.1. Application of ML

Detecting and diagnosis for COVID-19

Precise screening of COVID-19 is still a challenging task owing to the spatial complexity of three-dimensional volumes, the marking difficulty of infected regions, and the small variation between COVID-19 and other viral pneumonia in chest CT [19]. The study in [19] has introduced a new attention-based deep 3D multiple instance learning (AD3D-MIL) for the screening of COVID-19 with weak labels. The authors have gathered 460 chest CT: 230 CT images for COVID-19, 100 CT images for common pneumonia, and 130 CT images without pneumonia (healthy people or suffer from other diseases). The overall accuracy, AUC, and Cohen kappa score were 97.9%, 99.0%, and 95.7% respectively. These benefits demonstrate that this algorithm can be an efficient approach to help in the screening process of COVID-19.

SARS-CoV-2 causes serious respiratory infections. It is an RNA-type virus and may affect humans and animals [12]. In [12]. Three groups of chest images were used which are normal, pneumonia, and COVID-19. COVID-19 has been detected via a DL model. The fuzzy Color technique has been employed as a preprocessing step to restructure the dataset. Also, the stacking technique was utilized for creating a new dataset with enhanced quality by combining the structured images with original images. Two DL models (MobileNetV2, SqueezeNet) were trained using the stacked dataset. Also, the Social Mimic optimization method was employed to process the obtained features from models. After that, effective features have been merged and categorized via Support Vector Machines (SVM). The proposed method has achieved an overall classification rate of 99.27% which indicates that the model can effectively assist to detect COVID-19 disease.

In [15] a new approach has been used to differentiate COVID-19 from Influenza-A viral pneumonia using DL techniques. Three groups of CT samples were employed. The first group is the COVID-19 group which contains 618 CT samples from 110 patients. The second group contains 224 CT samples from 224 patients with Influenza-A viral pneumonia. The third group contains 175 CT samples from healthy people. Features were extracted using classical ResNet. Models with location-attention mechanisms have classified COVID-19 with an overall accuracy of 86.7 % which has proved that AI can be a potential method for diagnosis in the radiology department.

In [20] an AI-based test for COVID-19 initial diagnosis has developed. The test can be widely spread using a smartphone application called AI4COVID-19. Where the application needs to record a cough for two seconds to make the diagnosis. the cough samples are analyzed using an AI engine running in the cloud, then the application gives the initial diagnosis within a minute. However, cough is a common sign of more than twenty non-COVID-19 associated diseases. Therefore, it is difficult to diagnose COVID-19 only from cough and this is a massive challenge. The AI engine is composed of three parallel classification solutions that are designed by three independent groups. The classifiers results are cross-validated by an automated mediator. Every classifier possesses a veto power, for example, if the three classifiers do not match, the application displays ‘Test inconclusive’. This novel design increases the validity of the diagnosis, which makes it better than stand-alone classifiers with a binary diagnosis. It was found that the AI engine can differentiate COVID-19 patient cough from many kinds of non-COVID-19 cough with an accuracy of more than 90% [20].

In [25] a novel framework has been proposed for detecting COVID-19 via integrated cellphone sensors. The suggestion offers an affordable solution since all radiologists have been already using smartphones for various daily uses. Also, other individuals can employ the framework on their cellphones to detect the virus. Smart cellphones today have reached a significant level of performance with sturdy processors, RAM size, and a large number of sensors. The developed AI allows the framework to read the smart cellphone sensors’ measurements to foresee the level of seriousness of pneumonia and also anticipating the outcome of the disease. The framework consists of four layers which are: input sensors’ measurements layer, sensors setup layer, computing symptoms illness layer, and foresee the infection layer via mixed methods. Moreover, the ML model in the last step was enhanced by a transfer learning approach. The framework is trustworthy due to its dependence on multiple readings from numerous sensors according to the associated symptoms of the infection.

DL methods have been obtained great findings in detecting COVID- 19 from chest X-rays. In [26] effective convolutional network architecture was used to detect

COVID-19 from chest X-ray images. An efficient model has been produced with an overall accuracy of 93.9%, sensitivity of 96.8%, and positive prediction of 100%.

In [3] a fast and effective approach was used to diagnose COVID-19 via AI. Two groups of CT slices were employed. The first group is the COVID-19 group which contains CT slices from 108 patients which their infection was verified laboratory. The other group which is a non-COVID-19 group contains CT slices for 86 patients with other atypical and viral pneumonia diseases. The total number of CT slices that were used is 1020. Ten convolutional neural networks (CNNs) which are AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101, and Xception have been used to present an overview of the role of AI in diagnosis COVID-19 disease. The findings demonstrated that DL can recognize COVID-19 among other diseases with high accuracy. The highest performance was obtained using ResNet-101 and Xception. ResNet-101 could differentiate between COVID-19 and non-COVID-19 cases with an AUC of 0.994 (sensitivity, 100%; specificity, 99.02%; accuracy, 99.51%). Xception obtained an AUC of 0.994 (sensitivity, 98.04%; specificity, 100%; accuracy, 99.02%). On the other hand, the radiologists have performed moderately with an AUC of 0.873 (sensitivity, 89.21%; specificity, 83.33%; accuracy, 86.27%). ResNet-101 was the highest sensitivity model to diagnose COVID-19 infection.

In [27], CNN based transfer learning method was used for detecting COVID-19 from X-ray images. The dataset that has been employed were composed of 190, 1345, and 1341 for COVID-19, viral pneumonia, and normal chest X-ray images respectively. Four different CNNs (AlexNet, ResNet18, DenseNet201 &SqueezeNet) were trained using a training set consists of about 2600 images of every class. The image augmentation technique has been used for creating the training dataset. These CNN networks have been examined for the categorization of two distinct schemes (normal and COVID-19 pneumonia; normal, viral, and COVID-19 pneumonia). The results exhibited that SqueezeNet surpasses the other three deep CNN networks. The classification accuracy, sensitivity, specificity and precision for both the schemes were 98.3%, 96.7%, 100%, 100% and 98.3%, 96.7%, 99%, 100%, respectively. This study has proved that SqueezeNet can detect COVID-19 from X-ray images and distinguish them from normal and viral pneumonia images.

In [30], A deep CNN based on the concatenation of Xception and ResNet50V2 networks has been proposed to classify X-ray images into normal, pneumonia, and COVID-19. The dataset contains 180 images for COVID-19, 6054 chest images for pneumonia, and 8851 x-ray images for healthy people. Owing to the limited number of COVID-19 X-ray images, a new approach was proposed for testing the neural network (NN) when the dataset is not balanced. The training set was split into eight consecutive stages and in each stage, 633 images were used. The achieved average accuracy for the COVID-19 class was 99.50% and the overall accuracy was 91.4%. So, this trained network will be useful for medical diagnosis.

In [32] a deep CNN-based model (COVID-Net) was proposed to detect COVID-19 from chest X-ray images. The dataset involves 13975 chest X-ray images across 13870 patient cases. The proposed COVID-Net has achieved a test accuracy of 93.3%.

The early classification of COVID-19 disease is very crucial to facilitate control and treatment of the disease. CT imaging is the fastest and most reliable method to classify COVID-19 disease. Due to the availability of CT devices in hospitals, it can be relied upon in the early classification of COVID-19 patients. However, the specialist’s time is an important factor especially when the spreading of the disease increases rapidly. Therefore, an automated method must be found to analyze the CT images and preserve the time of specialists [6]. In [6], a multi-objective differential evolution (MODE)-based CNN has been utilized for classifying individuals into positive (infected) or negative (not infected). The findings have demonstrated that the proposed model surpasses competitive models, which are artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), CNN models in terms of accuracy, F-measure, sensitivity, specificity, and Kappa statistics by 1.9789%, 2.0928%, 1.8262%, 1.6827%, and 1.9276%, respectively. So, the proposed model can categorize the chest CT images with good accuracy. Table 1.1 Summarizes the ML approaches that have been used for diagnosis and detecting COVID-19.

In [36] a DL-based CNN model, called Truncated Inception Net, was proposed. The model was able to classify COVID-19 positive cases among pneumonia and healthy cases with an accuracy of 99.96%. It also obtained 99.92% accuracy in categorizing X-ray images of COVID-19 positive cases among pneumonia and tuberculosis cases.

In [38], a novel DL-based model to detect COVID-19 utilizing raw chest X-ray images was proposed. This model has achieved an accurate diagnosis for binary classification (COVID vs. No-Findings) and multi-class classification (COVID vs. No-Findings vs. Pneumonia) with a classification accuracy of 98.08% and 87.02% respectively.

In [52], DL-based CNN models have been used for detecting COVID-19 on chest X-ray images. In this work, Data augmentation was used. For evaluating performance, a data set of 6432 X-ray images for Covid-19 affected, normal, and pneumonia cases were gathered. The dataset was divided into 5467 images for training and 965 for

validation. The accuracy of three models which are Inception V3, Xception, and ResNeXt have been compared. The findings demonstrated that the Xception model outperforms the other models and it achieved the highest accuracy (97.97 %).
In [60], a DL system was proposed for diagnosis COVID-19 from X-ray images via integrating CNN with LSTM. The function of CNN is extracting the deep features. However, the detection process was done using LSTM. The dataset contains 4575 X-ray images which involve 1525 COVID-19 images. The achieved accuracy was 99.4%.

Table 1. Existing ML approaches for diagnosis and detecting COVID-19

Authors Name	**Proposed Technique**	**Advantages/Accuracy**	**The database used and limitation**
Z. Han et al [19]	AD3D-MIL for the screening of COVID-19 with weak labels	The overall accuracy, AUC, and Cohen kappa scores were 97.9%, 99.0% and 95.7% respectively.	Dataset: 460 chest CT: 230 CT images for COVID-19, 100 CT images for common pneumonia, and 130 CT images without pneumonia (healthy people or suffer from other diseases)
M. Toğaçar et al [12]	To detect COVID-19, the Fuzzy Color technique as a preprocessing step was performed, stacking technique was applied, DL models (MobileNetV2, SqueezeNet) has been used in training process and the feature sets obtained by the models have been processed using the Social Mimic optimization method. After that, effective features have been merged and categorized via SVM	Overall classification rate: 99.27%. It can detect the disease with 100% success. The proposed method can emerge into mobile smart devices such as smart phones. MobileNetV2 and SqueezeNet that has been used have a smaller parameter than other DL model so this method is rapid. It reduces the interference in each image in the dataset and gives effective features using stacking technique.	Dataset: 458 X-ray images consist of 295 images for COVID-19 class, 65 images for normal class, and 98 images for pneumonia class. Limitation: The number of COVID-19 images is limited. This study can't obtain success with different sizes of input images in the dataset. Also, there is a difficulty to deal with low image resolution. To perform Stacking technique, the resolution dimensions of both of originalimages and the structured images must be the same.
C. Butt et al [15]	Numerous CNN models were employed to differentiate COVID-19 pneumonia from Influenza-A viral pneumonia and healthy cases	overall accuracy: 86.7 %	Dataset: Three groups of CT samples were employed. The first group is the COVID-19 group which contains 618 CT samples from 110 patients. The second group contains 224 CT samples from 224 patients with Influenza-A viral pneumonia. The third group contains 175 CT samples from healthy people. Limitation: The number of training and test samples was limited
A. Imran et al [20]	Smartphone application called AI4COVID-19	AI engine can differentiate COVID-19 patient coughs from many kinds of coughs with more than ninety percent accuracy.	AI engine contains a cough detector that has been trained using ESC-50 dataset and this dataset is a publicly accessible. The authors were employed 993 cough sounds and 993 non-cough environmental sounds to train the cough detector.

		Cost-effective tool. Assist in retaining the social distance	Also, to train and test the cough diagnosis system, the authors have aggregated 102 bronchitis, 131 pertussis, 48 COVID-19, and 76 normal cough sounds Limitation: The performance of the proposed method is limited by the amount of training and testing data since there is a lack in cough data, quality of training and testing data and affirmation of performance clinically.
H. S. Maghdid et al [25]	AI-enabled Framework which consists of four layers, the last is applying ML techniques	The framework is trustworthy due to its dependence on multiple readings from numerous sensors according to the associated symptoms of the infection.	The framework reads the captured CT scan images of lung and videos using the smartphone camera, records a series of cough, and measures temperature using fingerprint touch
E. Luz et al [26]	The EfficientNet family of CNN was used To evaluate performance two methods were used which are flat classification and hierarchical classification. Efficient training for the deep NNs was done by applying transfer learning and data augmentation techniques	The best results were achieved with EfficientNet B3 with flat classification with overall accuracy of 93.9%, sensitivity of 96.8% and positive prediction of 100% (without false positives).	Dataset: 13,800 chest X-rays images, 183 of them was for COVID-19 patients Limitation: The number of COVID-19 images was small.
A. A. Ardakani, et al [3]	10 CNNs were used: AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101, and Xception	The non-COVID-19 group of CT slices contains slices that was performed for patients before COVID-19 outbreak to guarantee that no CT images for patient of COVID-19 exist in non-COVID-19 group The highest performance was obtained by ResNet-101 and exception The AUC of ResNet-101 was 0.994 (sensitivity, 100%; specificity, 99.02%; accuracy, 99.51%). Xception has obtained an AUC of 0.994 (sensitivity, 98.04%; specificity, 100%; accuracy, 99.02%). ResNet-101 is the highest sensitivity model in	Dataset: 1020 CT images Limitation: some patients were excluded incorrectly from this study because their PCR results was negative and they may have COVID-19 disease and their laboratory results was at early stage of infection

		diagnose COVID-19 disease	
M. E. H. Chowdhury et al [27]	DL CNNs based on transfer learning: AlexNet, ResNet18, DenseNet201 &SqueezeNet Two experiments were performed, the first experiment was without image augmentation techniques and the second one was with image augmentation to increase the training set for each category	SqueezeNet has achieved the highest performance for both experiments and the best performance was obtained with image augmentation techniques. The classification accuracy, sensitivity, specificity and precision using SqueezeNet with image augmentation for normal and COVID-19 pneumonia scheme were 98.3%, 96.7%, 100%, 100% and for normal, viral and COVID-19 pneumonia scheme were 98.3%, 96.7%, 99%, 100%.	Database: 190 x-ray images for COVID-19, 1345 x-ray images for viral pneumonia, and 1341 normal x-ray images. Limitation: Dataset was small so transfer learning and image augmentation were used.
M. Rahimzadeh and A. Attar [30]	Concatenation network of the Xception and ResNet50V2 networks was used. The training set was split into eight successive stages	The achieved average accuracy for COVID-19 class was 99.50% and the overall accuracy was 91.4%.	Database: X-ray images which composed of 180 images for COVID-19, 6054 chest images for pneumonia and 8851 images for healthy people. Limitation: Limited number of COVID-19 images.
L. Wang et al [32]	Deep CNN based model which is called COVID-Net	sensitivity for COVID-19 cases: 91.0% Positive Predictive Value for COVID-19 cases: 98.9% Accuracy: 93.3%	Dataset: 13,975 chest X-ray images which contains 358 X-ray images from 266COVID-19 patient cases. Limitation: limited amount of COVID-19 X-ray images
D. Singh et al [6]	MODE-based CNN has been utilized for classifying COVID-19-infected individuals as infected (positive) or not (negative).	Proposed model surpasses ANN, ANFIS, CNN models in terms of accuracy, F-measure, sensitivity, specificity, and Kappa statistics by 1.9789%, 2.0928%, 1.8262%, 1.6827%, and 1.9276%, respectively.	Dataset: chest CT images
D. Das et al [36]	Deep CNN based model which is called Truncated Inception Net	An accuracy of 99.96% has been obtained in classifying COVID-19 positive cases from mixed Pneumonia and healthy X-rays. Also, an accuracy of 99.92% was obtained in classifying COVID-19 positive cases from combined Pneumonia, Tuberculosis, and healthy	Datasets: Six distinct datasets were used to train the model by considering: COVID-19 positive, Pneumonia positive, Tuberculosis positive, and healthy cases into account. Limitation: The system depends entirely on visual cues in the input data. As a result, in the early stages of COVID-19, when radiologically observable cues have not yet been developed, the system may not be able to perform well.

		X-rays. Truncated Inception Net surpasses ResNet50 and SVM, COVID-Net, ResNet50, and Inception Net V3.	
T. Ozturk et al [38]	DL-based model called DarkNet was utilized to detect COVID-19	This model has achieved an accurate diagnosis for binary classification (COVID vs. No-Findings) and multi-class classification (COVID vs. No-Findings vs. Pneumonia) with a classification accuracy of 98.08% and 87.02% respectively.	Dataset: X-ray images Limitation: The number of COVID-19 images was small.
R. Jain et al [52]	DL models (Inception V3, Xception, and ResNeXt) were used for detecting COVID-19. Also, Data augmentation technique was used.	Xception model outperforms the other models and it achieved the highest accuracy (97.97 %).	Dataset: X-ray images Limitation: The number of COVID-19 images was small.
M. Z. Islamet al[60]	integrating CNN with LSTM	The achieved accuracy was 99.4%.	Dataset: X-ray images. Limitation: Limited number of COVID-19 images. This study has been applied to the posterior-anterior (PA) view of X-ray images only.

Employing ML in predicting

Researchers have conducted several studies to predict various diseases via ML techniques such as coronary artery disease and cardiovascular disease prediction. These prediction systems are very useful for managing these diseases efficiently [18]. The work in [18] exhibits the ability of ML models to predict the number of future patients influenced by COVID-19. Four standard predicting models which are linear regression (LR), least absolute shrinkage and selection operator (LASSO), SVM, and exponential smoothing (ES) were employed. Three significant types of predictions are performed by each model, such as the number of new affirmed cases, the number of deaths, and the number of recoveries in the next ten days. The findings have proved that employing these approaches for the current COVID-19 pandemic can be a potential procedure. It was found that the ES performance was the best among all the utilized models followed by LR and LASSO and it has performed well in predicting the novel affirmed cases, death rate as well as recovery rate, while SVM performance was the worst in all the prediction scenarios given the accessible dataset.

Sustainable development is the enhancement in all aspects of life and meeting the current needs without adversely affecting the needs of future generations. The epidemics are one of the obstacles that slow down sustainable development. COVID-19 epidemic affects the economic and social aspects. Therefore, many researchers seek solutions that help to combat this epidemic [13]. In [13] classification of affirmed cases of COVID-19 was done. Binary classification modeling has been employed by the group method of data handling (GMDH) type of NN which is one of the AI approaches. So, the Hubei province in China has been chosen as a case study to create the proposed model, and some significant factors which are highest, lowest, and average daily temperature, the density of a city, relative humidity, and wind speed, have been considered as the input dataset, and the number of affirmed cases has been chosen as the output dataset for one month. The suggested binary classification model offers greater performance in predicting the affirmed cases. Moreover, regression analysis was performed and both the trend of affirmed cases and the changes in daily weather parameters (wind, humidity, and average temperature) were observed. The findings exhibited that the relative humidity and maximum daily temperature had the greatest effect on the affirmed cases. The relative humidity in the main case study with an average of 77.9 percent, influenced positively the affirmed cases. However, the highest daily temperature with an average of 15.4 ℃ influenced negatively the affirmed cases.

The development of accurate forecasting models is extremely important to take appropriate action. Owing to the scarcity of basic data, the epidemiological models were tested in regards to providing better accuracy for long-term forecasting. As an alternative to the susceptible-infected-resistant (SIR)-based models, the work in [28] has proposed a hybrid ML method to forecast the COVID-19. Data from Hungary was used. The hybrid ML approaches of adaptive network-based fuzzy inference system (ANFIS) and multi-layered perceptron-imperialist competitive algorithm (MLP-ICA) have been proposed to foresee time series of infected people and death rate. The models foresee that at the end of May, the outbreak will fall considerably. The confirmation was carried out for 9 days with superb outcomes, which affirms the model accuracy. It is anticipated that the model will retain its accuracy. This work has exhibited the capability of ML for future research.

In [24] a hybrid AI model was presented to predict COVID-19 disease. It was found that conventional models deal with all infected people as they have the same infection rate. So, an enhanced model has been proposed to predict the variation of the infection rates. To create this hybrid model, the natural language processing (NLP) module, and the long short-term memory (LSTM) network was included. The experimental findings on the epidemic data of numerous typical provinces and cities in China demonstrate that people with COVID-19 have a greater infection rate within the third to eighth days after they were infected. Compared to conventional epidemic models, the proposed model can greatly decrease the errors of the prediction findings.

In [33], the Bayesian DL classifier was trained via a transfer learning approach on COVID-19 X-Ray images. It has been used for estimating model uncertainty. It was found that there is a significant correlation between model uncertainty and accuracy of prediction. The estimated uncertainty in DL yields a more trustworthy forecast, which can notify radiologists of false predictions. So, this will increase their trust in the ability of DL to help in disease detection.

In [37], a fine-tuned Random Forest model boosted by the AdaBoost algorithm has been proposed. This model employs the geographical, travel, health, and demographic data of COVID-19 patients to anticipate the seriousness of the case and the potential result- recuperation or death. An accuracy of 94% and an F1 score of 0.86 were obtained on the dataset utilized. The data investigation indicates a strong connection between the patients' gender and deaths and demonstrates that the most of patients are in the age scope of 20-70 years. It was found that male patients had a higher death rate contrasted with female patients. Also, it was proved that the Boosted Random Forest algorithm can achieve accurate Foresee even on imbalanced datasets.

Segmentation from CT Images

It is preferable to use CT scans instead of X-rays owing to its three-dimensional view of the lung. Some signs in the CT scans indicate the infection, for example, GGO in the early stages, and pulmonary consolidation in the advanced stages [22,23]. Automatic detection of infected areas in the lung from CT images provides a great potential to assist radiologists in detecting COVID-19. However, the segmentation process for these affected areas is still a challenging task due to the big difference in infection attributes and low-intensity contrast between infections and normal tissues. Also, gathering a large number of data in a short time is impractical. So, this will prevent the training of a deep model. To overcome these difficulties, the authors in [22] have proposed a new deep Network to segment COVID-19 Lung Infected from chest CT slices. To gather a high-level of characteristics and produce a global map, a parallel partial decoder has been employed. Also, the implicit reverse attention and explicit edge attention were employed for modeling the borders and improving the representations. Furthermore, to mitigate the lack of labeled data, a semi-supervised segmentation framework dependent on a randomly selected propagation method has been presented. In this framework, only a few labeled images and leverages of primarily unlabeled data are needed. Also, the learning capability is enhanced and a better performance can be obtained. This work focuses on the segmentation task of infected lung while clinically, it is needed to classify COVID-19 patients first. Then segmentation for infected regions can be done for further treatment.

Manual segmentation of CT images has become a difficult task with the rise in the number of suspected cases, leading to a growing need for a reliable and automated segmentation method. Due to the variation of imaging properties of COVID-19 and their similarity to the background, current image segmentation techniques unable to accomplish adequate performance [29]. In [29], a novel deep CNN (COVIDSegNet) was used to segment COVID-19 infection areas and the whole lung from chest CT images. A novel chest CT image dataset was maintained which composed of 21,658 annotated chest CT images from 861 patients with affirmed COVID-19. A specific block, named Feature Variation (FV) block has been proposed to present a solution to the issue of difficulties in recognizing COVID-19 pneumonia from the lung. Also, Progressive Atrous Spatial Pyramid Pooling (PASPP) has been introduced, which gradually collects information and gets more efficient contextual features.

Drug discovery

To combat this epidemic, it is necessary to find the best effective treatment for COVID-19. Thus, several researchers are trying to discover the most effective drug for this disease [48,49,50].

In [47], the DL model named Molecule Transformer-Drug Target Interaction (MT-DTI) was used to discover the efficient drugs that can act on viral proteins of COVID-19. The findings demonstrated that atazanavir is the best effective drug for COVID-19.

In [50], the DL approach was utilized for identifying the potential drugs for COVID-19 3C-like protease. In this work, a list of potential drugs was provided.

Challenges of using ML for COVID-19

To create efficient ML systems, a large set of data is required. Using ML for COVID-19 research is currently facing several challenges. One of the main challenges of using DL in diagnosis COVID-19 is the lack of standard data [40,41]. Also, the imbalance in the dataset samples is another challenging issue. There are a small number of X-ray and CT of COVID-19 samples compared to pneumonia and normal cases samples. The most utilized technique to overcome the challenge of an imbalanced dataset is data augmentation. This technique aims to produce new lesions via flipping, rotation, zoom, random noise addition, etc. from the given samples of COVID-19. The other benefit of this approach is that data augmentation can overcome overfitting issues [12,15,26,27,30,32,38,40,52,56].

The role of AI for IoT based COVID-19 monitoring strategies

Monitoring people's health is one of the most significant IoT applications. Where people need systems to help them check on their health without affecting their daily routine. Since it is significant to have systems that depend on the IoT to monitor the health of sick people remotely and alert caretakers in case of any emergency [16]. IoT is useful for capturing real-time data from infected patients. AI and IoT are unique technologies. However, the combination of both of them makes them very interesting and it helps to achieve a better future. Combining IoT with AI has a great impact on combat COVID-19.AI permits data analysis to make decisions that are similar to the human brain. AI adds more value to the IoT through a better interpretation of the data acquired from connected devices. The gathered data is analyzed using AI abilities. After the analysis process, valuable data are obtained [35]. Some IoT systems that are designed to monitor and detect COVID-19 disease are provided with face recognition techniques and they utilize ML algorithms to train the system on each of positive and negative images [64-67]. Intelligent IoT systems can be designed to diagnose and assist treatment COVID-19 by aggregating a huge amount of data from patients then data can be analyzed [68].

4.2. Application of IoT

IoT means a communicated group of anyone, anything, anytime, anyplace, any service, and any network [31]. One of the most important symptoms of COVID-19 is fever. It was found that eighty percent of COVID-19 patients have a fever [5,58]. The common method used to measure body temperature during this pandemic is thermal screening using infrared thermometers. However, this method is dangerous, as the infection can be transmitted from the infected person to the person who makes the screening and vice versa due to the direct contact [5]. In [5] a system that can identify COVID-19 automatically from the thermal image has been proposed. This system uses an intelligent helmet with an installed thermal Imaging System. The thermal camera technique is incorporated with the IoT technique to monitor the screening procedure to obtain real-time data. Furthermore, the suggested system is provided with a face recognition technique. ML algorithm was employed to train the system on each of the positive and negative images. This system can distinguish high body temperature in the crowd and sends an alert if a high temperature is detected. The GPS unit determines the coordinates of the location after it is marked and an alert is transmitted to the designated smartphones. The officer will obtain the person's face and temperature data to recognize the infected person. Fig 1 shows the flowchart of the system.

In [34], ‘‘COVID-19 Intelligent Diagnosis and Treatment Assistant Program (nCapp)” based on the IoT was used to diagnose COVID-19 in an early stage and to enhance its cure. Terminal eight functions can be performed in real-time online communication with the ‘‘cloud” using the page choice button. Based on available data, surveys, and check outcomes, the diagnosis is automatically produced as affirmed, suspected, or suspicious of COVID-19 disease. It categorizes patients into mild, moderate, serious, or critical pneumonia. Also, nCapp can create an online COVID-19 real-time update database, and it refreshes the model of diagnosis in real-time based on the recent real-world case data to make the diagnosis more accurate. Furthermore, nCapp can guide curing. Doctors and specialists are connected to perform consultation and protection. Moreover, nCapp can help in following patients in the long term. Using this technology, people can inhibit disease spreading, protect doctors from infection, and control epidemics.

The work in [17] introduces a real-time system that can detect COVID-19 disease rapidly from the thermal image through IoT based smart glasses technology. The intelligent glasses send the data to be viewed on a phone application. Moreover, the proposed system has been provided with face recognition technology to identify the suspected person in any crowded place. Also, the system

adds information of the visited places of the suspected person via Google Location History (GLH) to give reliable data on the detection procedure. Fig 2 illustrates the flowchart of the system.
In [59], an IoT-based framework for detecting and monitoring COVID-19 patients. This framework gathers real-time symptom data from individuals and detects any suspected cases. This system also can monitor the treatment response for the recovered cases. In this work, eight ML algorithms have been used for identifying the possible COVID-19 cases via analyzing the gathered data rapidly. It was found that NN, SVM, Naïve Bayes, K-Nearest Neighbor (K-NN), and Decision Table have achieved an accuracy of more than 90%. However, ZeroR, OneR, and Decision Stump have achieved low accuracy.

Also, IoT-based drones can play an effective role in detecting COVID-19 infected people among the crowd. The benefits of drones are that they can minimize the interaction between people. Moreover, they can access hard-to-reach places. Drones can assist in the diagnosis of COVID-19 by capturing the temperature of people. Furthermore, they can aid in the sterilization process to protect doctors from infection. Also, they can deliver the treatment to the patients [56].
The phone and its applications have an important role in spreading the disease. For example, an application was created in Poland whose aim is to ensure that patients remain at home, as the program asks the patient randomly to send selfies during the day and where downloading this application is a mandatory matter by the authorities [56].

Also, Robots can be designed and controlled remotely by humans for providing crucial services such as remote diagnosis and remote surgeries. It is also can be used for remote treatment. Using robots, the temperature can be measured remotely to reduce people's interaction. Robots can maintain social distance. Singapore has designed a robot to monitor the social distance [56,57].

Healthcare IoT challenges

Hardware and software need to be protected from damage, misuse, and unauthorized access to patient data. IoT systems contain wireless devices so these systems may vulnerable to intrusion or network attack. Many solutions have been presented to these security challenges like intrusion detection [69]. Additional procedures can be taken to increase the security level such as personal identification and authentication [39]. Thus, security measures should be integrated into the design of the IoT device [51].

Privacy means there is no any unauthorized intrusion. It is a significant challenge in the IoT based healthcare sector. Some organizations are hesitant to embrace the IoT given fears of privacy issues especially in the healthcare field which includes clinical information, in which keeping up the privacy of the patient is critical owing to the legal prerequisites, which thus influence trust to adopt the IoT in the medical services [39].

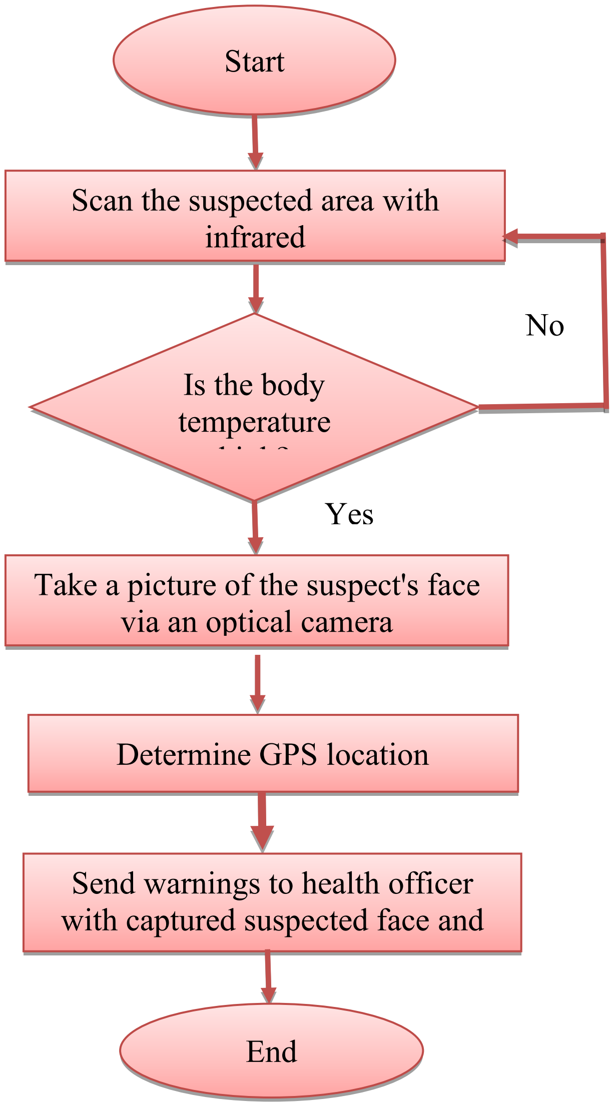

Figure 1. Flowchart of the system

There is a trust issue between the service provider and the user due to the sensitivity of the patient's data. To solve this issue, the security of the network can be enhanced via point-to-point encryption techniques dependent on cryptographic algorithms, message integrity verification techniques, and trusted routing mechanisms [39].

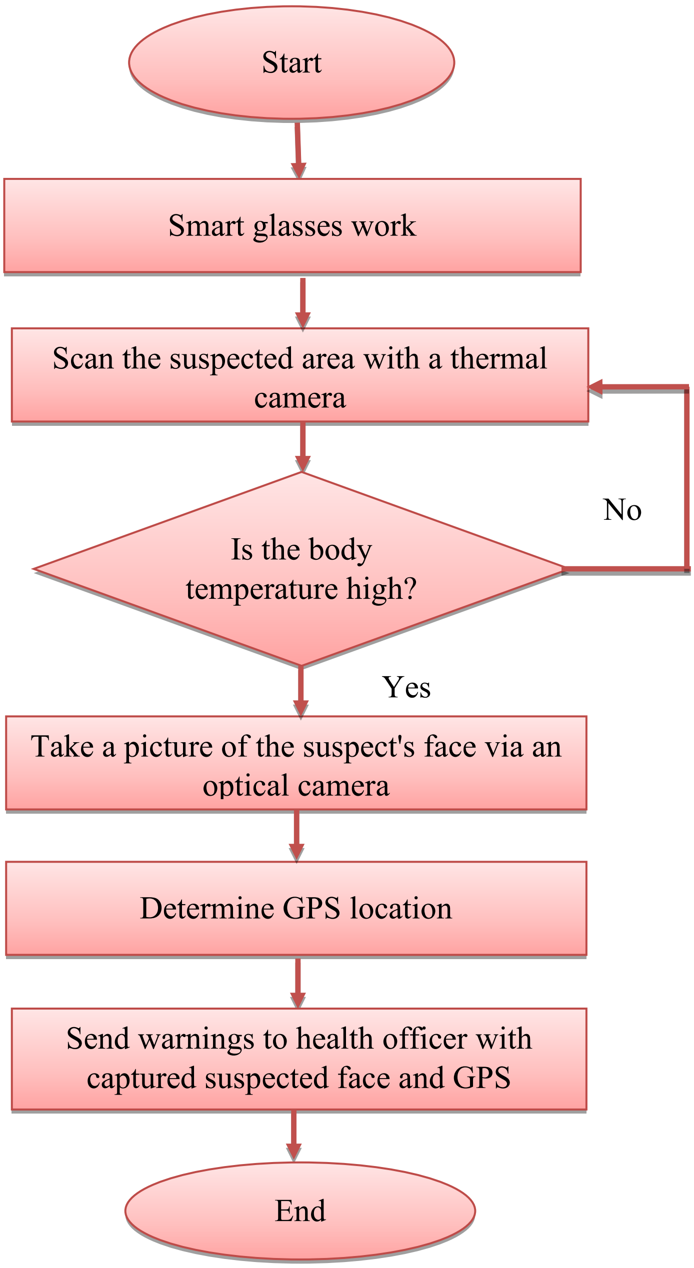

Figure 2. Flowchart of the system

5. Conclusion

This paper highlights AI and IoT researches which can make a significant contribution to confront the disease. AI has played a significant role in many sectors such as health. AI has been employed to assist fighting this disease. ML has emerging applications for Combating COVID-19 such as detecting and diagnosis, predicting, segmentation and drug discovery. It was found that ResNet-101 is a high accuracy and sensitivity model in diagnose COVID-19 disease. Moreover, SqueezeNet can acheive a high accuracy in detecting COVID-19 especially with image augmentation techniques when number of training samples is not enough. Also, Xception model can detect COVID-19 with high accuracy. In addition, it was found that Boosted Random Forest algorithm can achieve accurate results for predicting the severity of the case even with imbalance datasets. Also, ML-based drug discovery is a cost-effective, rapid, and efficient method that can reduce the failures in clinical trials. Furthermore, IoT plays a significant role in monitoring and diagnosis of the disease which will help to control the epidemic and reduce the spreading of the disease.

A review of recent studies demonstrates that not many researchers have performed IoT systems for confronting COVID-19 disease. So, future studies can be done by merging ML techniques with IoT to get powerful solutions with high accuracy. Moreover, future work can focus on creating systems for COVID-19 patient care and treatment based on ML. Also, as we know, there isn't much work related to the segmentation task. So, future studies can be performed to design a system that combines COVID-19 detection, lung infection segmentation, and infection area quantification.

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