A Survey of the COVID-19 Epidemic through the Eyes of Artificial Intelligence and Deep Learning: Challenges and Research Questions

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Abstract - *Recently, the COVID-19 epidemic has received significant attention from researchers interested in artificial intelligence and deep learning techniques. Neural networks and their family of techniques are employed to build intelligent systems for detecting and diagnosing COVID-19. Many works are presented in this domain and published in high-quality journals indexed by the IEEE, Science Direct, Web of Science and Scopus. However, there is a lack of surveys and papers that collect works focused on detecting and diagnosing COVID-19 using artificial intelligence and deep learning. Moreover, no work, to the best of our knowledge, has analyzed the works based on certain criteria that are tightly coupled with constructing strong intelligent systems. In this paper, we propose a maturity based statistical model that is used to analyses and evaluate previous works that proposed methods for detecting and diagnosing COVID-19. The proposed maturity model is driven by three main issues: dealing with blurry medical images, imbalanced medical data and COVID-19 detection using a real-time data stream. In addition, the properties that are required to build systems for COVID-19 detection and diagnosis are provided; these include ensuring the privacy of patents' profiles, securing medical data and examining regions of interest in medical images from various angles to extract different features for effective learning.*

Key Words: COVID-19; Artificial Intelligence; Deep Learning; Maturity; Criteria; Patients; Classifier.

1. INTRODUCTION

The medical sector is among the most important aspects of people's lives because staying healthy leads to higher work productivity and increased happiness. Relying on previous facts, governments always rank fighting epidemics as a top priority to ensure a strong economy and prosperity.

Motivation. In 2019, a group of patients in Wuhan, China, became infected with a serious new strain of coronavirus disease (known as COVID-19). Since then, COVID-19 has spread worldwide [1, 2]. Consequently, medical staff in governmental and private health companies have collaborated in their efforts to fight COVID-19. Even so, despite such great efforts in the medical sector, COVID-19 continues spreading and invading worldwide. The main reasons for this spread are related to a lack of effective treatments and the long time required to detect COVID-19 [3, 4]. As a part of the fighting team, researchers in the computer science field undertook the challenge of limiting the spread of COVID-19. Their role is represented by employing artificial intelligence (AI) and deep learning (DL) to develop accurate, reliable and fast detection systems. This work provides a review of studies focused on detecting COVID-19 using AI and DL techniques. Figure 1 illustrates a roadmap for this paper.

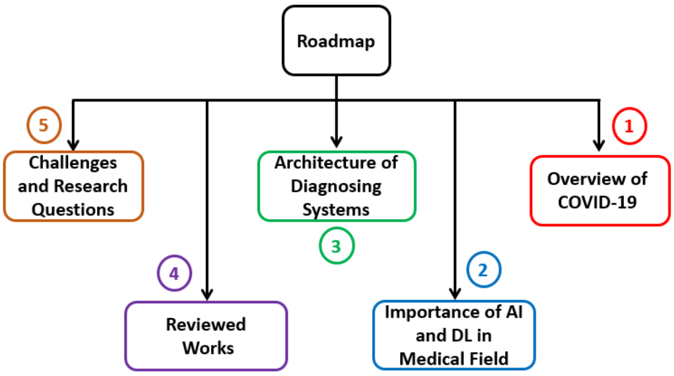

Fig. 1. Outlines of the presented paper.

As shown in Figure 1, the paper has five main axes. Each axis has its own topics, as shown in the following figures.

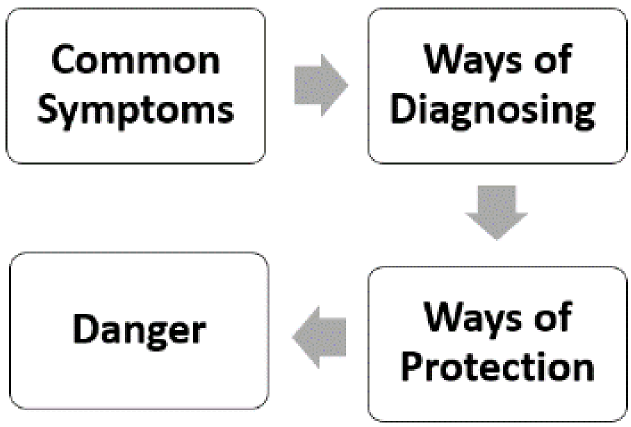

Fig. 2. Topics for the overview of COVID-19.

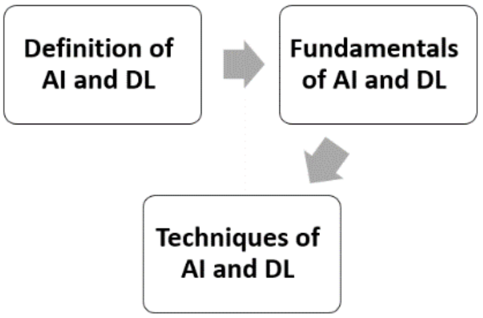

Fig. 3. Topics for the importance of AI and DL in medical field.

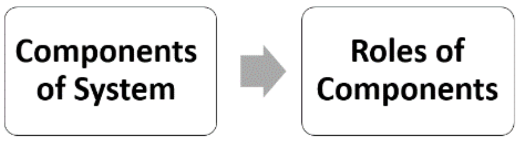

Fig. 4. Topics for the importance of architecture of diagnosing systems.

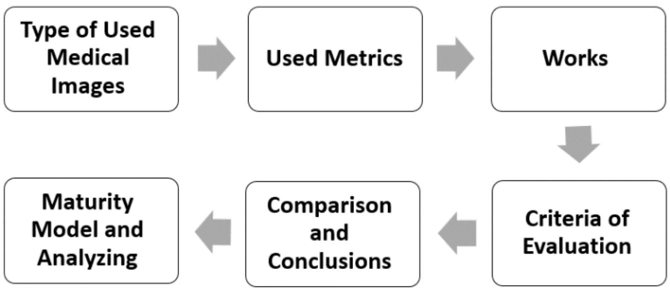

Fig. 5. Topics for the reviewed works.

Contribution. This work's contributions are as follows:

- We provide a statistical-based model called the maturity model to assess the robustness of AI and DL based COVID-19 detection systems. The proposed maturity model is based on the most criteria that negatively affect intelligent systems.
- Based on the proposed maturity model, we analyse the reviewed COVID-19 detection systems.
- Based on the findings of the analysis, we infer and summarise the challenges and research questions that contribute to strengthen the COVID-19 detection systems.

Organisation of the work. The rest of the work is structured as follows. In Section II, an overview of COVID-19 is presented from medical perspective. Section III highlights the importance of employing AI and DL in the medical sector and presents the corresponding benefits. The architecture used to build detection systems is discussed from the AI-based perspective in Section IV. Section V reviews previous works that propose ways to detect COVID-19 and presents the corresponding analyses using the proposed maturity model. In Section VI, the inferred challenges and research questions are drawn. Finally, we conclude the paper in Section VII.

2. OVERVIEW OF COVID-19

This section first presents the symptoms of COVID-19. Then, the ways of diagnosing and preventing COVID-19 are presented from a medical perspective. Finally, the danger of COVID-19 is highlighted.

2.1 Common Symptoms of COVID-19

The symptoms of COVID-19 can be classified into two main groups, common symptoms and additional ones, as shown in Figure 6.

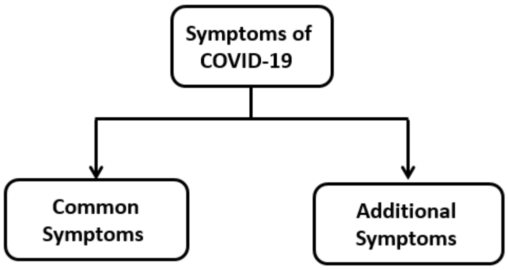

Fig. 6. Classification of the symptoms of COVID-19.

Most infected patients develop common symptoms (i.e. fever, fatigue and dry cough) [5], and others may experience additional symptoms (i.e. aches and pains, nasal congestion, runny nose, sore throat and diarrhoea) [6]. The additional symptoms are more dangerous when compared to the common symptoms because they can lead to death, especially if patients suffer from chronic diseases such as diabetes, high blood pressure or cancer.

The symptoms of COVID-19 typically appear within 2 to 14 days after initial exposure to the virus. Some people show few to no signs of illness during the early phase of infection but can still transmit the virus to others [7].

2.2 Ways of Diagnosing COVID-19

Methods for diagnosing COVID-19 depend on either traditional medical tests or the use of medical images, as illustrated in Figure 7.

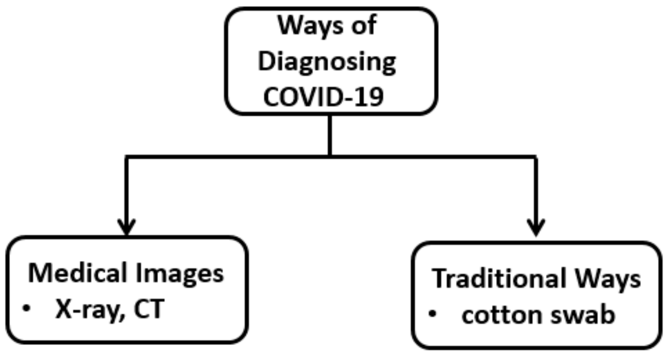

Fig. 7. Ways of diagnosing of COVID-19.

COVID-19 can be diagnosed similarly to other conditions caused by viral infections: using a blood, saliva or tissue sample. Most tests use a cotton swab to retrieve a sample from inside the nostrils. Using the cotton swab provided, people collect a nasal sample and mail it to a designated laboratory for testing [8]. Molecular approaches such as quantitative real-time reverse transcription–polymerase chain reaction (rRT-PCR) [9] and other methods such as serologic tests [10] and viral throat swab testing [11] are necessary and widely utilised for the detection of COVID-19.

Due to the severity of this epidemic, medical staff have moved towards using medical images to diagnose COVID-19. Studies have shown that chest radiographs (X-rays) [12] and chest computed tomography (CT) scans [13] can assist and reveal anomalies indicative of various lung diseases, including COVID-19.

2.3 Ways to Protect Against COVID-19

There are some proactive actions that can be taken to avoid COVID-19 infection. This following guidance is represented by some rules defined by the World Health Organization (WHO) [14]:

1. Clean your hands often.
2. Cough or sneeze in your bent elbow – not your hands!
3. Avoid touching your eyes, nose and mouth.
4. Limit social gatherings and time spent in crowded places.
5. Avoid close contact with someone who is sick.
6. Clean and disinfect frequently touched objects and surfaces.

Figure 8 shows the WHO's instructions for reducing the risk of COVID-19.

Fig. 8. Instructions for reducing the risk of COVID-19 [14].

It is worth mentioning that from a medical point of view, there is no 100% reliable or trusted vaccine for COVID-19.

2.4 Dangers Posted by COVID-19

COVID-19 invaded the world, causing many negative effects on all sectors of life ranging from industry to air travel and the economy. These negative effects, which reflect the dangers of COVID-19, can be summarised as follows:

1. COVID-19 exposed weaknesses in many countries' healthcare systems, and the inability of healthcare systems to manage patients has caused anxiety [15].
2. The COVID-19 pandemic is a global shock 'like no other', involving simultaneous disruptions to both supply and demand in an interconnected world economy. On the supply side, infections reduce labour supply and productivity, and lockdowns, business closures and social distancing also cause supply disruptions. On the demand side, layoffs and the loss of income from morbidity, quarantines and unemployment, as well as worsened economic prospects, reduce household consumption and firms' investment [16].
3. The current outbreak has had severe economic consequences worldwide, and no country appears to be unaffected. This has affected not only the economy, but all of society, leading to dramatic changes in how businesses and consumers behave [17].

Indeed, recently published papers have addressed the negative impact of COVID-19, such as [18-20].

3. IMPORTANCE OF AI AND DL IN THE MEDICAL FIELD

This section begins with the definition of AI and DL. Then, the fundamentals of AI and DL are explained. Finally, AI and DL techniques are presented.

3.1 Definition of AI and DL

AI is the science aimed at granting machines the ability to make decisions on behalf of humans [21].

DL is a technique that is driven from the artificial neural networks (ANNs). In general, ANNs were inspired by the biological research field. Thus, ANNs mimic the biological neural networks located in the human brain [22]. Figure 9 illustrates a biological neuron (connected with another one) with its main components.

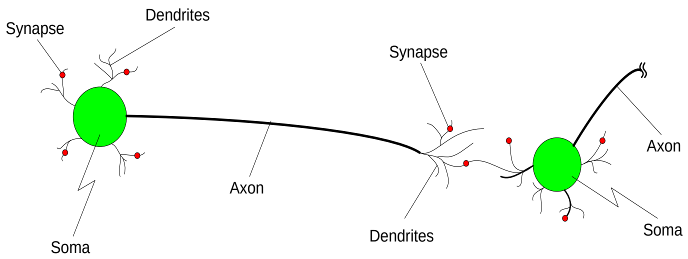

Fig. 9. Two interconnected brain cells (neurons).

The four components of biological neurons shown above are mapped to four components of artificial neurons. Table I shows this the mapping.

TABLE I. Biological Neuron vs Artificial Neuron

Biological neuron	Artificial neuron
Soma	Node
Dendrites	Input
Axon	Output
Synapse	Weight

ANNs compose of three main layers: the input layer, hidden layer and output layer. Figure 10 shows the three main layers of a typical ANN.

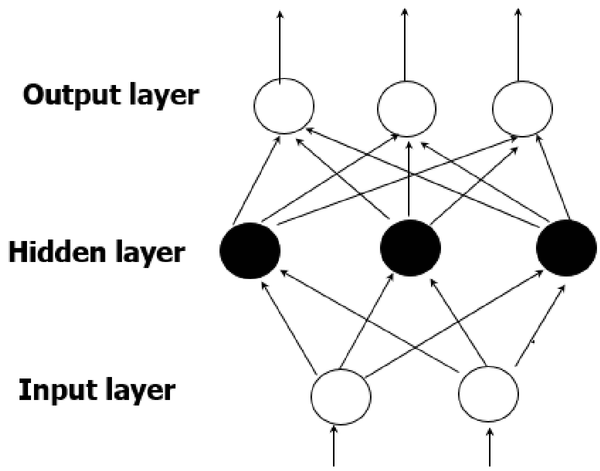

Fig. 10. Three layers of an ANN.

When an ANN has a series of hidden layers, a DL model is constructed. In other words, DL is nothing but the stacking of multiple hidden layers between the input and the output layer – hence the name [23]. Figure 11 shows how DL is based on ANNs.

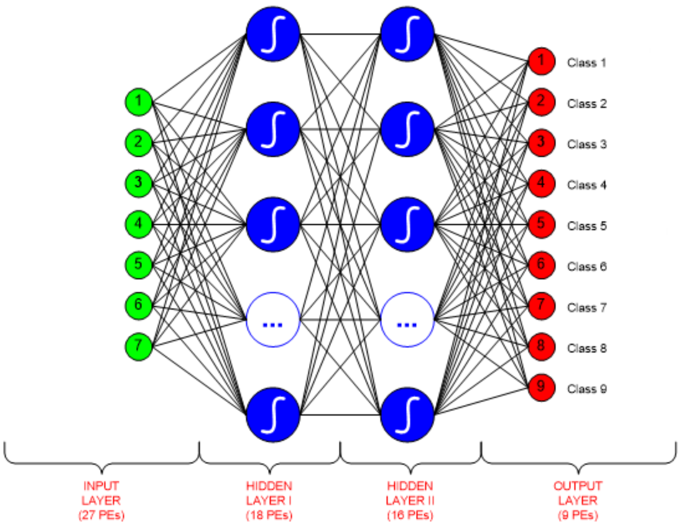

Fig. 11. Concept of DL [24].

3.2 Fundamentals of AI and DL

DL and NN have gained immense momentum in present day scientific research because they can learn from context [25]. Because DL models are constructed from ANNs, the main elements involved in ANNs are included in DL. These are the processing element (PE), the method of learning and the activation functions.

An ANN's PE can be defined as the unit used to process information mathematically. In this context, the summation of products is calculated based on the values of the inputs and weights. In addition, an activation (or transform) function is used to generate the output. Figure 12 illustrates the details of the PE.

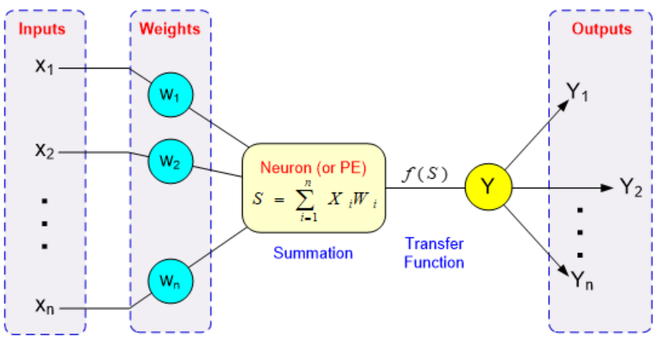

Fig. 12. Details of a PE in an ANN [26].

The most common method used to learn ANNs is called backpropagation. The key idea behind this method is to follow the steps listed below [27].

1. Initialise weights with random values and set other network parameters
2. Read in the inputs and the desired outputs
3. Compute the actual output by working forward through the layers
4. Compute the error (the difference between the actual and desired outputs)

5. Change the weights by working backward through the hidden layers
6. Repeat steps 2-5 until the weights stabilise

Activation functions are mathematical equations that determine a neural network's output. The function is attached to each neuron in the network and determines whether it should be activated ("fired") based on whether each neuron's input is relevant for the model's prediction. Activation functions also help normalise the output of each neuron to a range between 1 and 0 or between -1 and 1. In addition, activation functions must be computationally efficient because they are calculated across thousands or even millions of neurons for each data sample. Modern neural networks use a technique called backpropagation to train the model, which places an increased computational strain on the activation function, and its derivative function [28]. In a neural network, numeric data points, called inputs, are fed into the neurons in the input layer. Each neuron has a weight, and multiplying the input number with the weight gives the output of the neuron, which is transferred to the next layer. The activation function is a mathematical "gate" between the input feeding the current neuron and its output going to the next layer, as shown in Figure 13.

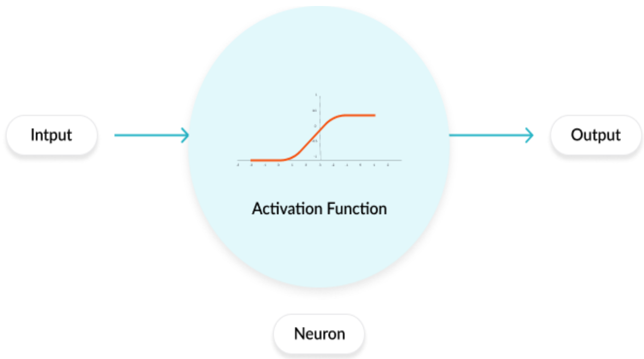

Fig. 13. Activation function as a gate [29].

Three common types of activation function are often used in ANNs:

1. Binary step function
2. Linear activation function
3. Non-linear activation functions

The most common activation function, Softmax, belongs to the third type. The Softmax activation function has the following advantages [30]:

1. It can handle multiple classes, compared to only one class in other activation functions, and it normalises the outputs for each class between 0 and 1 and divides by their sum, giving the probability of the input value being in a specific class.
2. It is useful for output neurons, whereas typically Softmax is used only for the output layer in neural networks that need to classify inputs into multiple categories.

Visually, the Softmax activation function is illustrated by Figure 14.

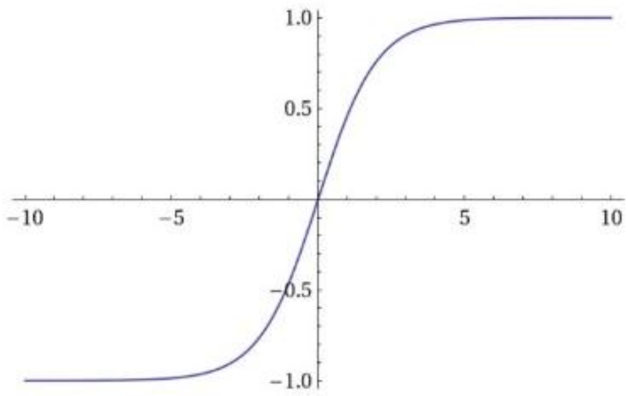

Fig. 14. Softmax activation function.

3.3 AI and DL Techniques in the Medical Sector

In general, DL techniques can be classified into three major groups, as shown in Figure 15.

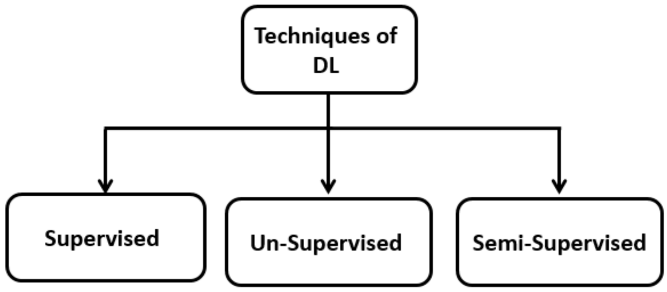

Fig. 15. Classification of DL techniques.

Table II summarises a simple comparison among the three DL techniques.

TABLE II. Comparison Among DL Techniques

DL techniques	Type of data	Main learning concept
Supervised	Labelled	The model is trained with a known input-output pair. Each known value constitutes an input vector and the desired value, which is referred to as the supervisory signal.
Un-Supervised	Unlabelled	Deals with knowing the inter-relations among the elements of the data set and then classifying the data without using

		labels.
Semi-Supervised	Labelled and Unlabelled	Falls between unsupervised learning and supervised learning.

In terms of statistics, AI and DL techniques contribute to saving huge amounts of money in medical sector. Ten AI and DL applications and advantages can be exploited to serve humanity, as illustrated by the 2026 estimation in Figure 16.

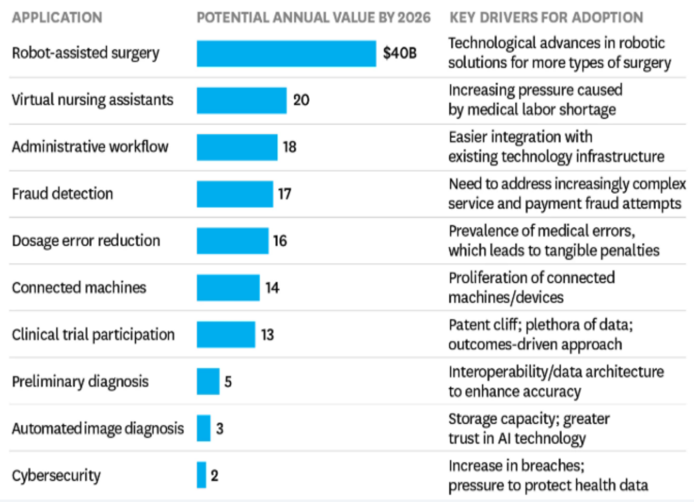

Fig. 16. Benefits of 10 AI applications by 2026 [31].

In terms of the variety of employing AI and DL techniques in the medical sector, Figure 17 illustrates the most common and valuable applications for healthcare purposes.

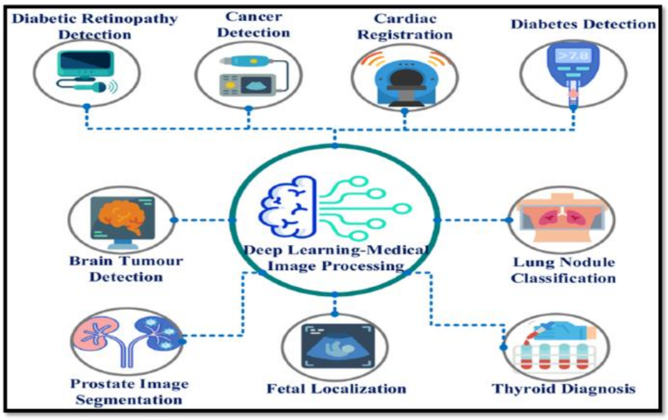

Fig. 17. Healthcare applications of AI and DL.

From the AI and DL perspective, employing the three learning types described above leads to five terms that are utilised for medical image processing, as shown in Figure 18.

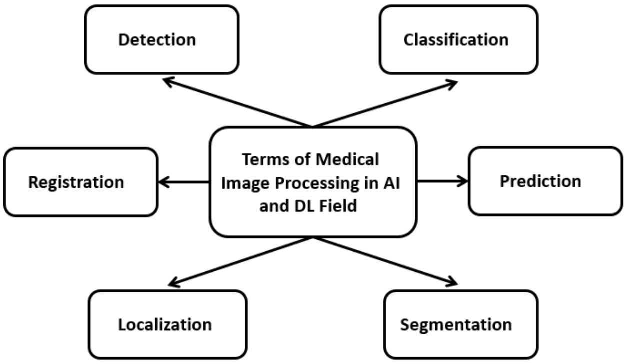

Fig. 18. Terms utilized for medical image processing in AI and DL research.

Classification. Classification is tightly coupled with computer-aided diagnosis (CAD). Classification also plays a significant role in medical image processing. During classification, one or more images are taken as input samples, and a single diagnosis factor is generated as an output which classifies the image. For example, [32] presents an intelligent system for diagnosing breast cancer in which the Softmax function is used at the final stage of the classification process.
Localisation. In the classification, images are fed to the intelligent model, and the contents of the image are revealed. After performing classification on the input image, the next step in the disease detection process is image localisation. In computer science terms, localisation is responsible for placing the bounding box around the output position. In medical terms, localisation refers to identifying the disease in the image. The localisation of anatomy is a crucial pre-processing phase in clinical diagnosis that enables the radiologist to recognise certain essential features [33].
Detection. There are various definitions of object detection, a computer vision technique used to identify instances of real-world objects. First, object detection allows for the recognition and localisation of multiple objects within an image or video. In addition, object detection techniques train predictive models or use matching templates to locate and identify objects. Object detection algorithms use also extracted features and learning algorithms to identify object type instances. In medical images, the object is the shape of the disease or the shape formed by ill cells. The course of action taken to detect ill cells is the same as described in the definitions [34].
Segmentation. Segmentation in the medical field contributes to enhancing the accuracy of disease diagnosis. In terms of inputs, processing and outputs, image segmentation takes a medical image as an input, divides it into several fragments. The output of medical image segmentation is a collection of medical segments covering the whole medical image. The final objective of medical image segmentation is to make digital images simpler and more comfortable to examine, which in turn leads to a higher accuracy during diagnosis [35].
Registration. Image registration can be defined as a way of converting data sets to a single coordinate model. Registration is necessary to analyse or integrate data from

several medical sources or distributed databases to form a uniform one. Here, the protocols of concurrency, consistency and avoiding locks are required [36].

Prediction. This process is linked with classification. In other words, the mechanism used to generate the outputs of a classifier depends on mathematical calculation. This calculation is a probability in origin, which in turn reflects prediction. The higher probability calculated during processing of medical images is the main factor in producing the final illness class [37].

The process of projecting the six terms mentioned above in the medical field using AI and DL requires techniques inspired by the main structure of ANNs. The most common technique used in this domain is the convolutional neural network (CNN). Figure 19 illustrates the general structure of a CNN.

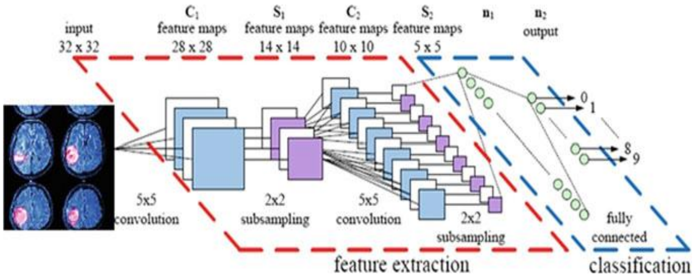

Fig. 19. Structure of a CNN [38].

Many types of ANNs (also referred to as DL techniques) are driven by mechanisms similar to those of CNNs. Table III summarises the various types of DL techniques driven by ANNs.

TABLE III. Types of DL Techniques

Name of neural network	Description of structure	Advantages	Disadvantages
Deep neural network (DNN)	The structure contains more than two layers. This in turn enables it to handle complex non-linear relationships.	It generates very high accuracy.	Because the error is propagated back to the previous individual layers, the training phase requires a long time.
Convolutional neural network (CNN)	It consists of convolutional filters which transform 2D into 3D.	Its performance is very good because it learns quickly using the given data.	It requires skilful handling of labelled data when it comes to classification.
Recurrent neural network (RNN)	It can learn sequences. The weights are shared across all steps and neurons.	It can model time dependencies.	It requires large data sets to be effective.
Deep conventional extreme learning machine (DC-ELM)	It uses the Gaussian probability function to build the network.	It generates high level of accuracy. It is computationally cheap and requires a short time for the training phase.	When the size of labelled data is small, the initialisation step may be weak especially if the function used for training is simple.
Deep Boltzmann machine (DBM)	It basically relies on Boltzmann machines. The hidden layers are connected utilising unidirectional links.	It uses feedback of top-down hierarchy. This gives it a strong inferences feature.	It is not applicable to big data in terms of optimisation.
Deep belief network (DBN)	It is used in both supervised and unsupervised machine learning. The hidden layers in the series of the sub-networks are visible layer for the next sub-networks.	It utilises greedy tactics aimed at maximising the likelihood.	It requires an initialisation step of inputs and weights. This in turn reflects high computational cost during the training phase.
Deep Autoencoder (dA)	It is common in un-supervised learning. The structure aims to handle the curse of dimensionality problem. The number of input is equal to number of output.	No labelled data are required.	It needs a pre-training step. Its training may be lost.

4. ARCHITECTURE OF DIAGNOSIS SYSTEMS

The framework of a diagnosis system in the medical field consists of doctors (users), machines for medical image capturing, medical images of patients and medical reports.

4.1 Diagnosis System Components in Terms of AI

As shown in Figure 20, a diagnosis system consists of four components that collaborate to deliver the doctor the result of prediction (i.e. the class of the processed medical image). These components are the pre-processor, feature extractor, classifier trainer, classifier tester and evaluator. All components are installed on machines that are used by doctors, specialists or even consultants.

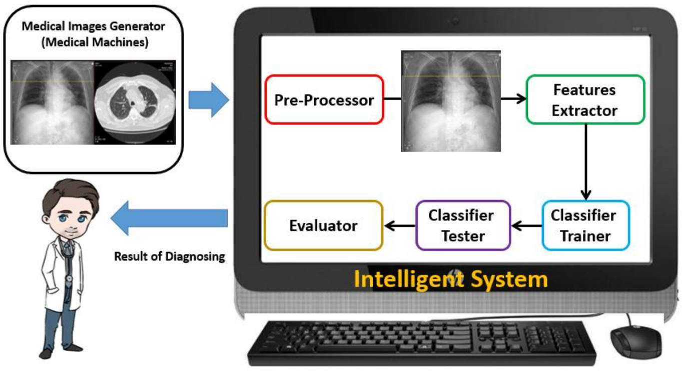

Fig. 20. Architecture of the diagnosis system in terms of AI and DL.

4.2 Role of Components

The components perform different tasks. Each task generates outputs that are required to be used as an input for the next task. The tasks are described below.

Pre-processor component. This component performs a cleaning task to enhance the quality of the medical images, leading to higher classification accuracy. The reason behind this is that the clearer edges and details, the greater the ability to identify the area of interest. Thus, the diagnosis is more accurate. Many techniques are used to achieve this task, such as histogram equalisation [39] and adoptive median filtering [40].

Feature extractor component. This component extracts distinguished features that accurately represent the cleaned medical images. This task can be achieved internally (i.e. as an integral part of the architecture of the training algorithm) or externally (i.e. as a separate part of the training algorithm). CNN has its own feature extraction technique, which is represented by the series of convolutional and pooling layers. The scale invariant feature transform (SIFT) is an example of an external feature extraction method [41].

Classifier trainer component. This component performs a task related to training the intelligent model (classifier) on the features extracted by the previous component. To end this task, any type of neural networks mentioned in Table III can be used.

Classifier tester component. This component performs a task related to calculating the accuracy of the intelligent model. To end this task, a certain part of the database containing medical images is taken as a testing set. Each medical image is used as an input for the classifier. Then, the output of the classifier (i.e. the class of the medical image) is observed to identify whether the classifier generates the correct class. For example, if 100 medical images are involved in the testing data set and the classifier classifies 99 medical images correctly, the accuracy is 99%.

Evaluator component. This component performs a task related to the usage of the intelligent model in reality. In other words, this component audits the work of the classifier when applying it in medical centres on real patients. The output of the task performed by the evaluator is to collect statistical data about the efficiency of the intelligent model in our realistic life.

5. REVIEWED WORKS

This section provides a description (including the types of medical images used and the metrics used for evaluation) of recent works aimed at diagnosing and detecting COVID-19. In addition, it presents an analysis that measures the maturity of the reviewed works based on pre-defined criteria.

5.1 Types of Medical Images

The most common types of medical images used to detect COVID-19 are X-rays and CT scans. Table IV shows the differences between the two types of medical images.

TABLE IV. Comparison Among DL Techniques

Term	X-ray	CT scan
Meaning	It utilises light or radio waves as radiation to scan the affected body part.	The CT scan process is a kind of advanced X-ray technique that provides the detailed structure of the affected body part and even clearer images of the internal soft tissues and organs.
Dimensions	2D	3D
Advantages	- Inexpensive - Readily available	- Generates deep and high-quality images - Uses a 360-degree X-ray beam, and images produced can be seen on the computer screen which is more powerful and clearer
Disadvantages	- Internal organ injuries and details are not clearly visible - Radiation can sometimes be harmful without precautions	- Expensive - Not easily available in rural and small hospitals
Example of COVID-19		

5.2 Used Metrics

In general, the confusion matrix (CoMa) is an effective benchmark for analysing how well a classifier can recognise the images of different classes. The CoMa is formed considering the following terms [42]:

1. True positives (TPs): Positive images that are correctly labelled by the classifier
2. True negatives (TNs): Negative images that are correctly labelled by the classifier
3. False positives (FPs): Negative images that are incorrectly labelled as positive.
4. False negatives (FNs): Positive images that are mislabelled as negative.

Table V shows the CoMa in terms of the TP, FN, FP and TN.

TABLE V. Confusion Matrix

Actual class (predicted class)	Confusion matrix		
	C1	¬ C1	Total
C1	True positives (TP)	False negatives (FN)	TP + FN = P
¬ C1	False positives (FP)	True negatives (TN)	FP + TN = N

By relying on the CoMa, the accuracy (Acc), specificity (Spe), precision (Pre) and recall (Rec) metrics are driven.
For a given classifier, Acc can be calculated by considering the recognition rate, which is the percentage of the test set images that are correctly classified. In other words, it calculates the overall effectiveness of a classifier. It is given by the following formula:

$$Acc = \frac{(TP+TN)}{number\ of\ all\ records} \quad (1)$$

Spe refers to how effectively a classifier identifies negative labels. It is given by the following formula:

$$Spe = \frac{TN}{N} \quad (2)$$

Pre refers to class agreement of the data labels with the positive labels given by the classifier. In other words, it calculates the exactness (what percentage of tuples that the classifier labelled as positive are actually positive). It is given by the following formula:

$$Pre = \frac{TP}{TP+FP} \quad (3)$$

Rec (or Spe) refers the completeness (the percentage of positive tuples the classifier labelled as positive). In other words, it calculates the effectiveness of a classifier to identify positive labels. It is given by the following formula:

$$Rec = \frac{TP}{TP+FN} \quad (4)$$

Another important metric is the area under ROC curve (AURC). It refers to the classifier's ability to avoid false classification and is given by the following formula:

$$AURC = \frac{1}{2} \times \left(\frac{TP}{TP+FN} + \frac{TN}{TN+FB}\right) \quad (5)$$

In addition to the AI-based metrics mentioned above, researchers also use performance based metrics in the evaluation procedure. The most common performance based metric is processing time.

5.3 Works

A few works published in 2020 surveyed studies that used AI and DL to detect and diagnose COVID-19, such as [43, 44]. The authors of [44] reviewed 9 works published in 2020. However, they did not provide a critical analysis to measure the maturity of the reviewed works. In [43], the authors addressed the reviewed works based on types of classification (i.e. binary, multi-class, multi-labelled and hierarchical classifications). In this work, we review the intelligent models provided in [44] based on predefined criteria, and we provide a maturity score for each one.
Table VI summarises a comparison among the reviewed works.

TABLE VI. Comparison Among DL Based COVID-19 Detection Systems

Ref	Medical image	Technique	Data set size	Results
Works from [44]				
[45]	X-ray	CNN	6000 images	98.08% accuracy
[46]	CT scan	Logistic regression	99 images	89.47% sensitivity (recall), 67.42% specificity
[47]	CT scan	DNN	121 images	81 % accuracy
[48]	Electronic medical records	Regression analysis	18 images	100% sensitivity (recall), 93.55% specificity, 95.24% accuracy.
[49]	CT scan	CNN-COVNet	3,322 images	90% sensitivity (recall), 96% specificity
[50]	CT scan	CNN	126 images	97% sensitivity (recall)
[51]	CT scan	CNN	100 images	0.996 AUC, 98.2% sensitivity, 92.2% Specificity
[52]	CT scan	2D slice analysis, 3D volume analysis	157 images	98.2% sensitivity, 0.996 AUC, 92.2% specificity
[53]	X-ray	CNN-COVID-	13,975	93.3% test

		Net	images	accuracy
Other works				
[54]	X-ray and CT-Scan	AlexNet network	170 X-ray images and 361 CT images	94.1% accuracy
[55]	CT-Scan	DC-ELM	10 images	80 % accuracy
[56]	X-ray	Bayes-SqueezeNet	5949 images	98.26% accuracy
[57]	X-ray	Restnet with segmentation	502 images	85.9 % accuracy
[58]	X-ray	MobileNetV2, SqueezeNet)	295 images	99.27% accuracy
[59]	X-ray and CT-Scan	CNN-ConvLSTM	56 images	99 % accuracy
[60]	X-ray	CNN	396 images	99.9 % sensitivity
[61]	X-ray	CNN	1821 images	97 % accuracy
[62]	X-ray	CNN	201 images	98.3% accuracy, 96.72% precision

5.4 Evaluation Criteria

Three criteria were used for evaluation purposes in this work. These criteria are directly linked to the most important metric used to indicate the strength of COVID-19 detection\diagnosing systems. They are as follows:

1. Imbalanced data, which refers to data used for training in which one class of the data is dominated by the other (i.e., the majority of data belong to one class and the rest belong to the another). This negatively affects the detecting accuracy [63, 64]
2. Noisy data (or blurry images), which illustrate the existence of outliers within the data employed for training. Outliers can be seen outside the normal context of the data. This also leads to poor detection accuracy [65].
3. The concept of drift, which refers to the behaviour of the client's changes resulting in change of data stream when dealing with online data detection in real time [66, 67].

5.5 Comparison and Conclusions

Based on the criteria listed above, Table VII summarises a comparison among works reviewed in Table VI.

TABLE VII. Criteria Based Comparison

	Term / Type of medical image	Criteria: Imbalanced data	Noisy (blurry) images	Concept of drift
Reviewed works	X-ray images			
	[45]	√	×	√
	[53]	×	×	√
	[56]	√	×	×
	[57]	√	×	×
	[58]	√	×	×
	[60]	√	√	×
	[61]	√	×	×
	[62]	√	×	×
	CT scan images			
	[46]	√	×	×
	[47]	√	×	×
	[49]	√	×	×
	[50]	√	×	×
	[51]	√	×	×
	[52]	√	×	×
	[55]	√	×	×
	Mixed medical images			
	[48]	√	×	×
	[54]	√	×	×
	[59]	√	×	×

Conclusions. As shown in Table VII, almost all intelligent models provided in the reviewed works were able to deal with imbalanced medical images. The reason behind this is that the medical images were collected accurately (i.e. taking into consideration such criteria). However, when dealing with random samples of medical images in the process of learning intelligent models to detect COVID-19, this leads to lower accuracy levels. Most of the reviewed works suffered from blurry medical images and the concept of drift. That is because the intelligent models presented in the reviewed works were trained on static medical images. This in turn reflects poor COVID-19 detection in real time.

5.6 Maturity Model and Analysis

To show the negative impact of the criteria, we propose a statistical model called the maturity model. This model is an indicator of the power of the intelligent models used to detect and diagnose COVID-19.

Our evaluation relies on three options to measure the negative impact of the criteria factors. Table VIII provides a description of the three used options.

TABLE VIII. Measurement Options

Option	Description
√	When the factor has high negative impact
×	When the factor has a low negative impact
P	When the factor has a partially negative impact

Table IX below (appendix A) can be read horizontally or vertically, as illustrated in Figure 18.

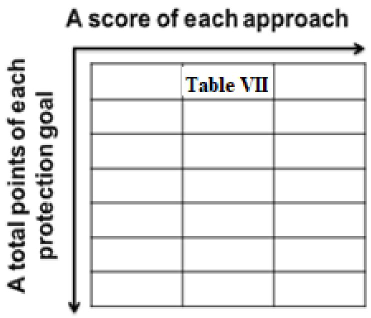

Fig. 21. Horizontal and vertical reading of Table VII.

If Table IX is read horizontally, the numbers table represent the total points that each approach obtained from all the criteria for each of the three options. Each option has a score that varies in the range of [0, 1, 2, 3]. For instance, the corresponding numbers for [45] are 1, 1 and 1 for the √, × and P options, respectively. This means that the criteria have a moderate impact on the intelligent system because the score for the √ option is 1. Thus, the maturity of [45] is moderate. The same scenario can be followed to extract the maturity of other intelligent models in the other reviewed works.

If Table IX is read vertically, the numbers represent the total points that each protection goal obtained for each of the three options. This total is related to all of the provided approaches to detecting and diagnosing COVID-19. Based on the numbers in Table IX, the (√) option had a total of 14 points. These points are distributed among the criteria with values of 2, 12 and 0, respectively. For the (×) option, the criteria achieved values of3, 0 and 18 points from the subtotals, for a total of 21. The corresponding values related to the criteria for the (P) option are 13, 6 and 0 points from the subtotals, respectively, with a total of 19. In terms of percentages, Figure 22 (a) above shows the negative impact of each criterion.

6. CHALLENGES AND RESEARCH QUESTIONS

Based on the analysed reviewed works using the proposed maturity model, the following three research questions are highlighted:

1. How can high accuracy be ensured when detecting and diagnosing COVID-19, given the impact of imbalanced medical images? The whole training procedure is negatively affected if the medical images collected in the data set are dominated by only one class, such as COVID-19, normal lungs or other diseases of the lung. In contrast, when utilising balanced data for training intelligent or DL based models, accuracy will be high, which reflects higher level of credibility in realistic scenarios. Therefore, from a practical point of view, imbalanced data must be taken into account when building COVID-19 detection systems in the context of AI and DL.
2. How can the high quality of medical images (both the X-ray and CT scan types) be ensured to facilitate the training procedure? Sometimes the motion of the patient when capturing medical images leads to noisy or blurry images. Such noisy data should be cleaned. Otherwise, accuracy is negatively affected because of training on poor-quality medical images.
3. How can COVID-19 be diagnosed and detected effectively in real time? There is a need for a method that guarantees timely handling of the data stream. Detecting COVID-19 in real time contributes to limiting its spread because decisions related to the isolation of infected patients can be made immediately.

In the context of medical sector, there are three additional main challenges:

1. Due to the sensitivity of the medical data, privacy must be preserved. In other words, the need for a novel method that ensures that patients' personal information will be revealed only to trusted parties is pressing. Therefore, the information included in patients' profiles must be protected from being revealed. Many works addressed the privacy issue, highlighting the need to protect personal data [68-72]
2. The security of the medical information itself should be ensured. Therefore, the medical data should be protected using cybersecurity terms such as confidentiality, integrity, availability when transmitted for manipulation using AI and DL methods. Steganography and other security

measures can be implemented [73-76] with low computational cost and processing time.

3. Handling the shape of the ill cells related to COVID-19 is a critical issue and represents a challenge. That is because when looking at the shape of the ill cells from different angles, different features can be extracted. Because the features extracted are used in the training phase, the intelligent model provides strong ability to identify the disease from different angels. This in turn contributes to increasing the accuracy level.

In summary, a powerful intelligent system used to detect and diagnose COVID-19 should have the following features:

1. Ability to deal with imbalanced medical images, blurry medical images, different types of medical images and the concept of drift.
2. Ability to ensure the security of the medical data with a considerable processing time.
3. Ability to preserve patients' privacy.
4. Ability to present a high level of accuracy.

7. CONCLUSION

When detecting and diagnosing COVID-19, researchers in the computer science field employ AI and DL techniques to limit the spread of this epidemic. In this work, we reviewed many studies from the AI and DL research fields aimed at detecting and diagnosing COVID-19. X-ray and CT scans are the most common medical images types used in the reviewed works. Three main criteria were presented in this work in the context of comparing the reviewed studies: imbalanced data, noisy (blurry) medical images and the concept of drift. Based on these three criteria, a maturity model was proposed to determine the score of each reviewed work. The maturity model provided statistical data that reflected the efficiency of the reviewed works. Finally, six research questions were presented for consideration by researchers when building COVID-19 detection systems.

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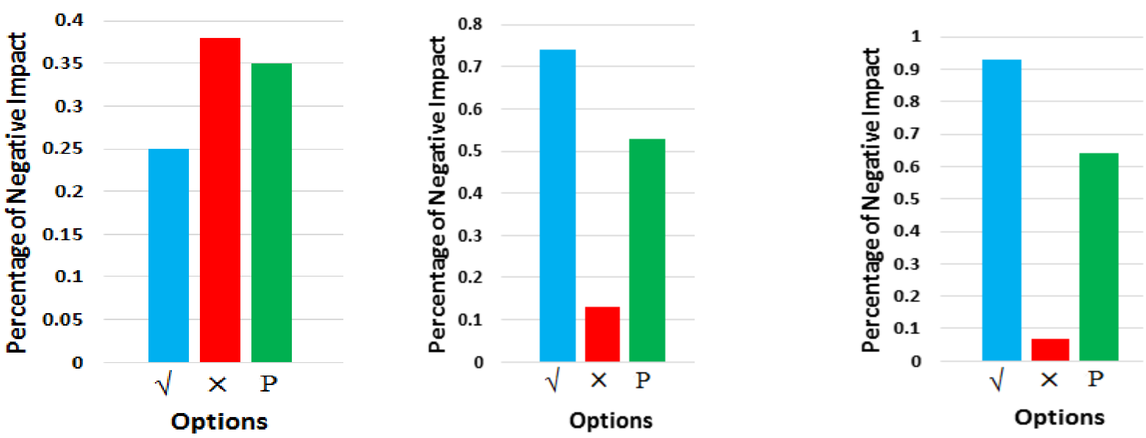
Appendix A

TABLE IX. Maturity Model Based Analysis.

Type of medical image \ Term		Criteria: Imbalanced data	Criteria: Noisy (blurry) images	Criteria: Concept of drift	Subtotals: √	Subtotals: ×	Subtotals: P
Reviewed works	X-ray images			Maturity: 7			
	[45]	P	√	×	1	1	1
	[53]	×	√	×	1	2	0
	[56]	P	√	×	1	1	1
	[57]	P	√	×	1	1	1
	[58]	P	√	×	1	1	1
	[60]	P	P	×	0	1	2
	[61]	×	√	×	1	2	0
	[62]	×	√	×	1	2	0
	CT scan images			Maturity: 7			
	[46]	P	√	×	1	1	1
	[47]	P	√	×	1	1	1
	[49]	√	√	×	2	1	0
	[50]	√	P	×	1	1	1
	[51]	P	P	×	0	1	2
	[52]	P	P	×	0	1	2
	[55]	P	√	×	1	1	1
	Separation of privileges			Maturity: 1			
	[48]	P	√	×	1	1	1
	[54]	P	P	×	0	1	2
	[59]	P	P	×	0	1	2
Subtotals:							
√	High negative impact	2	12	0	14		
×	Low negative impact	3	0	18	21		
P	Partial negative impact	13	6	0	19		
Total:					54		



(a): Negative impact of imbalanced data (b): Negative impact of blurry images (c): Negative impact of the concept of drift

Fig. 22. Overall negative impact based on the three criteria.