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Diagnostic COVID-19 based on chest imaging of COVID-19: A survey

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Abstract

As of June 24, 2020, the coronavirus infection (COVID-19) has infected more than 9.3 million people and resulted in more than 0.47 million deaths globally. COVID-19 cannot be diagnosed or treated without chest imaging procedures such as computed tomography and X-rays. Due to the highly infectious nature of this disease, radiologists are under continual pressure to diagnose and treat patients. As a possible solution to these issues and to enhance diagnostic accuracy, artificial intelligence (AI)-based image analysis techniques are being investigated. This assessment focuses on the present state of chest imaging analysis techniques using artificial intelligence for COVID-19. Note in particular the imaging analysis methodologies of two common viral types of pneumonia that may be used as a reference for assessing the illness utilizing chest pictures. Examine in deeper depth the progress of AI-assisted illness diagnosis and assessment, finding that AI approaches in this application are extremely useful. Focus on the role of artificial intelligence in the Corona epidemic and analyze the feme dataset utilized in prior studies as well as any relevant articles.

Keywords: COVID-19, artificial intelligence (AI), Chest imaging, dataset
2020 MSC: 68T01, 68T09

1 Introduction

The spread of "COVID-19" is a new global health emergency that threatens the population (Coronavirus Disease-2019). Since December 2019, when Covid-19 originated in the Hunan seafood market in Wuhan, South China, and rapidly spread around the globe, the World Health Organization has labeled the virus outbreak a global public health emergency (WHO) [4]. Recently, a severe acute respiratory "syndrome coronavirus 2 (SARS-CoV-2)"-caused new coronavirus known as "(COVID-19)" has spread over the world. The number of those afflicted and those who succumb to the disease are both on the rise. The silent cases of the novel coronavirus are the most prevalent, and they represent an even higher danger to public health than the more obvious signs of fever, dry cough, myalgia, dyspnea, and headache [19]. The "COVID-19" virus is rapidly becoming one of the worst pathogens to ever endanger human civilization [16]. Utilizing sophisticated healthcare tools and facilities, creative solutions have been created over the last few decades to help in the diagnosis, prevention, and management of illness. In particular, imaging techniques like CT and X-ray are among the most effective for COVID-19 diagnosis [25]. Complementing real-time reverse-transcription polymerase chain reaction (RT-PCR) testing with imaging methods such as computed tomography (CT) and chest

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X-rays is possible. According to RT-PCR statistics, the sensitivity and accuracy of disease infection detection on chest CT images are 97% and 68%, respectively [11]. However, radiologists have a substantial workload due to the manual effort and time required by traditional techniques of diagnosis and processing for CT/X-ray scans. Due to the superiority of AI in medical imaging analysis, artificial intelligence (AI) techniques based on deep learning have recently attracted a great deal of interest from researchers. These techniques might help overcome these obstacles and improve the accuracy of diagnosis [34]. Deep learning-based artificial intelligence is presently widely used in medical imaging since it significantly outperforms more traditional methods [18].

2 Covid-19

Human respiratory sickness can be caused by the coronavirus family of viruses. The spikes on their surface resemble a crown, hence the name ”corona.” Human sickness can be caused by coronaviruses, and some of the most well-known instances are severe acute respiratory syndrome (SARS), Middle East respiratory syndrome (MERS), and the common cold. SARS-CoV-2, a novel coronavirus, was initially discovered in December 2019 in Wuhan, China. It has now reached every nation on Earth [32].

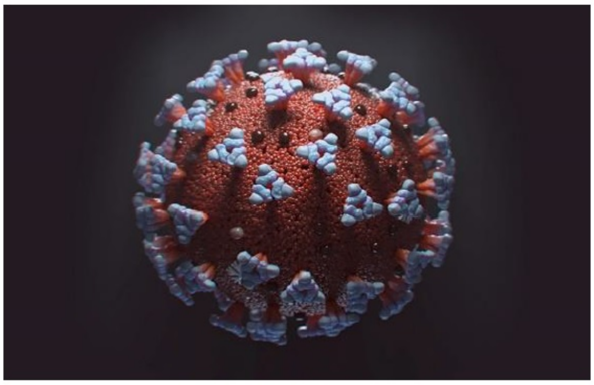

Figure 1: Coronavirus disease 2019 (COVID-19) [4].

Bats, cats, and camels are common hosts for coronaviruses. The animals host the viruses, but they do not infect them. There have been instances of these viruses spreading to new species of animals. Transmission to new species raises the possibility that the viruses will undergo some sort of alteration (mutation). A virus can spread from animals to people over time. In the case of ”SARS-CoV-19,” it is thought that the first individuals to get the virus did so at a food market that sold not only meat and fish, but also live animals. The ”ARS-CoV-2 virus”, which is responsible for COVID-19, can enter the body through the mouth, the nose, or the eyes (”directly from the airborne droplets or from the transfer of the virus from hands to face”) [34]. After entering the nasal cavity, the virus travels to the back of the throat and infects the mucosal lining there. It then attaches to cells, multiplies, and spreads throughout the blood and lymph systems before eventually reaching the lungs. If the virus enters one tissue, it may easily replicate and infect additional cells. In table 1 below, we’ve included the most crucial phrases and words to know about the Corona pandemic.

Table 1: important vocabulary related to the Corona pandemic [4, 16, 34]

vocabulary	**Description**
spread	• The virus is transferred via the air by the droplets produced when an infected person coughs, sneezes, speaks, sings, or even simply breathes in close quarters. Infection may occur if these droplets are breathed in. • Coronavirus may also be spread by direct face contact after close physical contact (touching, shaking hands) with an infected person.
disease incubation period	COVID-19 Symptoms may not appear for many days, although the disease is communicable throughout this period. no longer infectious 10 days after the first signs of illness appeared.

prevention	The most effective method for preventing the spread of COVID-19 is to: • Maintain a 6-foot distance from people whenever feasible. • Wear a cotton mask that covers your mouth and nose while in public. • In the absence of soap, regularly wash your hands with an alcohol-based hand sanitizer containing at least 60% alcohol. • Keep away from crowded places indoors. Try to open as many windows as you can to bring in as much natural light and air. • Self-isolate at home if you are experiencing symptoms that might be COVID-19 or if a test for COVID-19 is positive. • Clean and disinfect areas often touched.
risk	Those who are most susceptible to developing COVID-19 include: • Currently located in, or having just visited, an area with ongoing, active transmission. • Be in a close relationship with someone who has the COVID-19 virus, either proven or suspected by a laboratory. The World Health Organization defines close contact as coming within 6 feet of an infected person for 15 minutes or more during a 24-hour period. • Have preexisting medical issues or a weaker immune system and are above the age of 60.
symptoms of COVID-19	COVID-19 symptoms differ from individual to individual. In fact, some infected individuals exhibit no symptoms (asymptomatic). In general, persons infected with COVID-19 have the following symptoms: Most common symptoms: • fever • cough • tiredness • loss of taste or smell Less common symptoms: • sore throat • headache • aches and pains • diarrhoea • a rash on skin, or discoloration of fingers or toes • red or irritated eyes Symptoms may emerge anywhere between two and fourteen days following exposure to the virus. Children exhibit comparable, but often less severe symptoms than adults. People with severe underlying medical issues and older folks are at a greater risk for COVID-19 complications.

The following are some statistics belonging to the organization who:

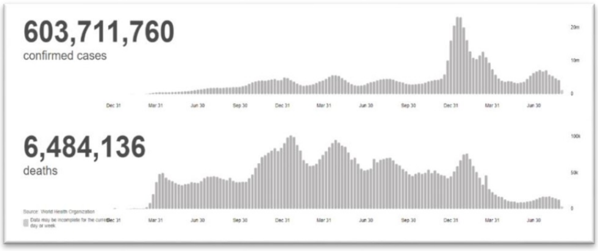

Figure 2: confirmed cases and deaths 2022 [7].

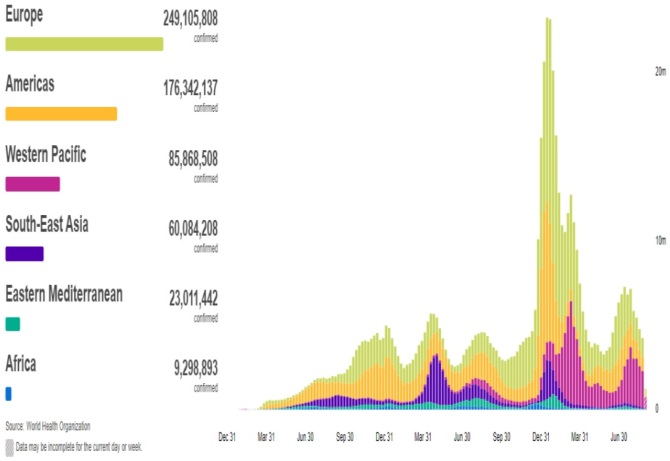

Figure 3: detail of counter about confirmed cases and deaths 2022 [36].

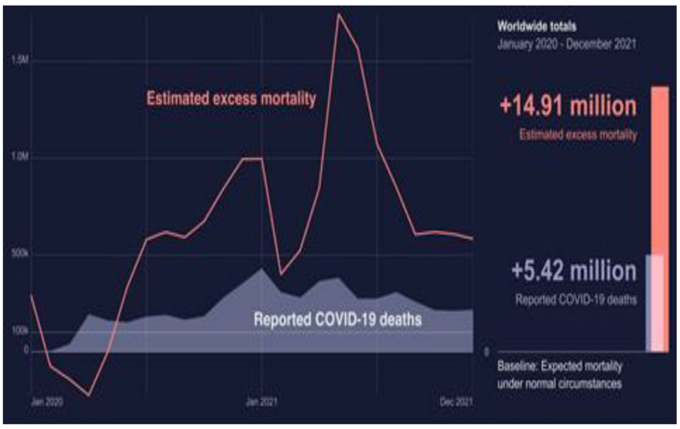

Figure 4: Global excess deaths associated with COVID-19, January 2020-December 2021 [36].

3 Diagnostic of covid-19

Since "SARS-CoV-2 is an RNA virus", any existing RNA detection format may be employed to identify the virus6. Reverse transcriptase must be used to transform the viral genome into a DNA complement so it may be suited to the most prevalent diagnostic DNA detection formats. Instantaneous simulations of these exams were among the first to be developed. Since similar tests were developed for SARS-CoV and Middle East respiratory syndrome coronavirus (MERS-CoV), it seemed plausible to use a PCR-based diagnostic approach for SARS-CoV-2. SARS-CoV-2 infected patients may be located and the efficacy of future vaccination campaigns can be evaluated if the host's immune response is tracked. There are several different assays available for identifying particular SARS-CoV-2 antigens and antibodies, comparable to those established for SARS-CoV and MERS-CoV. The detection and characterisation of SARS-CoV-2 has been a major focus in recent months, with all available technologies being used to build extremely sensitive and specific assays in a short amount of time. These alternative test configurations and methods are summarized in table

2 below. Covid-19 was enlarged on diagnostic chest x-rays and computed tomography scans.

Table 2: Diagnostic of covid-19 [2, 11, 38, 43]

PCR	**Definition** The polymerase chain reaction (PCR) test for COVID-19 is a molecular test that examines a sample from your upper respiratory tract to check for genetic material (ribonucleic acid or RNA) of the SARS-CoV-2 virus, the causative agent of COVID-19. which may pick up traces of DNA even in small quantities.
	Limitation • Polymerase chain reaction testing is considered the most reliable method for detecting COVID-19. However, it is complicated to carry out and calls for specialized tools, knowledge, and reagents. It may cause delays if any of these are in limited supply. • Most "PCR tests for COVID-19" include submitting nasal or throat swabs to a lab for examination, which might take a few days. Whether you get a positive PCR result, it's probable that you have the virus, but it's difficult to establish if you're still contagious or not. Some scientists propose utilizing the cycle threshold value to quantify the amount of virus in a sample and assess the possibility of transmission from a person who tests positive for the virus. • False negative findings, in which an infected individual tests negative for SARS-CoV-2 while having the virus, are another problem, occurring in an estimated 2% to 29% of cases. This may occur if swabbing is conducted incorrectly or if it is performed too soon in the course of an illness. It's dangerous because the infected individual could unknowingly spread the disease to others. • Real-time reverse transcriptase polymerase reaction (RT-PCR) of viral nucleic acid is inaccurate due to the high rate of false negative results.
Saliva tests	As a replacement for uncomfortable swabbing of the nose and throat, researchers are developing PCR tests that use samples of a person's saliva instead. Even while they don't seem to be as sensitive as swabbing, they might be more suited for some groups like kids.
Rapid PCR tests	These tests guarantee a result in 90 minutes, unlike standard PCR, and may be conducted with minimum training utilizing portable table-top devices. A company named DnaNudge, which originated at London's Imperial College, has produced one such test. The government of the United Kingdom placed an order for 5.8 million of their kits in August with the purpose of deploying them in hospitals and care homes to speed up the process of detecting and isolating persons with COVID-19. Recent research has shown that this method is just as accurate as traditional PCR in diagnosing COVID-19. Each machine can only process a maximum of 16 tests per day, thus they won't be very useful for screening the general population for coronavirus infection.
Pooled testing	This is an alternative strategy for attempting to improve national testing capacities and shorten the time it takes to get results back from viral tests. Red Cross uses it to check given blood for HIV, Zika, and hepatitis, and it was tested for SARS-CoV-2 in the San Francisco Bay Area. When dealing with a large number of samples, it is more efficient to examine them all together than to do individual polymerase chain reaction (PCR) tests on each one. It is safe to assume that all individual samples are negative for SARS-CoV-2 if the pooled sample results are negative. If a positive result is found from a group sample, further testing is done on each individual specimen to pinpoint where the infection originated. Sample pooling has the potential to reduce the overall cost of viral testing by reducing the total number of tests performed. The number of impacted people directly correlates to the cost. Researchers have predicted that pooled testing would reduce test usage by roughly 50% if 9% of a population were infected, and by nearly 90% if 0.1% of a population were afflicted.

Antibody tests	Antibody assays are a kind of immune response analysis that looks for evidence of previous "SARS-CoV-2" exposure by detecting the production of antibodies by B cells. The presence of these antibodies in the blood is a strong indication of previous infection with the virus and, perhaps, protection against further infections. Due to the delayed nature of antibody development and the possibility that antibodies may decline over time, a negative result on an antibody test is not conclusive evidence that a person has not been exposed to COVID-19 or does not have some level of protection against it. Antibody tests still have value because they tell public health agencies what percentage of the population has been exposed to a pathogen. Researchers interested in understanding the evolution of resistance to SARS-CoV-2 will also find these helpful.
X-ray and CT chest	• Electromagnetic waves are a form of radiation that includes X-rays. Internal images of the body are captured by X-ray machines. The photos depict the bodily components in a variety of black and white tones. This is due to the fact that various types of tissue absorb radiation in varying degrees. Because of the high calcium content in bones, they appear white on x-ray. Soft tissues such as fat have a lower absorption rate and appear grayer. Lungs seem dark because air is the least absorbent medium. • A computed tomography (CT) scan combines a series of X-ray images taken at different angles to create cross-sectional views (slices) of the bones, blood vessels, and soft tissues within your body. Pictures taken from a CT scan provide more information than standard X-rays. Although CT scans may be used for a variety of diagnostic purposes, they are especially well suited to the urgent examination of patients who may have sustained internal injuries in a car crash or other traumatic event. A computed tomography (CT) scan can show detailed pictures of almost any part of the body. This helps doctors in medicine, surgery, and radiation therapy figure out what's wrong and how to treat it. • Managing patients with COVID-19 requires a combination of clinical assessment and laboratory markers, and radiological imaging is an integral part of that combination. At the height of the first wave of the pandemic in China, chest X-ray (CXR) was used because it was more specific (99%) and sensitive (95%) than chest X-ray (CXR) in diagnosing this sickness.

4 Challenge in Diagnostic of covid-19

Laboratory diagnosis of "COVID-19" illness is most reliably accomplished by use of molecular methods for nucleic acid detection. These tests are sensitive and specific enough to identify "COVID-19" infection in patients at an early stage. While RT-PCR is the gold standard, its high price and specialized equipment and personnel requirements may make it inaccessible in nations with lower incomes. Alternatives like "LAMP and CRISPR-Cas" may be examined in these nations because of their low cost and simplicity, and since the FDA has authorized their use [43]. In comparison to molecular detection methods, antigen detection methods are more straightforward and productive, but they lack the sensitivity required for certain applications. Negative nucleic acid tests for "SARS CoV-2" could still be able to be performed 7 days after the onset of symptoms, due to antibody detection methods including "lateral flow IC, ELISA", and "MIA" [37]. Although these techniques can monitor illness development, they cannot determine whether a patient is infectious. Although lateral flow IC is quick and just requires a minimal amount of technical skill, it has poor sensitivity; in contrast, ELISA and MIA have great sensitivity but take more time and need expert employees. Due to its ease of use and widespread availability, CXR may be the primary imaging modality for "COVID-19" patients. However, it can also lead to false-positive results in cases of modest lung abnormalities [32]. A CT scan has a sensitivity of 98% and may aid in the diagnosis of asymptomatic pneumonia; however, it is of little benefit in the identification of asymptomatic, presymptomatic, or mildly symptomatic patients who do not have pneumonia [43].

5 The Role of Artificial Intelligence in The Corona Pandemic

Artificial intelligence (AI) is changing the way we live by attempting to give computers and robots human intelligence so they can solve new kinds of issues. The first AI programs were designed to accomplish very basic goals, such winning a chess game, recognizing a language, or retrieving an image from a database. Complex issues are being solved more quickly, cheaply, and effectively by artificial intelligence as a result of technical developments. There is no denying the superiority of AI in healthcare over more traditional approaches to analytics and clinical decision-making [6]. As a subset of artificial intelligence (AI), machine learning (ML) algorithms are able to mine massive datasets for hidden patterns. Their accuracy and precision improves with exposure to training data, allowing for novel insights into early illness diagnosis, medication development, diagnostics, healthcare systems, treatment variability, and patient outcomes. But how helpful are AI algorithms during an epidemic or pandemic? The pandemics that occurred after the year 2000 served as a test of how successfully AI could handle catastrophes. The effectiveness of AI algorithms is heavily influenced by the accessibility of both historical and real-time data, as well as computer capacity. During pandemics, AI helps with early warnings and alerts, predicting and finding outbreaks of diseases, real-time disease monitoring around the world, analyzing and showing spreading trends, predicting infection rate and trend, making quick decisions to find the best treatments, studying and analyzing pathogens, and finding new drugs [23]. All of these processes are expedited using AI. The World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC) (in the United States) are receiving information on a variety of illnesses and global circumstances. Different institutions may access all of this data in real time through contemporary computer architecture and the internet in order to create an AI model capable of doing a variety of jobs on its own or with the assistance of other AI models. Using natural language processing (NLP) methods, AI can collect information from news sites, forums, healthcare reports, travel data, social media postings, and other sources in different languages throughout the globe, in addition to the official data, and determine which are the most significant [35]. Instance histories, geographical occurrences, and social media postings all related to a new case of pneumonia are analyzed with lightning speed, totaling many terabytes of data. In contrast to supervised ML/DL, which must be trained on a small, hand-picked dataset, unsupervised ML/DL may learn to recognize patterns on its own by sifting through historical and real-time data. Artificial intelligence models that have been taught to predict one illness may be retrained using data from another condition. Among the many notable applications of AI in the fight against the COVID19 pandemic are the ones listed below [11, 20]:

- AI has the potential to be utilized as an early epidemic warning system; BlueDot, an AI-driven program, not only identified the Zika virus outbreak in Florida 4 but also COVID19, 9 days before the WHO issued its declaration.
- An artificial intelligence (AI) diagnostic tool (XGBoost machine learning-based prognostic model) was developed by scientists at Huazhong University of Science and Technology (HUST) and Tongji Hospital in Wuhan, Hubei, and it is 90% accurate in predicting survival rates of "COVID-19"-infected patients by analyzing blood samples.
- In Wuhan, China, an artificial intelligence diagnostic tool analyzes chest CT scan pictures to quickly identify COVID19 from other kinds of pneumonia. The authors assert that their novel approach has the potential to ease the workload of frontline radiologists, enhance the speed with which patients are diagnosed, isolated, and treated, and ultimately aid in the containment of the epidemic.
- "COVID-Net" is a deep learning system designed to detect COVID-19 positive cases from chest X-rays and expedite treatment for those patients who need it the most.
- "Google's DeepMind" has predicted the protein structure of SARS-CoV2, which is assisting researchers in their efforts to learn more about the virus and the severe acute respiratory illness it causes.
- Multiple computer vision camera systems powered by artificial intelligence have been installed in China and elsewhere to monitor crowds for signs of COVID-19.
- FluSense is a contactless syndromic surveillance tool that may be used to forecast seasonal flu and other viral respiratory epidemics like the COVID-19 pandemic or SARS.
- Wuhan, China, is home to some of the world's first medical use cases of the humanoid robot "Cloud Ginger (aka XR1)," which is driven by artificial intelligence. The first is meant to help medical staff bring food and medication to patients, while the second is designed to keep people entertained while they're in isolation.

A few AI models are also hit-or-miss owing to a dearth of prior training data. AI has not fully advanced to defeat a pandemic; nonetheless, the role of AI during COVID19 is far greater than in past pandemics, and it is being utilized appropriately as a tool to supplement human intellect. With high-performance computers, pandemic outbreaks may be predicted [14].

5.1 Artificial intelligence techniques

When the proper solution to a data-related query is known, labeled data is acquired. When the correct answer cannot be determined with confidence, unlabeled data is produced [21]. The strength of machine learning algorithms is derived from their capacity to learn from available data. Two kinds of machine learning models exist [33]: Both supervised and unsupervised learning are possible. Figure 5 shows the kind:

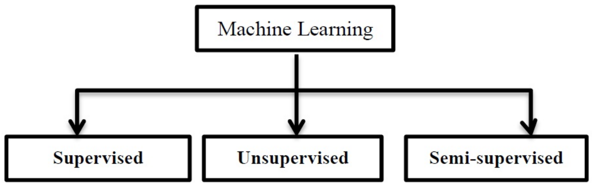

Figure 5: Type Of Machine Learning [21].

These categories are summarized in the following table (3), which also highlights the differences between the two main types:

Table 3: supervised vs. Unsupervised [9, 13, 22].

Supervised	Unsupervised
Definition: This method of learning utilizes labeled data sets. These datasets may be used to "supervise" or teach computers to identify data and forecast future occurrences. The model's correctness may be verified using explicitly specified inputs and outputs, and it may be improved over time.	**Definition:** Using machine learning approaches, unlabeled data sets are examined and clustered. Without human assistance, these algorithms uncover hidden data patterns (thus the term "unsupervised").
Types of problems: • **Classification:** Algorithms are used to properly allocate test results to certain categories, such as identifying apples from oranges. Real-world applications of supervised learning algorithms might include filtering out spam from your mailbox. Classification utilizes several approaches, including support vector machines, decision trees, and random forests. • **Regression:** In order to establish the connection between the dependent and independent variables, an algorithm is used. Numbers, such as projected sales revenue for a business, may be predicted with great accuracy using a regression model. Typical regression studies make use of linear regression, logistic regression, and polynomial regression.	**Types of problems:** • **Clustering:** is a method of unsupervised data mining in which groups of data points are created based on their shared features and differences. In K-means clustering, for instance, K signifies the number of groups created and the degree of separation between them. This technique has a broad variety of applications, such as market segmentation and picture compression. • **Association:** Unsupervised learning relies on a number of factors to determine which variables in a dataset are related to one another. For example, "Customers Who Bought This Item Also Bought" is a common tactic employed by market basket analysis and recommendation engines. • **Dimensionality reduction:** This method of learning is implemented if a dataset has an excessive number of features (or dimensions). Inputs are limited while data security is maintained. Autoencoders, for instance, use this technique to clean up visual input and improve image quality by reducing noise.
Goals: The purpose of supervised learning is to enable users to make accurate forecasts based on recent data. You are already aware of the kind of repercussions that might be expected.	**Goals:** Using unsupervised learning methods, important information is extracted from vast volumes of fresh data. Using machine learning, computers may determine what is odd or exciting in data sets.

Applications: There are many various uses for supervised learning models, including spam detection and sentiment analysis.	**Applications:** Exemplary applications of unsupervised learning include recommendation engines and consumer personas.
Complexity: Supervised learning is a simple machine learning approach that is often implemented using computer languages like R or Python.	**Complexity:** To manage massive volumes of unclassified data, you will need sophisticated unsupervised learning techniques. Unsupervised learning methods are computationally costly since obtaining the required results requires a large training set.
Drawbacks: Training supervised learning models takes time, and labels for input and output variables need prior information.	**Drawbacks:** Without human intervention to validate the output variables, unsupervised learning algorithms may provide wildly inaccurate results.
Labeled data: By making frequent predictions on the data and adjusting to the proper answer, the algorithm "learns" from the training dataset. Despite being more accurate than unsupervised models, supervised models still require human input to recognize data. A supervised learning model can forecast travel time based on time of day and weather. This requires many steps.	**Labeled data:** Unsupervised learning models, on the other hand, function independently to expose the structure of unlabeled data. Notably, human intervention is still required to validate output variables. Using an unsupervised learning model, online shoppers typically purchase many items at once. A data analyst, on the other hand, would need to confirm that a recommendation engine can use goods such as baby clothes, diapers, applesauce, and sippy cups.

Semi-supervised learning combines the two strategies. Data scientists may contribute labeled training data to a model, but the model is free to explore and learn from it [3]. In order to find hidden patterns in exploratory data or to categorize it into data sets, the most used unsupervised learning approach is cluster analysis. Clusters are created using a similarity measure expressed in terms of either Euclidean or probabilistic metrics [33]. Image recognition, audio processing, automatic speech recognition, and other information processing applications are now using machine learning and deep learning [1, 5], The most well-known learning algorithms are presented in Figure 6 below.

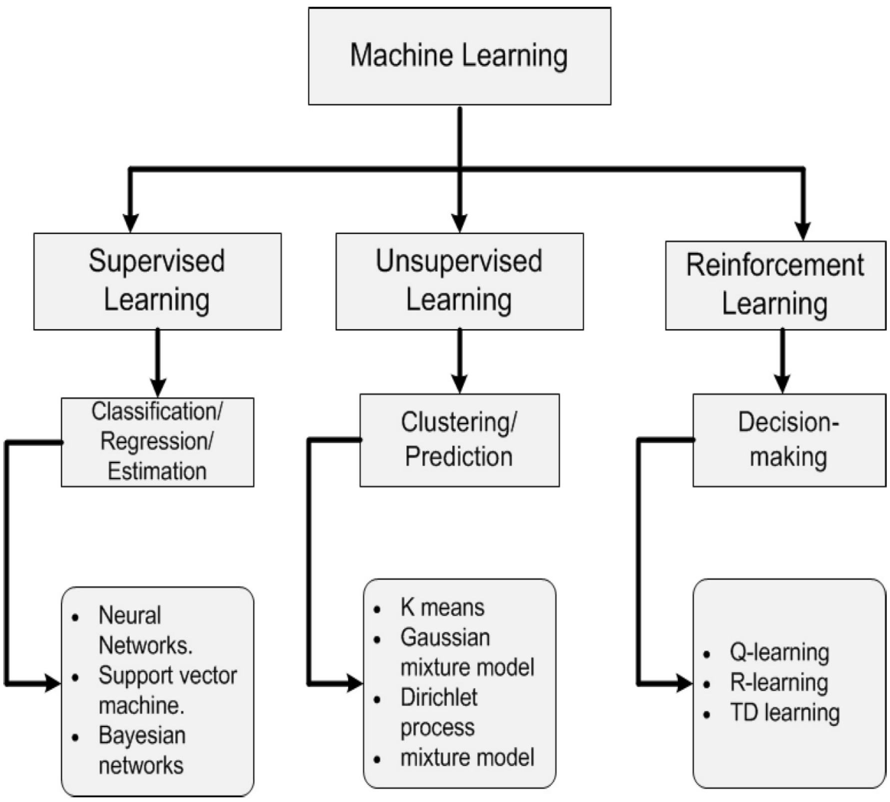

Figure 6: Classification Of Machine Learning [21, 31, 39].

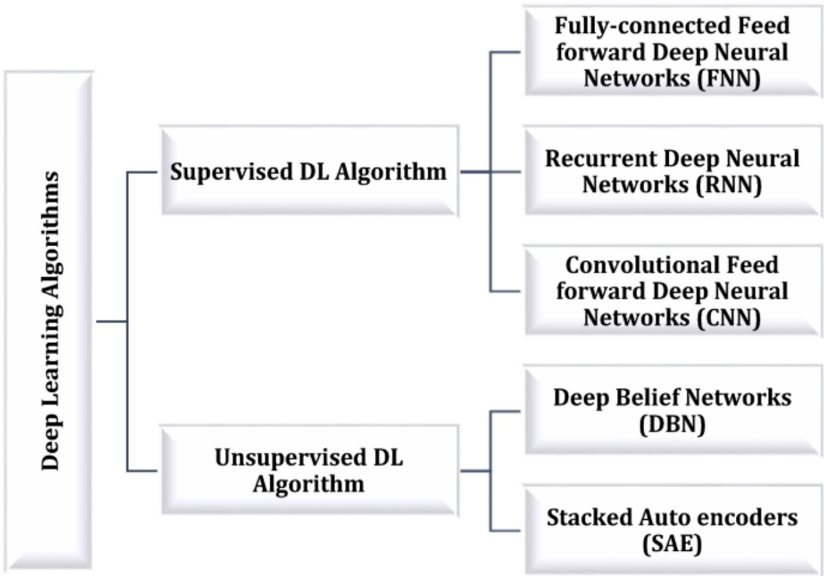

Figure 7: Classification Of Deep Algorithms [21, 31, 39].

6 Review the most important data sets

The data set is considered the cornerstone of each system and the most important step. The following is a table showing some data sets that were used by researchers in diagnosing corona disease.

Table 4: dataset in diagnosing corona disease.

RF.	Name	Description	Size
[45]	Chest X-Ray Images (Pneumonia)	The typical chest X-ray (left panel) displays lungs with no aberrant opacification. Bacterial pneumonia (center) often presents as a localized lobar consolidation, in this example in the right upper lobe (white arrows), but viral pneumonia (right) displays a more widespread "interstitial" pattern in both lungs. Each picture type (Pneumonia/Normal) has its own subfolder inside the dataset's main three folders (train, test, val). (Pneumonia/Normal). Retrospective cohorts of pediatric patients aged one to five at the Guangzhou Women and Children's Medical Center, Guangzhou, were used to choose chest X-ray pictures (anterior-posterior). All chest X-rays were taken as part of the regular medical treatment for the patients.	5,863 images, 2GB
[46]	CoronaHack -Chest X-Ray-Dataset	Using the Chest X-Ray dataset, create a machine learning model to distinguish between healthy and Pneumonia (Corona) afflicted patients, and utilize this model to power the AI application to test for the Corona Virus in a quicker phase. Collecting chest X-rays from patients with healthy vs those with pneumonia (Corona), as well as those infected with SARS (severe acute respiratory syndrome), streptococcus, and ARDS (acute respiratory distress syndrome), among other categories.	5800, 1GB
[47]	corona chest x-ray prediction	Chest X-ray images with Corona - COVID19 dataset	183MB
[26]	COVID-19 Chest CT image Augmentation GAN Dataset	COVID-19 chest CT scan digital images.	2GB

[42]	COVID-CT-Dataset	open-source dataset called COVID-CT, which includes 463 non-COVID-19 CTs and 349 COVID-19 CT scans from 216 individuals. A senior radiologist who has been diagnosing and treating COVID-19 patients from the start of the epidemic attests to the usefulness of this dataset.	1GB
[28]	MOSMEDDATA	Create an artificial intelligence (AI) application that can rapidly test for the Corona virus based on X-rays of patients' chests and utilize a machine learning model to distinguish between X-rays from healthy and patients with Pneumonia (Corona). Collection of Chest X-Rays from Healthy Individuals, Individuals with Pneumonia (Corona), Individuals with SARS, Individuals with Streptococcus Infections, and Individuals with Acute Respiratory Distress Syndrome.	2GB

7 Review of previous studies

The global spread of the novel coronavirus (COVID-19) has created a catastrophic scenario and made this virus one of the most pressing and serious health concerns of the last century. Every day, more and more individuals throughout the globe get infected with the COVID-19 virus. Despite the lack of a vaccine for the current pandemic, deep learning algorithms have been shown to be an effective tool for the automated diagnosis of COVID-19. The purpose of this work is to provide an overview of the newly created systems based on deep learning methods and using several medical imaging modalities, such as computer tomography (CT) and X-ray. Examples of deep learning implementations in COVID-19 datasets are provided in Table 5.

Table 5: Deep learning implementations in COVID-19 datasets.

RF.	dataset	methods	Metrics	Research Challenges
[10]	Dataset of Anteroposterior Chest X-Rays from the Guangzhou Women and Medical Center, China, for Children Aged 1 to 5	Customized CNN model- VGG16	Precision, recall, AUC, and accuracy Focus, Fit, and Mean Circle Distance	Method of Random Sampling Was Employed. In extremely nonlinear locality, how well the model's predictions hold up This was ignored throughout the research
[40]	CT scans from the First Affiliated Hospital of Xi'an Jiaotong University, the First Hospital of Nanchang University, and the No.8 Hospital of Xi'an Medical College	AI and DL based Framework	Precision, sensitivity, and exactness	Examining the connection between CT scans' hierarchical characteristics and Data on genetics and epidemiology exclude from the research
[17]	a data collection of images from a CT scan of the chest clinic for public health in Shanghai	Human-In-the-Loop Machine Learning-Informed Strategy Data Mining and Network Segmentation - VB Net	Pearson's Dice Index of Correlation Time-Varying Correlation Coefficient Segmentation and Contouring by Hand Accuracy	Imaging metric quantification and causality analysis disorders, epidemiology, and therapeutic responses not covered by the study
[12]	Radiographs Showing the Back and Front (PA) a segment of Dr. Cohen's lungs The addition of Chest to the GitHub repository Kaggle Dataset X-Ray Images	Use of Drop Weights Inverse Bayesian Convolutional Neural Networks	Uncertainty and Accuracy in Predictions	No attempt was made to compare the findings to more conventional, state-of-the-art models. To get further understanding of picture markers, the 'Omics' dataset was not taken into account.

[8]	Datasets of x-ray images from GitHub and Cohen, the RSNA, Radiopedia, and the Italian Society of Medical and Interventional Radiology (SIRM)	Learning Transfer Using CNN as a Source.	preciseness, sensitivity, and specificity	additional research with greater datasets and the creation of models that can tell COVID-19 apart from other viral infectious diseases are needed.
[24]	present the COV19-CT-DB database It consists of roughly 5,000 3-dimensional computed tomography images and has been annotated for COVID-19	CNN	F1	Extending prior work by combining deep learning with knowledge-based encoding is not included.
[14]	Datasets of chest X-rays and the COVID-19-Radiography-Dataset (CRD) includes 3616 COVID-19-positive cases, 10,192 normal cases, 6012 lung opacity cases, and 1345 viral pneumonia pictures. A total of 21,165 pictures make up the dataset.	Using a technique called transfer learning (TL), the 2DCNN model receives the weight of a previously trained ResNet-50 model.	preciseness, sensitivity, and specificity	COVID-19 diagnosis efforts are not centered on the use of sophisticated models such as transfer learning, federated learning, deep learning, or any other data sets.
[36]	This COVID-19 negative dataset is comprised of frontal pictures drawn from two sources: the MIMIC-CXR (14) (a random sample of 23,611 images taken between 2011 and 2016) and the Open-i (2013) Indiana University Chest Radiograph Collection (15). (random sample of 3814 images)	CNN	precision, memory, and accuracy Objectivity and the F-Score	As a result, the artificial intelligence model is unable to detect lung opacities in certain areas.

Summary of deep learning-based COVID-19 diagnosis in CT images utilizing a pre-trained model and deep transfer learning is provided in table 6 below.

Table 6: Summary of deep learning based COVID-19 diagnosis in CT images using pre-trained model with deep transfer learning

RF.	year	Task	Method	Dataset	Result	Limitation
[44]	2020	"Segmentation: COVID-19 infection regions"	"U-Net with Focal Tversky Loss function"	"473 CT images"	"83.10% Dice 86.70% Sen. 99.30% Spe."	limited by the small dataset, not apply a larger training dataset to refine our model, and achieve more competitive results
[41]	2020	"Segmentation: COVID-19 infection regions"	"Contextual twostage U-Net"	"204 CT images"	"0.912± 0.044 IOU 6.447± 9.052 HD95"	
[27]	2020	"Classification: COVID-19/non-COVID-19"	"Detail-Oriented Capsule Networks"	"349 COVID-19 397 non-COVID-19"	"0.96 AUC"	Not experimentation with a larger dataset is recommended, our results indicate that architectures like DECAPS could be used to assist radiologists in the CT mediated diagnosis of COVID-19.

[29]	2020	”Classification: COVID-19/non-COVID-19”	”VGG-16 GoogLeNet ResNet-50 SVM”	”52 COVID-19 98 non-COVID-19”	”98.27% Acc. 98.93% Sen. 97.60% Spe. 0.98 F1-score”	limited by the small dataset, not apply a larger training dataset to refine our model, and achieve more competitive results
[15]	2020	”Classification: COVID-19/non-COVID-19”	”DenseNet-169 Self-Trans”	”349 COVID-19 397 non-COVID-19”	”0.85 F1-score 0.94 AUC”	limited by the small dataset, not apply a larger training dataset to refine our model, and achieve more competitive results
[30]	2021	”Segmentation: COVID-19 infection regions”	”MiniSeg”	”100 CT images”	”97.42% Spe. 77.28% Dice”	The comparison between MiniSeg and state-of-the-art image segmentation methods demonstrates that MiniSeg not only achieves the best performance but

8 Conclusion

As a result of the spread of ”COVID-19”, the world faces a major health concern. Intelligent analysis of medical imaging is important. The relevance of chest imaging in COVID-19 diagnosis and treatment necessitates immediate implementation. This paper explored AI-assisted approaches for analyzing ”COVID-19” chest imaging, which provided precise, rapid, and secure imaging solutions. X-ray and CT scan pictures are presented in particular. used to illustrate the efficacy of AI techniques based on deep learning in ”COVID-19” applications. In order to improve the performance of AI-based solutions, it is required to create a database for public study and determine how to access it in order to accurately eradicate lesions. Effective deep learning models for ”COVID-19” applications also need more study. Since pictures from various imaging modalities may only portray the anatomical or functional characteristics of ”COVID-19” patients, it is crucial that multisource data may be included into the diagnosis, monitoring, and prognosis of ”COVID-19.” In this case, imaging data need to be integrated with other types of multisource data observables including clinical symptoms, pathological traits, blood tests, etc. Researchers may examine the connection between these datasets gathered from different sources in order to develop analytical models with aim. With this, ”COVID-19” applications may make better use of AI.

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