Convolution Neural Network for Classification of COVID-19 and Non-COVID-19 Chest X-Ray and Computed Tomography Images

Serena Low Woan Ching[1], Joon Huang Chuah[1], Clarence Augustine TH Tee[1], Shazia Anis[2], Muhammad Ali Shoaib[1], Amir Faisal[3], Azira Khalil[4], Khin Wee Lai[2*]

[1]Department of Electrical Engineering, Faculty of Engineering, University of Malaya, 40603, Kuala Lumpur, Malaysia

[2]Department of Biomedical Engineering, Faculty of Engineering, University of Malaya, 40603, Kuala Lumpur, Malaysia

[3]Department of Biomedical Engineering, Faculty of Production and Industrial Technology, Institut Teknologi Sumatera, Lampung 35365, Indonesia

[4]Faculty of Science and Technology, Universiti Sains Islam Malaysia, 71800 Nilai, Negeri Sembilan, Malaysia

Abstract.

In the late December of 2019, a novel coronavirus was discovered in Wuhan, China. In March 2020, WHO announced this epidemic became a global pandemic, and the novel coronavirus may be mild to most people, but some people may experience a severe illness that resulted in hospitalised or maybe death. COVID-19 classification remains a challenging task due to the ambiguity and similarity with other known respiratory diseases such as SARS, MERS and other viral pneumonia. The typical symptoms for COVID-19 are fever, cough, chills, shortness of breath, loss of smell and taste, headache, sore throat, chest pains, confusion and diarrhoea. It is difficult to identify the type of pneumonia by and chest X-ray (CXR) Computed Tomography (CT). This study aims to streamline the COVID-19 detection process for both professionals and beginners and automatically identify COVID-19 infection using CT images. This research paper suggests the concept of transfer learning. The method uses CT images extracted from public data sources to detect COVID-19 using different neural network models. The datasets of 746 images of CT images of COVID-19 and non-COVID-19 were divided for training, validation and testing. Various augmentation techniques were applied to increase the number of datasets except for testing images. The images were then pre-trained using CNN to obtain a binary class. ResNet50, AlexNet, GoogleNet and DenseNet201 have the best results of 98.51% accuracy. ResNet50, GoogleNet and DenseNet201 have 100% sensitivity and 97.06% specificity while ResNeXt has 96.97% sensitivity and 100% specificity. In conclusion, CNN models can obtain high accuracy and can be considered a screening tool to detect COVID-19.

Keywords:

Artificial neural networks, Deep Learning, Transfer Learning, Multi-task Learning, Object Detection, Localisation, Segmentation

Corresponding Email: lai.khinwee@um.edu.my

1.0 Introduction

The emergence of various pneumonia such as Severe Acute Respiratory Syndrome (SARS) had a substantial cause of fatalities worldwide and continued to threaten the nation. Despite the latest technology development in the field, it is difficult to predict and detect new emerging diseases [1]. Pneumonia was estimated 18% of 1.4 million children less than five years old die of pneumonia yearly [2]. Two billion people suffer from pneumonia annually. There were numerous outbreaks of novel infectious diseases that cause viral pneumonia. These diseases can infect animals to animals, ranging from bird flu, swine flu, SARS, MERS, and Ebola. The number of COVID-19 outbreaks has increased, which is four times the rate since the 1980s. The spike increase of outbreaks has resulted in the World Health Organisation (WHO) repeatedly reminded that the time would come when an epidemic will strike among us. On New Year's Eve 2019, China's health authorities had activated a profound response level after an outbreak of novel viral pneumonia in central China.

A rapidly growing number of people developed a dry cough and fever before it was diagnosed as pneumonia, some of the infected patients who were diagnosed experienced severe illness, including death. The Chinese health authorities tried to trace its origin, and the likely source was at a food market called Huanan Market, Wuhan, China [3]. The earlier reported first 41 patients contacted with the disease stated that 27 of them had visited the food market. Chinese officials immediately shut down the market because it had happened before. In 2002, a coronavirus had emerged at a similar market in southern China, specifically at Foshan, Guangdong province, that spread to 29 countries and killed 800 people. After almost two decades later, the current coronavirus has infected 221 countries and territories and with 106,295,553 cases and claimed 2,371,923 lives as of 6 February, 2021 [3] [4].

The SARS-CoV-2 or Severe Acute Respiratory Syndrome Coronavirus 2 is 120 nanometers (billionths of a meter) across. A hundred million viral particles are required to fit the head of a pin needle. However, human beings only need a few hundred particles to get infected and develop symptoms [5]. The symptom is now widely known to us as COVID-19.

1.1 Background on COVID-19

Generally, viruses that make us sick were originated in animals. Some viruses that cause influenza come from birds and pigs. HIV/AIDS comes from Chimpanzees. The deadly Ebola virus originated from bats. In COVID-19, the virus originated from bats, spread to pangolin and finally infected humans. COVID-19 can transmit among us concealed and contaminate almost everyone, reproduce in its host and simultaneously infect other hosts as well. The virus has able to evade itself from our body's immune system. Like all viruses, they are mindless scraps of genetic materials, able to adapt to any environment through evolution. The COVID-19 is the most significant public health crisis of the last hundred years. COVID-19 virus is made of a single-stranded ribonucleic acid (RNA) virus, with the size of the virus approximately 26 to 32 kilobases. The RNA stores all the genetic information to reproduce. The composition of the COVID-19's RNA is more superficial than our human being's DNA. The short strand of the COVID-19 RNA is protected by a fatty outer membrane coat that breaks apart easily when it encounters soap and water [6].

Therefore, the nation is advised to do frequent and more prolonged handwashing activities. The outer membrane of the virus has protruding stud-like spikes like crowns. The spikes' function is to infiltrate our cells, which is what the vaccine creators are targeting. COVID-19 can be transmitted from one human to another by breathing, coughing, and sneezing. Once COVID-19 can obtain a new host, it will invade the cells. The human cells have a fatal weakness where an enzyme called ACE2 controls the body's blood pressure on the surface.

The COVID-19 virus spikes share a similar shape to attached themselves tightly to the ACE2 enzymes. Once the virus's binding onto the enzyme is complete, the human cells open, allowing the virus to slip into the cells and take control. The ACE2 enzymes are found throughout the body, including the throat, lungs, eyes and nose. Therefore, handwash as frequently as possible and resist the urge to touch the nose or rub the eyes. Once the virus enters the cell, it releases a genetic code and immediately take-overs the cell. The virus then begins to generate endless copies of itself and simultaneously infecting more cells in the process. The virus can multiply itself a million-fold. Generally, any virus evades into the human body and starts reproducing; the human body's immune system will be able to fend the evaders off and unleash an attack upon the virus. COVID-19 virus, however, it can trick the human body's immune system and covers the spikes with a layer of glycan sugar and disguised itself as viral proteins, which helps them evade the body's immune system. The COVID-19 virus devastates the human body with a swift, incognito, powerful attack; it is a battle between the COVID-19 virus and the human body's immune system, which dictates its severity of illness. COVID-19 virus can silence the alarm of the human body's immune system, and thus most infected people start showing symptoms several days later. Hence, people exposed to a person infected with COVID-19 must quarantine themselves, regardless of whether the COVID-19 test is positive or negative. Some people have COVID-19 viruses in their body but never show symptoms at all. These people are known as "asymptomatic carriers". They travel everywhere blissfully unbeknownst that they are distributing potential lethal viruses everywhere they go.

The difference between COVID-19 viruses and other coronaviruses is the ability of a person who does not show significant symptoms of the COVID-19 virus and infects others. SARS-CoV a.k.a SARS, in 2002, an American businessman who travelled from China to Singapore transited in Vietnam was caught with symptoms similar to pneumonia during the

flight and was immediately taken off the plane to a hospital in Hanoi. Subsequently, the businessman passed away; the medical staff treated him later, developed symptoms, and one of them died. SARS showed to be deadlier than COVID-19 as it killed 10% of the infected people. However, SARS displayed its symptoms first before it became infectious. The SARS virus cannot bind itself to the ACE2 enzymes in the human body's respiratory tract as efficiently as COVID-19 making it less infectious than the latter. Since the SARS virus could not hide its presence from the human boy's immune system or bind itself efficiently, it did not cause a pandemic. There were 8,000 reported SARS cases and 774 deaths. In 2004, there were no new SARS cases reported.

Once the COVID-19 virus enters the body, it will infect the nose's cells and the upper throat. Hence the first symptom is usually a dry cough. Some of the viruses will pass the throat and bind to the intestines' ACE2 enzymes, causing diarrhoea. The virus will be deadlier when it travels through the windpipe and infiltrate the lungs, subsequently bind itself with ACE2 enzymes in the lungs causing pneumonia-like symptoms, including fever, cough, chills, shortness of breath and chest pain. The symptoms are indications that the body is battling against the COVID-19 viruses. The human body's innate immune system will activate neutrophil, i.e. a type of white blood cells and macrophages. A healthy human being can rely on the innate immune system to keep the COVID-19 virus under control. However, some might experience severe illness because the COVID-19 virus has travelled from the throat to the lungs, causing the dry cough to be more severe; the person will typically develop a fever over 100.4 ℉, shortness of breath develops bone ache. When the infection became severe, the T-killer cells are activated to destroy cells that COVID-19 viruses have infested. Plasma B cells release billions of antibodies and try to eliminate COVID-19 viruses. Since the COVID-19 virus is novel, the human body has never encountered the particular virus before. The antibodies require a longer time to develop into the exact shape that binds to the COVID-

19 viruses' spikes. Therefore, once the antibodies are developed, they can be during the later stage of the illness. A person with a healthy and active immune system is essential to overcome COVID-19 viruses. Hence, senior citizens who are over 60 years old tend to have weaker immune systems, and the adaptive response to the COVID-19 viruses is slower in response. Unexpectedly, most senior citizens' immune systems will overreact while battling with the COVID-19 viruses, creating a surge of aggressive immune cells that can damage the lungs and other organs in the body, causing them to be even weaker. Some COVID-19 patients will recover, and some will not. COVID-19 patients who did not recover will increasingly experience shortness of breath, and they will need to get their lungs scanned by chest X-ray (CXR) or computed tomographer (CT).

The radiologist will be looking for "ground-glass opacities." The lungs' fuzzy spots are signs of the worst form of pneumonia called acute-respiratory-distress syndrome, or ARDS. Alveoli in the lungs fill with fluid, reducing the COVID-19 virus patient's ability to absorb oxygen, thus causing the patient to be breathless. The immune system will surge the area with T-killer cells, antibodies and cytokines eager to destroy the virus and simultaneously destroying healthy tissues. Once the alveoli in the lungs are filled with fluid, the body has insufficient oxygen to supply other organs, especially the brain. The patient will be sent to the intensive care unit, where doctors and nurses will be fully garbed with personal protective equipment (PPE). The patient will be gasping for air uncontrollably. The medical providers will decide if the patient requires an oxygen mask, intubation or use ventilators depending on the severity of the illness. For patients who use ventilators, the possibility of dying is high. Patients who survived the ventilator could never be fully recovered. At this point, the immune system is not only targeting the lungs; it has spread all over the body through the bloodstream. The liver, kidneys, guts and brain will be simultaneously attacked. When the COVID-19 viruses travel

through the bloodstream, they will form blood clots and subsequently cause heart inflammation. Once the COVID-19 virus reaches the brain, it can cause seizures.

The pathology of COVID-1 also greatly resembles SARS with general symptoms of fever, dry cough, shortness of breath and fatigue [1].

1.2 Convolutional Neural Networks and Deep Learning

One of the branches of computer science is artificial intelligence (AI). For medical imaging, the AI-focused primarily on radiology, cardiology, and pathology. An example of radiology includes the automated detection of microcalcifications and masses on mammography, lung nodules on chest X-rays and CT scans [7]. Computer-Aided Diagnosis (CAD) became a backup diagnosis for specialists and physicians. CAD applications are myriad and provide hypothesis based on the algorithm to identify abnormality within the organs such as breasts, lungs, heart, gastrointestinal tract, neuro and whole-body imaging. However, if the algorithm in the CAD system lacks accuracy, it would create false positive and misdiagnosed or misidentified the patient for having an abnormality, which ultimately ends up otherwise.

Therefore human beings are leveraging Artificial Intelligence (AI) tools to improve CAD system efficacy. The CAD algorithm is divided into two parts, i.e. initial lesions identification and false-positive reduction. The initial lesion identification consists of pre-processing, segmentation of body regions, candidate generation and feature extraction, whereas the false-positive reduction consists of classification, visual presentation of CAD findings to the radiologist. The interpretation of CAD systems has been challenging and protracted. The development of CAD systems is time-consuming and labour-intensive. Once the medical data and reference standard have been obtained, the data must be annotated [7]. The abnormality

and the precise location must be determined by a professional. The images are best annotated by several experts so that the assessment's probability is to identify the lesion's location is accurate. Hence, the best evidence usually comes from large datasets, but they are usually unattainable unless it is a well-funded study.

Deep learning was introduced to improve neural network types by having more layers to permit high levels of abstraction. Deep learning successfully recognised objects in authentic world images and learned the features from the training data. Hence, some researchers found that CAD systems that required hand-chosen parameters and hand-crafted features to be manually selected and annotated are costly, time-consuming, fragile and will not be reliable when applied to new data [7]. Deep learning can avoid such manual hand-tuning procedure.

Artificial Intelligence, Machine Learning, Deep Learning and Convolutional Neural Network are terms used interchangeably in conversation. However, the usage of these terms are ambiguous and requires clarifications. Machine Learning is the subset of Artificial Intelligence; Deep Learning is the subset of Machine Learning; Neural Network is the pillar of deep learning algorithms. Artificial Intelligence (AI) is a computer science branch that allows machines to execute human-intelligence tasks; it is used to predict, automate, and optimise tasks that human beings executed before, for instance, speech and facial recognition, decision making, and translation. There are three types of AI: Artificial Narrow Intelligence(ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). AGI and ASI are considered more superior than ANI, as both types incorporate more human behaviour and can interpret tones and emotions. AGI would perform on par with another human, whereas ASI will supersede human intelligence and ability. With the evolution of AI and Internet-of-Things (IoT), medical equipment has rapidly changed, which provide many possibilities in medical radiology.

Machine learning (ML) techniques can achieve the objective of AI. It is the subset of AI to allow computer systems with the learning ability and implement tasks with the data automatically without manual programming. Deep Learning (DL) is a subset of machine learning related to methods stimulating by neurons of the human brain [8] [9]. The implementation of ML is to apply DL as an essential subject with its technology in classification, recognition, and identification of images or videos. The algorithm stirred the information to process patterns impersonating the human neural system. DL is currently an essential subject with its technology in classification, recognition, and identification of images or videos. DL functions on algorithms for cognitive method simulation and data mining developing concepts [10]. DL maps input data consists of hidden deep layers required to be labelled and analysed concealed patterns within the complex data [11]. Between ML and DL, DL can automatically classify features and provide accurate results with high-end GPU help. However, ML requires a wide-range of data to be pre-processed as the features need to be extracted manually. ML integrates various computational models and algorithms to mimic the human neural system, but the DL-based network is more profound and is created with many hidden layers compared to conventional ANN. DL algorithms do not require many feature classifications and acquire directly from the data to display their higher problem-solving aptitudes. DL can interpret data and extract a wide range of dimensional features, notwithstanding if the features are visible or invisible to the naked human eye. This diminishes manual data pre-processing such as segmentation. DL can handle complex data representations and mimic trained physicians by identifying and detecting the features to make clinical decisions. DL architectures are applied in medical X-ray detection and various areas such as image processing and computer vision in medical [8]. DL progresses in the medical sector to comprehend higher results, expand disease possibility, and to execute valid real-time

medical image [12] [13], disease recognition systems [14]. Table 1 shows the neural network's significant contributions to deep learning [14] [15].

Table 1. Significant contributions of the neural network to deep learning [14] [15].

Milestone/Contribution	***Year***
McCulloch-Pitts Neuron	*1943*
Perceptron	*1958*
Backpropagation	*1974*
Neocognition	*1980*
Boltzmann Machine	*1985*
Restricted Boltzmann Machine	*1986*
Recurrent Neural Networks	*1986*
Autoencoders	*1987*
LeNet	*1990*
LSTM	*1997*
Deep Belief Networks	*2006*
Deep Boltzmann Machine	*2009*

2.0 Data

In December 2019, a lower respiratory tract feverish illness of unfamiliar derivation was informed in a cluster of patients in Wuhan City, Hubei Province, China. Coronavirus disease 2019 (COVID-19) is accountable for this epidemic to date. Other corresponding pulmonic conditions have been documented as being triggered by other strains of the coronavirus family. The most notable instances are the severe acute respiratory syndrome (SARS) and the Middle East respiratory syndrome (MERS). The SARS epidemic was under controlled with no human contaminations reported since 2003; small MERS occurrences continue to be stated. Hence, imaging is an essential tool of the analytical procedure, observing disease development, and the development of coronavirus-related pulmonary syndrome [16]. Imaging structures in critical and chronic phases of SARS and MERS are inconsistent and

inexplicit [17]. The first accounts of imaging discoveries of COVID-19 have also described as inconclusive [18] [19] [20]. Researchers are conducting various studies to distinguish further and identify the imaging features of this new coronavirus syndrome, but the information is still inadequate.

The incident of COVID-19 intensified beyond human beings comprehension, more clusters and incidences are reported daily by the several ten thousand in some parts of the world. The etiologic and medical structures of the disorder are comparable to those of SARS and MERS, the knowledge and aptitude from those pulmonary syndromes can be supportive for handling the sharp increase of COVID-19 eruption. This review segment will allow us to be familiar with the radiologist and imaging spectrum of coronavirus syndromes and discuss the reported imaging features of COVID-19.

SARS was discovered in 2003 as the first epidemic of the new era in Guangdong Province, China which clinical discovery presented as novel viral pneumonia. The clinical disease-infested 8,422 individuals demanded 916 lives before the plague was confined, and no occurrence has been reported ever since [21]. MERS was revealed in Saudi Arabian where a patient's sputum consisted of the novel coronavirus in 2012 [21]. The disease has infected 2,492 individuals worldwide, and 858 human lives were sacrificed as the latest discovery was reported in December 2019 [21].

Table 2: Comparison of Clinical and Radiologic Features of COVID-19, SARS and MERS [21]

Feature	***COVID-19***	***SARS***	***MERS***
Clinical sign or symptom			
Fever or chills	*Yes*	*Yes*	*Yes*
Dyspnea	*Yes*	*Yes*	*Yes*
Malaise	*Yes*	*Yes*	*Yes*
Myalgia	*Yes*	*Yes*	*Yes*
Headache	*Yes*	*Yes*	*Yes*
Cough	*Dry*	*Dry*	*Dry or productive*
Diarrhoea	*Uncommon*	*Yes*	*Yes*
Nausea or vomiting	*Uncommon*	*Yes*	*Yes*
Sore throat	*Uncommon*	*Yes*	*Yes*
Arthralgia		*Yes*	*Uncommon*
Imaging finding			
Acute phase			
Initial imaging			
Normal	*15 – 20% of patients*	*15 – 20% of patients*	*17% of patients*
Abnormalities			
Common	*Peripheral multifocal airspace opacities (GGO, consolidation, or both) on chest radiography and CT.*	*Peripheral multifocal airspace opacities (GGO, consolidation, or both) on chest radiography and CT.*	*Peripheral multifocal airspace opacities (GGO, consolidation, or both) on chest radiography and CT.*
Rare	*Pneumothorax*	*Pneumothorax*	*Pneumothorax*
Not Seen	*Cavitation or lymphadenopathy*	*Cavitation or lymphadenopathy*	*Cavitation or lymphadenopathy*
Appearance	*Bilateral, multifocal, basal airspace; normal chest radiography findings (15%)*	*Bilateral, multifocal basal airspace on chest radiography or CT (80%); isolated unilateral (20%)*	*Unilateral, focal (50%); multifocal (40%); diffuse (10%)*
Follow-up imaging appearance	*Persistent or progressive airspace opacities*	*Unilateral, focal (25%); progressive (most common, can be unilateral and multifocal or bilateral with multifocal consolidation)*	*Extension into upper lobes or perihilar areas, pleural effusion (33%), interlobular septal thickening (26%)*
Indications of poor prognosis	*Consolidation (vs GGO)*	*Bilateral (like ARDS), for or more lung zones, progressive involvement after 12 d*	*Greater involvement of the lungs, pleural effusion, pneumothorax*
Chronic Phase	*Unknown, but pleural effusion and interlobar septal thickening have not yet been reported*		
Transient reticular opacities		*Yes*	*Yes*
Air trapping		*Common (usually persistent)*	
Fibrosis	*More than one-third of patients*	*Rare*	*One-third of patients*

Note: Severe acute respiratory syndrome (SARS), Middle East respiratory syndrome (MERS), COVID-19 = coronavirus disease 2019, ground-glass opacity (GGO), acute respiratory distress syndrome (ARDS) [21].

There are various imaging features of SARS and MERS that share similarity to one another, but some differences are shown in Table 2. The analysis of COVID-19 is hypothesised on the foundation of indications of pneumonia (e.g. dry cough, lethargy, myalgia, malaise and dyspnea similar to symptoms of SARS and MERS) as well past travelling activities to China or acquaintance with a COVID-19 patient. The development of the diseases and its severity rely on chest imaging to acquire valuation, discovery and identification. Portable chest X-ray (CXR) is used as the first-line modality for COVID-19 patients instead of CT scans, as CT scans are applied in specific situations. Portable chest X-ray (CXR) has the benefit of discarding patients' need to travel from one location to another and diminish the use of personal protective equipment (PPE). The arrangement is to avoid nonessential imaging and transportations to the radiology department. As Guan, et al. and Wong et al. discovered that Chest X-ray is insensitive in the early detection of COVID-19 with the sensitivity of only 59 % [22]. Chest X-ray is not recommended for patients with flu/influenza-like symptoms. It is also not recommended to be used on confirmed COVID-19 patients with mild symptoms. Therefore, Chest X-ray is designated for COVID-19 patient with acute respiratory status or COVID-19 patients with mild symptoms but has high-risk factors for developing severe disease. Chest radiography and tomography cannot be used as first-line screening or diagnosis in COVID-19, even with a normal chest X-ray and CT images cannot rule out the possibility of COVID-19 as a patient might be asymptomatic, and the lung condition maintains to be expected. However, information of COVID-19 patients initially declared hostile on the virus using the real-time reverse transcriptase-polymerase chain reaction (RT-PCR) was discovered to have COVID-19 via early CT findings [21]. In the meantime, initial findings in imaging

might show normal conditions of the lungs. Hence standard chest imaging does not rule out the possibility of being infected with COVID-19 [21].

2.1 Artificial Intelligence on Chest X-Ray (CXR) and CT scans

The struggle against the COVID-19 rapid infection, active screening and immediate medical response for the infected patients is a desperate need. RT-PCR is the common screening application which manual, time-consuming, intricate, arduous with only 63% positivity rate [23] [24]. Research regarding early identify COVID-19 by using CXR, and other imaging modalities are still in development. The Guardian reported information shared by a respiratory physician that COVID-19 pneumonia is different from common viral pneumonia cases [25]. However, the images of several viral cases of pneumonia are comparable with other infectious and inflammatory lung diseases [23]. The COVID-19 symptoms being similar to other viral pneumonia can result in wrong diagnosis and prognosis, while many hospitals, especially in the emergency department, are overloaded and understaff [23].

Today, many biomedical problems and complications such as brain tumour detection, lung disease detection, breast cancer detection and other oncological emergencies are using Artificial Intelligence (AI) solutions [23]. Convolutional Neural Network (CNN), a deep learning technique has been advantageous in revealing image features that are not obvious in the original image [23]. The accuracy of the deep learning algorithm relies on imaging quality, and CNN can improve imaging quality in low-light images from a high-speed video endoscopy, discover pulmonary nodules through CT images, identify paediatric pneumonia from CXR images, and automatically labelling of polyps in a colonoscopy and cystoscopic image analysis from videos [23]. Hence, only confirmed positive COVID-19 patients' images were selected. Wong et al. (2017) have shown to accumulate datasets which allow significant developments in medical imaging, tools to progress in the prediction of various pneumonia and the outcome

towards the infected patient [26] [27]. Rajpurkar et al. (2017) and Cohen et al. (2019) works both organised models to foresee various pneumonia [26] [28] [29]. Deep learning models and algorithm are tools that can be developed for triage cases during the shortage of physical tests, particularly RT-PCR [26] [30] [31]. Although the American College Radiology (ACR) only recommend portable CXR in an ambulant care facility when required and strongly discourage towards CT to apply and inform decisions on a suspect COVID-19 patient on whether to conduct RT-PCR test, admit the patient, provide other treatment, dissuade the patient from being quarantines or others [22]. However, deep learning models and algorithms should predict patient outcomes as severity level, survival, and permitting the physician to immediately facilitate care and management [26] [32]. COVID-19 considered extraordinary extreme situations, where physicians could be faced with decisions to select which patient to assign for which healthcare resources based on the severity level [32]. The tools would serve to monitor the development of COVID-19 positive patients' ailment evolution [26].

2.1.1 Approached Techniques and Neural Network Architecture

Deep learning is a subsection of machine learning, and convolutional neural network is a type of deep learning commonly applied in the computer vision domain. Examples of CNN architectures are LeNet, AlexNet, GoogLeNet, Visual Geometry Group (VGG) Net, ResNet and others [33]. The goal is to apply deep learning neural network architectures to create useful applications to improve diagnosis and prognosis performance [33].

CNN was based on biological processes of the visual cortex of the human and the animal brain. CNN consists of multiple layers where a higher layer is connected to a lower layer to study abstract features of the images by considering the spatial relationships between the receptive fields. This allows CNN to recognise patterns and identify images within the layers of images. Various CNNs models apply different layers, the number of neurons and receptive fields in the respective layers, and algorithm [33]. Integrating transfer learning into the technique modifies the CNN models applied to pre-train many radiology image datasets to diagnose COVID-19 problems [33]. This technique bypasses the hassle to train all the images from scratch every time new cases or images are identified. However, this method would not be valid with the amount of radiology images dataset available for the public.

Based on the studies in Table 3, several studies use deep learning for COVID-19 diagnosis using radiology images.

Table 3: Summary of deep learning methods and CNN Architectures for COVID-19 using radiology images.

No.	*Papers*	*Data*	*Types of Images*	*AI Methods to establish the algorithm*	*CNN Architecture*	*Results for detecting COVID*
1	*[33] [34]*	*4,356 total images from 3,322 patients from 6 medical centers: 1,296 COVID-19 images, 1,735 community acquire pneumonia images and 1,325 non pneumonia images*	*CT*	*3D Deep Learning Method*	*ResNet-50, specifically COVNet*	*Area Under the Curve (AUC): 0.96*
2	*[33] [35]*	*618 imaging samples: 219 images from 110 COVID-19 patients, 224 mages from 224 influenza-A (H1N1, H3N2, H5N1, H7N9, etc.) patients and 175 images from normal people with healthy lungs*	*CT*	*3D CNN Model for Segmentation; Classification to categorise all images into 3: COVID-19, Influenza-A viral pneumonia and irrelevant-to-infection*	*Location-attention network and ResNet-18*	*Accuracy of 86.7%; Average Time Taken to read: less than 30 s (70 layers of data processing)*
3	*[33] [36]*	*5,941 posterior-anterior (PA) images) Normal: 1,583 images; Bacterial Pneumonia: 2,786 images; Non Covid-19 Viral pneumonia: 1,804 images ; COVID-19: 68 images*	*CXR*	*Drop weights based Bayesian CNNs*		*Accuracy of 89.92%*
4	*[33] [37]*	*COVID-19 positive with diagnoised viral pneumonia images: 453; Training images: 217;*	*CT*	*Inception Migration-learning Model*		*Internal Validation: Accuracy: 82.9%; Specificity: 80.5%; Sensitivity: 84% External Testing Dataset: Accuracy: 73.1%; Specificity: 67%; Sensitivity: 74%*
5	*[33] [37]*	*Total: 1,065 images; COVID-19 images: 325; Viral pneumonia images: 740*	*CT*	*Modified inception transfer-learning model*		*Accuracy of 79.30%; Specificity: 0.83; Sensitive: 0.67;*
6	*[33] [38]*	*Total patients: 133; Severe/critical patients: 54; Non severe/critical patients: 79*	*CT*	*Multilayer perception and long short term memory (LSTM)*		*Area Under the Curve (AUC): 0.954*
7	*[33] [39]*	*Total images: 4,266; COVID-19 Images: 2,529; CAP images: 1,338; Influenza A/B images: 135; Normal images: 258; from Total patients: 3,177; COVID-19 patients: 1,502; Influenza A/B patients: 83; CAP patients: 1,334; Healthy subjects: 258*	*CT*	*2D Deep Learning CNN*	*ResNet 152*	*Accuracy of 94.98%; AUC 97.71%; Sensitivity: 90.19%; Speciificity: 95.76%; Average Time Taken to read: 2.73s*
8	*[33] [40]*	*Total 1,136 cases from 5 hospitals; COVID-19 positive: 723 images; COVID-19 negative: 413 images*	*CT*	*3D Deep Learning Method*	*UNet ++ & ResNet-50*	*Specificity: 0.922; Sensitive: 0.974;*

9	*[33] [41]*	*COVID-19 patients: 50; Normal people: 50; Implemented 3 different binary classifications (COVID-19, normal, viral pneumonia and bacterial pneumonia)*	*CXR*	*5 Pre-trained CNN*	*ResNet-50, ResNet101, ResNet52, InceptionV3 & Inception-ResNetV2*	*Best performance from ResNet-50 with the accuracy of 98.0%*
10	*[33] [42]*	*13,975 images from 13,870 patients*	*CXR*	*Deep Learning CNN*	*COVID-Net*	*Accuracy of 92.4%*
11	*[33] [43]*	*Images from 157 international patients from China and the US*	*CT*		*ResNet-50*	*Area Under the Curve (AUC): 0.996*
12	*[33] [23]*	*Normal Images: 1,341; Viral Pneumonia: 1,345; COVID-19: 190*	*CXR*		*AlexNet, ResNet-18, DenseNet-201, SqueezeNet*	*Accuracy of 98.3%*
13	*[33] [44]*	*COVID-19 images: 170 CXR Images & 361 CT Images from 5 different*	*CT & CXR*	*CNN with transfer learning*	*Pre-trained AlexNet*	*Accuracy CXR images 98.3%; CT images 94.1%*
14	*[45]*	*Location: Guangzhou Women and Children's Medical Centre; Total Images: 5,232; Normal images: 1,346; Bacterial Pneumonia images: 2,538; Viral pneumonia images: 1,345*	*CXR*	*Deep learning framework using transfer learning*	*Pre-trained on ImageNet; Trained using AlexNet, ResNet18, Inception V3, DenseNet121, GoogLeNet, & Ensemble model*	*The ensemble model being the highest test accuracy compared with all the individual models:: Accuracy 96.4% with a recall of 99.62% of unseen data*
15	*[2]*	*Data: Kaggle; Total images: 5,247; Bacterial Pneumonia images: 2,561; Viral pneumonia images 1,345; Normal images: 1,341;*	*CXR*	*Pre-trained deep CNN and used for transfer learning*	*AlexNet, ResNet18, DenseNet201, SqueezeNet; 3 deep learning task: Normal & Pneumonia; Normal, Bacterial Pneumonia & Viral Pneumonia; and Bacterial and Viral Pneumonia;*	*DenseNet201 outperforms the other three different deep CNN networks. Accuracy for Normal: & Pneumonia: 98%; Bacterial: 97% & Viral pneumonia:99%; Normal: 95%, bacterial: 95% & viral pneumonia: 96%*
16	*[8]*	*A dataset from Dr Joseph Cohen; Total images: 306; divided into four categories the number of images (COVID-19: 69 /normal: 79/pneumonia bacterial: 79/pneumonia virus: 79*	*CXR*	*Deep Transfer Learning: Using GAN Network to generate more images to help detect the virus. Three deep transfer models. The dataset number increases to 8,100 images after using the GAN network.*	*AlexNet, GoogLeNet, Restnet18 with performance measures in different scenario and classes*	*Testing Accuracy: AlexNet: 66.67%; GoogLeNet: 80.56%; ResNet18: 69.46%*
17	*[46]*	*Dataset was collected from medRix and bioRxiv; COVID-19 Images: 349, from 216 patients*	*CT*	*Multitask learning and self supervised*	*DenseNet-169; ResNet-50*	*F1 Score: 0.90; AUC: 0.98; Accuracy: 0.89*

18	*[25]*	*Total images: 2,200; COVID-19 images: 800; Viral pneumonia images: 600;*	*CT*	*Machine Learning Technique using Microsoft Azure*	*ResNet*	*High Accuracy: 91%; Overall Accuracy: 87.6%*
19	*[47]*	*Total images: 15,495; Normal images: 12,544; COVID-19 image: 2,951*	*CXR*	*CNN Model*	*UNet; UNet++;DLA; DenseNet-121; CheXNet; Inception-v3; ResNet-50*	*F1 Score: 85.81%; Sensitivity: 98.37%; Specificity: 99.16%*
20	*[48]*	*Diverse datasets from different source*	*CT*	*Deep Fully Convolutional Networks (FCN)*	*UNet; ResDense FCN;*	*DSC: 0.780; Sensitivity: 0.822; Specificity: 0.951*
21	*[49]*	*Total images: 954; COVID-19 images: 308; Normal images: 323; Pneumonia images: 323 images;*	*CXR*	*Deep learning modules using stacked architecture concept*	*DenseNet; GoogleNet*	*Sensitivity: 0.91; Specificity: 0.95; F1 Score: 0.91; AUC: 0.97*

2.2 COVID-19 Radiology Data Sources for Potential Modelling

This section describes the radiology imaging data source available for researchers to exploit the capabilities of deep learning techniques using CNN architectures to overcome COVID-19. The variability of the data requires different AI methods to study. Radiology images like CXR and CT images are high dimensional data requiring CNN-based models to process the images like LeNet, AlexNet, GoogLeNet, VGGNet and ResNet [33]. AlexNet is a category of convolutional neural network (CNN) designed by Alex Krizhevsky in 2012. It is a popular CNN that sets the essential milestones to its incomers like Network-in network [50] by Lin et al. [51] , VGGNet [52] by Simonyan et al., and GoogLeNet (Inception v-1) by Szegedy et al.

CNN architectures application requires a large dataset for training, testing and validating. Table 4 describes the available data sources for COVID-19 radiology images, mainly CXR and CT images.

Table 4: Available data sources about COVID-19 radiology images for both Chest X-Ray and CT images

No.	*Sources*	*Data Type*	*No. of Images*	*Image Type*	*Types of Images*	*Links*
1	*J. P. Cohen's GitHub*	*Viral Pneumonia: COVID-19, SARS, Varicella, Influenza; Bacterial pneumonia: Streptococcus spp., Klebsiella spp., Escherichia coli, Mycoplasma spp., Legionella spp., Unknown, Chlamydophilla spp., Fungal: Pneumocystis spp., Lipoid: N/A*	*Raw: 910; Annotated: 210*	*jpg &png*	*CXR*	*https://github.com/ieee8023/covid-chestxray-dataset*
2	*European Society of Radiology*	*Total cases or images unknown; Information included: clinical history, imaging findings, discussion, differential diagnosis and final diagnosis*	*N/A*	*pdf*	*CXR & CT*	*https://www.eurorad.org/advanced-search?search=COVID*
4	*Kaggle*	*Patient ID, offset, sex, age, finding (which pneumonia), survival, view (for example, PA, AP, or L for X-rays and Axial or Coronal for CT scans) modality (CT, X-ray, or something else), date (the date the image was acquired) Location (hospital name, city, state, country)*	*Normal: 1,576 Pneumonia ARDS: 2 Pneumonia Viral: 1,493 COVID-19: 58 SARS: 4 Bacterial Pneumonia: 2,772 Bacterial Streptococcus: 5*	*png, jpg, jpeg & others*	*CXR & CT*	*https://www.kaggle.com/bachrr/covid-chest-xray*
5	*UCSD-AI4H*	*Total: 349 images from 216 patients*	*COVID-19: 349 images Non COVID-19: 397 images*	*jpg &png*	*CT*	*https://github.com/UCSD-AI4H/COVID-CT*
6	*MedSeg*	*images were segmented by a radiologist using 3 labels: ground-glass (mask value =1), consolidation (=2) and pleural effusion (=3).*	*Image volumes – 9 volumes, total of >800 slices Covid19 masks 350 annotated slices Lung masks >700 annotated slices*	*jpg*	*CT*	*http://medicalsegmentation.com/covid19/*
7	*COVID-19 Radiography Database*		*COVID-19: 219 Normal: 1,341 Viral Pneumonia: 1,345*	*png*	*CXR*	*https://www.kaggle.com/tawsifurrahman/covid19-radiographydatabase*

The data sources depicted in Table 4 are the standard open-source of radiology images available for the public to access, study and characterise using CNN architectures. However, based on the table, there are minimal COVID-19 data to comprehensively utilise AI techniques to conduct an intensive study. This creates concerns and difficulties when utilising these techniques to real-world practice with the limited number of datasets available.

3.0 Experiment

In theory, utilising AI is to eliminate fake news that can be found on the worldwide web and various social media platforms to ensure authenticity, responsible and dependable information about the pandemic. However, scientists face many challenges and limitations to produce ethical and reliable results for the public.

Table 5: Challenges of Radiology Imaging addresses and AI applications

No	*Applications*	*Type of Data*	*Challenges*	*AI Methods*	*Studies*
1	*COVID-19 early detection using radiology images. Typically CXR & CT images*	*CXR images*	*Limited availability of annotated medical images and medical images classification remains the biggest challenge in medical diagnosis.*	*DeTraC Deep Convolution Neural Network*	*[53]*
2		*CXR images*	*Finding optimal parameters for the SVM classifier can be seen as a challenge. Finding optimal parameters for the SVM classifier can be seen as a challenge. Finding optimal values for the Relief algorithm can be seen as another limitation of the study*	*COVIDetectioNet*	*[54]*
3		*CT images*	*Redundant data such as interferential vessels can be misdiagnosed as pathology. Radiologists have difficulty differentiating COVID-19 and other atypical and viral pneumonia diseases, which are the same in CT imagery and have similar symptoms.*	*AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101,Xception*	*[55]*
4		*CXR images*	*Due to the sudden existence and infectious nature of COVID-19, systematic collection of the extensive data set for CNN training is formidable. Biomarkers found in the CXR images can be misleading.*	*Patch Based Convolutional Network*	*[56]*
5		*CXR images*	*The research is facing with images taken directly from patients with severe COVID-19 or some form of pneumonia. However, in the real world, more people are unaffected by pneumonia. The limited number of data available provides a limitation to provide feasible results.*	*Multi-class classification& hierarchical classification, using texture descriptors and also pre-trained CNN model*	*[57]*
6		*CXR images*	*Insufficient pulmonary diseases data limit us to conduct verification techniques.*	*Localise the areas in CXR symptomatic of the COVID-19 presence*	*[58]*
7		*CT images*	*Shortage of radiology image labelled data*	*Segmentation Deep Network (Inf-Net)*	*[59]*

4.0 Conclusion & Future Works

The COVID-19 plague has disrupted the lives of the people worldwide. The number of casualties related to the disease cannot be contained and increased by the thousands daily. AI technologies have existed to help us live comfortably and have many successes and contributions in streamlining processes and procedures. However, the spread of COVID-19 is exceptionally lethal as it transmits faster and broader than ever. The coronavirus is also continuously revolutionising with new spikes, and protein mutations have been reported in countries like Malaysia, United Kingdom, South America, Australia, the Netherlands and Singapore. The clinical impact of this discovery and its infectivity or aggressiveness is still unknown. Whether the mutation will affect the development of radiography imaging is also still a mystery.

Based on the worldmeter website: https://www.worldometers.info/coronavirus/, some countries failed to respond to the plague, some are barely tackling the situation, and some are handling the situation much more successfully. The virus is still able to infect many peoples lives in a blink of an eye. Hence, a country that managed to have the situation under control might experience a spike increase overnight if society became lenient in taking proper measures.

Although many researchers have published their works, the number of contributions and AI applications towards tackling COVID-19 is rudimentary. With the petrifying number of deaths and infected patients discovered daily and the virus's mutation undergoing speedily and unknowingly under our nose, we are nowhere near applying AI on radiography imaging to identify that the patient is infected with COVID-19. The development of AI and radiography imaging is slow due to the limited availability of COVID-19 datasets. With the number of people affected worldwide, AI methods require massive data and several computational models and CNN architectures to learn and acquire knowledge. The current data that most researchers acquired in opensource websites is insufficient. Even with the best available data, it is far from

perfect, data alone cannot explain the pandemic's whole situation. Therefore, for future research and development, in terms of acquiring radiography imaging data, the best way is to have access to reliable, global, open data and research to build an infrastructure that allows researchers who are experts in the field of radiology, artificial intelligence, deep learning and imaging to navigate and understand this data and its development.

Most of the COVID-19 radiography images datasets are stored in different formats, standards, sizes and quality, which are obstacles for scientists to speed up development for related COVID-19 AI research. Therefore, in future development, COVID-19 radiography images should have standard operating procedures to allow researchers or scientists and anyone who has the passion and are interested in contributing and utilising the information freely. A future study on deep learning models identifying and distinguishing the difference between COVID-19 images and viral pneumonia is essential. The study would help radiologists and physicians understand the virus and evaluate future coronaviruses using CT and CXR images more efficiently and effectively.

ACKNOWLEDGEMENT

This work is supported by RU Geran University Malaya (ST014-2019)

5.0 References

[1] A. Gulati, “Lung AI: A Deep Learning Convolutional Neural Network for Automated Detection of COVID-19 from Posteroanterior Chest X-Rays,” medRxiv, 23 12 2020. [Online]. Available: https://www.medrxiv.org/content/10.1101/2020.12.19.20248530v2.full. [Accessed 22 3 2021].

[2] R. Tawsifur, E. H. C. Muhammad, K. Amith, R. I. Khandaker, F. I. Khandaker, B. M. Zaid, A. K. Muhammad and K. Saad, “Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray,” *Applied Sciences,* vol. 10, no. 3233, pp. 1 - 17, 2020.

[3] VOX, “YouTube,” 6 March 2020. [Online]. Available: https://www.youtube.com/watch?v=TPpoJGYlW54. [Accessed 7 February 2021].

[4] American Library Association, “Worldmeter,” [Online]. Available: https://www.worldometers.info/coronavirus/. [Accessed 10 AUGUST 2020].

[5] A. James, C. Yves, L. Carmen, Pessoa-Silva, J. Paul, L. Yuguo and S. Wing-Hong, “Natural Ventilation for Infection Control in Health-Care Settings,” World Health Organisation (WHO), Canberra, Australia, 2009.

[6] R. Wölfel, V. M. Corman, W. Guggemos, M. Seilmaier, S. Zange, M. A. Müller, D. Niemeyer, T. C. Jones, P. Vollmar, C. Rothe, M. Hoelscher, T. Bleicker, S. Brünink, J. Schneider and R. Ehmann, “Virological assessment of hospitalized patients with COVID-2019,” *Nature,* vol. 581, pp. 465 - 469, 2020.

[7] L. Le, Z. Yefeng, C. Gustavo and Y. Lin, “Deep Leaning and Convolutional Neural Networks for Medical Image Computing Precision Medicine, High Performance and Large-Scale Datasets,” *Springers,* p. 4, 2017.

[8] L. Mohamed, F. S. and K. Nour Eldeen M., “Within the Lack of Chest COVID-19 X-ray Dataset: A Novel Detection Model Based on GAN and Deep Transfer Learning,” *Symmetry,* pp. 1 - 19, 2020.

[9] D. Rong, L. Xie and Y. Ying, “Computer vision detection of foreign objects in walnuts using deep learning,” *Computer Electronic Ariculture,* vol. 162, pp. 1001-1010, 2019.

[10] G. Eraslan, Ž. Avsec, J. Gagneur and F. Theis, “Deep learning: new computational modelling techniques for genomics.,” *Nat. Rev. Genet.* , vol. 37, pp. 389 - 403, 2019.

[11] J. Riordon, D. Sovilj, S. Sanner, D. Sinton and E. Young, “Deep Learning with Microfluidics for Biotechnology,” *Trends Biotechnol.,* vol. 37, pp. 310 - 324, 2019.

[12] A. Lundervold and A. Lundervold, “An overview of deep learning in medical imaging focusing on MRI.,” *Z. für Med. Phys.,* vol. 29, pp. 102 - 127, 2019.

[13] A. Maier, C. Syben, T. Lasser and C. Riess, “A gentle introduction to deep learning in medical image processing.,” *Z. für Med. Phys,* vol. 29, pp. 86 - 101, 2019.

[14] A. Shrestha and A. Mahmood, “Review of Deep Learning Algorithms and Architectures.,” *IEEE,* vol. 7, pp. 53040 - 53065, 2019.

[15] S. Pouyanfar, S. Sadiq, Y. Yan, H. Tian, Y. Tao, M. Reyes, M.-L. Shyu, S.-C. Chen and S. Iyengar, "A Survey on Deep Learning: Algorithms, Techniques, and Applications.," *ACM Comput. Surv.,* vol. 51, pp. 1 - 36, 2018.

[16] J. Al-Tawfiq, A. Zumla and Z. Memish, "Coronaviruses: severe acute respiratory syndrome coronavirus and Middle East respiratory syndrome coronavirus in travelers.," *Curr Opin Infect Dis,* vol. 27, p. 411–417, 2014.

[17] L. Ketai, N. Paul and K. Wong, "Radiology of severe acute respiratory syndrome (SARS): the emerging pathologic-radiologic correlates of an emerging disease.," *J Thorac Imaging ,* vol. 21, p. 276–283, 2006.

[18] M. Chung, A. Bernheim, X. Mei and e. al., "CT imaging features of 2019 novel coronavirus (2019-nCoV).," *Radiology ,* 2020.

[19] J. Chan, S. Yuan, K. Kok and e. al., "A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster.," *Lancet,* vol. 395, pp. 514 - 523, 2020.

[20] P. Liu and X. Tan, "2019 novel coronavirus (2019-nCoV) pneumonia.," *Radiology,* 2020.

[21] M. Hosseiny, S. Kooraki, A. Gholamrezanezhad, S. Reddy and L. Myers, "Radiology Perspective of Coronavirus Disease 2019 (COVID-19): Lessons from Severe Acute Respiratory Syndrome and Middle East Respiratory Syndrome," *AJR,* vol. 214, pp. 1078 - 1082, 2020.

[22] M. Cynthia Czawlytko, M. Rydhwana Hossain and M. Charles S White, "COVID-19 Diagnostic Imaging Recommendations," *Applied Radiology,* pp. 10-15, 2020.

[23] M. E. H. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M. A. Kadir, Z. B. Mahbub, I. Khandakar R., K. Muhammad Salman, A. Iqbal, N. Al-Emadi, M. B. I. Reaz and M. T. Islam, "Can AI help in screening Viral and COVID-19 pneumonia?," *IEEE Access,* vol. XX, pp. 1 - 12, 2020.

[24] W. Wang, Y. Xu, R. Gao, R. Lu, K. Han and e. a. G. Wu, "Detection of SARS-CoV-2 in Different Types of Clinical Specimens," *Jama,* vol. XX, 2020.

[25] S. Sharma, "Drawing insights from COVID-19 infected patients using CT scan images and machine learning techniques: a study on 200 patients," *Environmental Science and Pollution Research,* 2020.

[26] C. Joseph Paul, M. Paul and L. Dao, "Covid-19 Image Data Collection," *arXiv.org,* pp. 1-4, 2020.

[27] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri and R. M. Summers, "ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localisation of Common Thorax Diseases.," *In Computer Vision and Pattern Recognition,* pp. 369 - 373, 2017.

[28] J. P. Cohen, P. Bertin and V. Frappier, "Chester: A Web Delivered Locally Computed Chest X-Ray Disease Prediction System," *arXiv,* 2019.

[29] P. Rajpurkar, A. Y. Hannun, M. Haghpanahi, C. Bourn and A. Y. Ng, "Cardiologist Level Arrhythmia Detection with Conviolutional Neural Networks," vol. 7, 2017.

[30] M. Satyanarayana, “Shortage of RNA extraction kits hampers efforts to ramp up COVID-19 coronavirus testing,” vol. 3, 2020.

[31] M. Kelly Geraldine, Interviewee, *Testing backlog linked to shortage of chemicals needed for COVID-19 test.* [Interview]. 2020.

[32] M. Yascha, Interviewee, *Coronavirus: Extraordinary Decisions For Italian Doctors - The Atlantic.* [Interview]. 2020.

[33] T. T. Nguyen, “Artificial Intelligence in the Battle against Coronavirus (COVID-19): A Survey and Future Research Direction,” *arXiv.org,* vol. XX, pp. 1 - 14, 2020.

[34] L. Lin, Q. Lixin, X. Zeguo, Y. Youbing, W. Xin, K. Bin, B. Junjie, L. Yi, F. Zhenghan, S. Qi, C. Kunlin, L. Daliang, W. Guisheng, X. Qizhong, F. Xisheng, Z. Shiqin, X. Juan and X. Jun, “Artificial Intelligence Distinguishes COVID-19 from Community Acquired Pneumonia on Chest CT,” *Radiology,* pp. 1 -16, 2020.

[35] B. Charmaine, G. Jagpal, C. David and A. B. Benson, “Deep learning system to screen coronavirus disease 2019 pneumonia,” *Applied Intelligence,* pp. 1 - 7, 2020.

[36] G. Biraja and T. Allan, “Estimating Uncertainty and Interpretability in Deep Learning for Coronavirus (COVID-19) Detection,” *arXiv,* pp. 1 - 14, 2020.

[37] W. Shuai, K. Bo, M. Jinlu, Z. Xianjun, X. Mingming, G. Jia, C. Mengjiao, Y. Jingyi, L. Yaodong and M. Xiangfei, “A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19),” *medRxiv,* pp. 1 - 19, 2020.

[38] B. Xiang, F. Cong, Z. Yu, B. Song, L. Zaiyi, C. Qianlan, X. Yongchao, X. Tian, G. Shi, X. Xudong, S. Dejia, D. Ronghui, Z. Chunhua, C. Chengyang, N. Dianer, T. Dandan, Z. Changzheng, L. Xiaowu and Q. Lixin, “Predicting COVID-19 malignant progression with AI techniques,” *medRxiv,* pp. 1 - 26, 2020.

[39] J. Cheng, C. Weixiang, C. Yukun, X. Zhanwei, T. Zimeng, Z. Xin, D. Lei, Z. Chuansheng, Z. Jie, S. Heshui and F. Jianjiang, “Development and Evaluation of an AI System for COVID-19 Diagnosis,” *medRxiv,* pp. 1 - 39, 2020.

[40] J. Shuo, W. Bo, X. Haibo, L. Chuan, W. Lai, Z. Wei, H. Xuexue, M. Wenshuo, X. Zhengqing, Z. Zhuozhao, S. Wenbo, L. Lan, Z. Wei, M. Xiangdong, S. Chenxin, W. Zhongxiao, L. Jihae, J. Zijian, L. Minggui and J. Hongbo, “AI-assisted CT imaging analysis for COVID-19 screening: Building and deploying a medical AI system in four weeks,” *medRxiv,* pp. 1 - 22, 2020.

[41] N. Ali, K. Ceren and P. Ziynet, “Automatic Detection of Coronavirus Disease (COVID-19) Using X-ray Images and Deep Convolutional Neural Networks,” *arXiv.org,* pp. 1 -31, 2020.

[42] W. Linda, L. Zhong Qiu and W. Alexander, “COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images,” *Nature,* pp. 1 - 12, 2020 .

[43] G. Ophir, F.-A. Ma’ayan, G. Hayit, P. D. Browning, Z. Huangqi, J. Wenbin, B. Adam and S. Eliot, “Rapid AI Development Cycle for the Coronavirus (COVID-19) Pandemic: Initial Results for Automated Detection & Patient Monitoring using Deep Learning CT Image Analysis,” *arxiv.org,* pp. 1 - 22, 2020.

[44] S. M. Halgurd, T. A. Aras, Z. G. Kayhan, S. Ali Safaa and K. K. Muhammad, “Diagnosing COVID-19 Pneumonia from X-Ray and CT Images using Deep Learning and Transfer Learning Algorithms,” *arxiv.org,* 2020.

[45] C. Vikash, S. Sanjay Kumar, K. Aditya, G. Deepak, T. Prayag, M. Catarina, D. Robertas and d. A. Victor Hugo C., “A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images,” *Applied Science,* vol. 559, no. 10, pp. 1 - 17, 2019.

[46] Y. Xingyi, H. Xuehai, Z. Jinyu, Z. Yichen and Z. Shanghang, “COVID-CT-Dataset: A CT Image Dataset about COVID-19,” *arXiv.org,* pp. 1 -14, 2020.

[47] D. Aysen, A. Mete, Y. Mehmet, K. Serkan, E. H. C. Muhammad, H. Khalid, H. Tahir, M. Rashid and G. Moncef, “COVID-19 Infection Map Generation and Detection from Chest X-Ray Images,” *arXiv.org,* 2020.

[48] A. Omar Ibrahim, “Automatic Deep Learning System for COVID-19 Infection Quantification in chest CT,” *keras.io,* pp. 1 - 6, 2020.

[49] A. Ridhi, B. Vipul, B. Himanshu, K. Rahul, J. S. Vinodh, Narayanan, N. P. Ganesh and R. Balasubramanian, “AI-based Diagnosis of COVID-19 Patients Using X-ray Scans with Stochastic Ensemble of CNNs,” *MTAP-D-20-03975,* pp. 1 - 26, 2020.

[50] S. Christian, I. Sergey, V. Vincent and A. Alex, “Inception-v4 Inception-ResNet and the Impact of Residual Connections on Learning,” *arXiv.org,* pp. 1 - 12, 2016.

[51] L. Min, C. Qiang and Y. Shuicheng, “Network in Network,” *arXIv.org,* pp. 1 - 10, 2014.

[52] S. Karen and A. Zisserman, “VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION,” *arXiv.org.*

[53] A. Asmaa, M. A. Mohammed and M. G. Mohamed, “Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network,” *medRxiv,* 2020.

[54] T. Muammer, “COVIDetectioNet: COVID-19 diagnosis system based on X-ray images using features selected from pre-learned deep features ensemble,” *Applied Intelligence,* pp. 1 - 14, 2020.

[55] A. Ali Abbasian, K. Alireza Rajabzadeh, A. U. Rajendra, K. Nazanin and M. Afshin, “Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks,” *Computers in Biology and Medicine,* pp. 1 - 9, 2020.

[56] O. Yujin, P. Sangjoon and Y. Jong Chul, “Deep Learning COVID-19 Features on CXR using Limited Training Data Sets,” *Transactions on Medical Imaging,* 2020.

[57] P. Rodolfo M., B. Diego, T. Lucas O., N. S. J. Carlos and C. Yandre M.G., “COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios,” *Computer Methods and Programs in Biomedicine,* 2020.

[58] B. Luca, M. Francesco, R. Alfonso and S. Antonella, “Explainable Deep Learning for Pulmonary Disease and Coronavirus COVID-19 Detection from X-rays,” *Computer Methods and Programs in Biomedicine,* 2020.

[59] F. Deng-Ping, Z. Tao, J. Ge-Peng, Z. Yi, C. Geng, F. Huazhu, S. Jianbing and S. Ling, “Inf-Net: Automatic COVID-19 Lung Infection Segmentation from CT Images,” *IEEE,* 2020.

[60] Centers for Disease Control and Prevention, “Coronavirus Disease 2019 (COVID-19),” 9 August 2020. [Online]. Available: https://www.cdc.gov/coronavirus/2019-ncov/cases-in-us.html.. [Accessed 10 August 2020].

[61] Ministry of Health Malaysia, “COVID-19 Malaysia,” Ministry of Health Malaysia, 10 August 2020. [Online]. Available: http://covid-19.moh.gov.my/. [Accessed 10 August 2020].

[62] Healthline, “How is COVID-19 pneumonia different from regular pneumonia?,” 10 August 2020. [Online]. Available: https://www.healthline.com/health/coronavirus-pneumonia#vs-regular-pneumonia. [Accessed 10 August 2020].

[63] WebMD, “Coronavirus and Pneumonia,” WebMD LLC. All rights reserved., 10 August 2020. [Online]. Available: https://www.webmd.com/lung/covid-and-pneumonia#1. [Accessed 11 August 2020].

[64] Occupational Safety and Health Administration, “COVID-19,” UNITED STATES DEPARTMENT OF LABOR, UNITED STATES, 2020.

[65] Centers for Disease Control and Prevention, “Centers for Disease Control and Prevention,” 28 October 2020. [Online]. Available: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/how-covid-spreads.html. [Accessed 8 December 2020].

[66] New Straits Times, “New Straits Times,” New Straits Times, 8 December 2020. [Online]. Available: https://www.nst.com.my/world/world/2020/12/647620/who-against-mandatory-covid-19-vaccines. [Accessed 9 December 2020].

[67] BBC News, “Covid: FDA approves Pfizer vaccine for emergency use in US,” BBC, 12 12 2020. [Online]. Available: https://www.bbc.com/news/world-us-canada-55265477. [Accessed 13 12 2020].

[68] H. Bai, B. Hsieh, Z. Xiong, K. Halsey, J. Choi, T. Tran, I. Pan, L.-B. Shi, D.-C. Wang and J. Mei, “Performance of radiologists in differentiating COVID-19 from viral pneumonia on chest CT,” *Radiology ,* 2020.

[69] G. Rubin, C. Ryerson, L. Haramati, N. Sverzellati, J. Kanne, S. Raoof, N. Schluger, A. Volpi, J.-J. Yim, I. Martin and e. al., “The Role of Chest Imaging in Patient Management during the COVID-19 Pandemic: A Multinational Consensus Statement from the Fleischner Society.,” *Radiology,* 2020.

[70] S. Rajaraman and S. Antani, “Weakly Labeled Data Augmentation for Deep Learning: A Study on COVID-19 Detection in Chest X-Rays,” *Diagnostics,* vol. 358, no. 10, pp. 1-17, 2020.

[71] D. Kermany, M. Goldbaum, W. Cai, C. Valentim, H. Liang, S. Baxter, A. McKeown, G. Yang, X. Wu, F. Yan and e. al., “Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning.,” *Cell,* vol. 172, pp. 1122 - 1131, 2018.

[72] ACR, “ACR Recommendations for the use of Chest Radiography and Computed Tomography (CT) for Suspected COVID-19 Infection,” American College of Radiology, 22 March 2020. [Online]. Available: https://www.acr.org/Advocacy-and-Economics/ACR-Position-Statements/Recommendations-for-Chest-Radiography-and-CT-for-Suspected-COVID19-Infection. [Accessed 13 December 2020].