Chapter 2
Comparative Study and Detection of COVID-19 and Related Viral Pneumonia Using Fine-Tuned Deep Transfer Learning

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Abstract Coronavirus (or COVID-19), which came into existence in 2019, is a viral pandemic that causes illness and death in the lives of human. Relentless research efforts have been on to improve key performance indicators for detection, isolation and early treatment. The aim of this study is to conduct a comparative study on the detection of COVID-19 and develop a Deep Transfer Learning Convolutional Neural Network (DTL-CNN) Model to classify chest X-ray images in a binary classification task (as either COVID-19 or Normal classes) and a three-class classification scenario (as either COVID-19, Viral-Pneumonia or Normal categories). Dataset was collected from Kaggle website containing a total of 600 images, out of which 375

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M. Mehta et al. (eds.), *Tracking and Preventing Diseases with Artificial Intelligence*,
Intelligent Systems Reference Library 206,
https://doi.org/10.1007/978-3-030-76732-7_2

were selected for model training, validation and testing (125 COVID-19, 125 Viral Pneumonia and 125 Normal). In order to ensure that the model generalizes well, data augmentation was performed by setting the random image rotation to 15 degrees clockwise. Two experiments were performed where a fine-tuned VGG-16 CNN and a fine-tuned VGG-19 CNN with Deep Transfer Learning (DTL) were implemented in Jupyter Notebook using Python programming language. The system was trained with sample datasets for the model to detect coronavirus in chest X-ray images. The fine-tuned VGG-16 and VGG-19 DTL models were trained for 40 epochs with batch size of 10, using Adam optimizer for weight updates and categorical cross entropy loss function. A learning rate of $1e^{-2}$ was used in fine-tuned VGG-16 while $1e^{-1}$ was used in fine-tuned VGG-19, and was evaluated on the 25% of the X-ray images. It was discovered that the validation and training losses were significantly high in the earlier epochs and then noticeably decreases as the training occurs in more subsequent epochs. Result showed that the fine-tuned VGG-16 and VGG-19 models, in this work, produced a classification accuracy of 99.00% for binary classes, and 97.33% and 89.33% for multi-class cases respectively. Hence, it was discovered that the VGG-16 based DTL model classified COVID-19 better than the VGG-19 based DTL model. Using the best performing fine-tuned VGG-16 DTL model, tests were carried out on 75 unlabeled images that did not participate in the model training and validation processes. The proposed models, in this work, provided accurate diagnostics for binary classification (COVID-19 and Normal) and multi-class classification (COVID-19, Viral Pneumonia and Normal), as it outperformed other existing models in the literature in terms of accuracy.

Keywords Convolutional neural networks · Coronavirus · COVID-19 test results · Deep transfer learning · Machine learning

2.1 Introduction

Viral pandemics have been known to be a serious threat to the world, and coronavirus disease 2019 (COVID-19) is not an exception. The World Health Organization (WHO) in 2020 reported that coronavirus is from a huge body of viruses that are responsible for ailments in humans or animals. Several coronaviruses are known in humans as the basis for varieties of respiratory disease such as common cold to more severe illnesses such as Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS) [63]. The recently discovered coronavirus is the purported cause of COVID-19. This virus contaminates people and multiplies effortlessly from person-to-person. On March 11, 2020, the COVID-19 epidemic was described as a deadly disease by the World Health Organization (WHO). According to WHO, one million, seven hundred and seventy-five thousand and seven hundred and seventy-six (1,775,776) humans have lost their lives as a result of the COVID-19 epidemic as at the 30th of December, 2020, 9:26 AM CET.

As at the time of writing this chapter, the number of confirmed cases stands at 82,502,518 the world over. The fatality rate is still being assessed [66]. Numerous researchers globally are putting their efforts to collect data and develop solutions. The constant emphasis has been on advancing key performance metrics, for example, gradually increasing the speed of case identification, segregation and early cure. The introduction of these containment procedures was maintained and made possible by the innovative and effective use of cutting-edge technology. This work is, therefore, aimed at showing how Artificial Intelligence (AI), specifically machine learning, can help in identifying who is most at risk and diagnose patients early. According to BBC [8], a superhuman attempt is required towards the ease of the global epidemic killing. AI may have been overestimated—but in the case of medicine, it already has established evidence. According to Arora et al. [6], the role of AI is going to be crucial for predicting the outcome based on symptoms, CT-Scan, X-ray reports, etc.

Laboratory checking of suspected cases are described with extended periods and an exponential rise in request for tests [25]. Speedy prognosis with shorter turnaround times within a range of 10–30 mins have been to ameliorate the problem, although the majorities are presently going through clinical validation and therefore not in regular use [16]. In the process of result expectation, there is a need to continue to self-isolate. Once results are received, there is a need to remain on self-isolation until the symptoms resolve after being in seclusion for at least 14 days. In situations where the symptoms worsen during the seclusion time or continued after the 14 days, the patient would be asked to contact the accredited healthcare providers. Even the Rapid Test Kits deliver results after hours. Therefore, there is much interest to develop computer algorithms and methods to optimize screening and early detection, which is the primary purpose of this research where deep learning, most especially Convolutional Neural Network (CNN) is deployed. Deep learning provides the chance to increase the accuracy of the early discovery by automating the primary diagnosis of medical scans [31]. A CNN is a type of a DNN consisting of many hidden layers such as a convolution layer, a Rectified Linear Unit (ReLU) layer, a pooling layer and a fully connected layer.

CNN divides weights in the convolutional layer, thus reducing memory footprint and increasing network efficiency [44]. There are existing deep learning approaches to the detection of COVID-19 in clinical images (especially chest X-ray) in literature. However, it is the opinion of the authors of this chapter that the detection accuracies obtained in these approaches could be improved upon. The aim of this chapter therefore is to deploy Deep Transfer Learning Convolutional Neural Network Model to classify real-life COVID-19 dataset consisting of X-ray images. X-ray data are used since most hospitals have X-ray equipment and now the COVID-19 X-ray dataset is available on the Internet.

The rest of this chapter is organized thus: Sect. 2.2 gives an overview of literature where some current related works that are relevant to this chapter are explored, while Sect. 2.3 details the methodology used in this chapter for the detection of COVID-19 and related Viral Pneumonia. Section 2.4 of this chapter presents the results obtained from the experiments carried out by the authors of this chapter, and performance comparison drawn with other related works, while Sect. 2.5 concludes the chapter.

2.2 Literature Review

This section provides a brief review of literature tied to this work.

2.2.1 The COVID-19 Coronavirus

The COVID-19 coronavirus was initially observed in the Wuhan province of China and is fast spreading to all parts of the world [34]. The attention of the WHO was drawn to a collection of cases of the novel pneumonia discovered in the City of Wuhan, Hubei Province, China. The coronavirus disease (COVID-2019) was recognized as the contributory virus by Chinese authorities on January 7, 2020. On January 30, 2020, the WHO Director-General stated that the outbreak constitutes a Public Health Emergency of International Concern (PHEIC), by following the recommendations of the Emergency Committee. WHO has activated the R&D Blueprint in reaction to the occurrence to speed up diagnostics, vaccines and therapeutics for this new coronavirus [64]. The spread was so frightening that it became a source of concern globally, such that as at 28/04/2020, over two million cases (2,954,222), and 202,597 deaths have been recorded. Africa has over 22,239 cases, 881 death [36]. Nigeria, as of April 29, 2020, has about 1532 cases with 44 deaths and 255 recoveries with 12,004 tested samples [36]. The coronavirus is transmitted through droplets from coughing or sneezing and on close contacts with infected persons. The incubation period of COVID-19 is about 14 days; it attacks the lung, and it is highly contagious.

Nadeem [34] presented a short review of coronavirus that was made available by various journals and companies around the world. The review reported that the following journals/publishers had decided to make their COVID-19, coronavirus-related articles and the obtainable supporting data, accessible in PubMed Central (PMC), and authorized it for reuse: "American Chemical Society (ACS), The British Medical Journal (BMJ), American Society for Microbiology, Bulletin of the World Health Organization, Annals of Internal Medicine, Chinese Journal of Lung Cancer, Cambridge University Press (CUP), Cell Press, eLife, Elsevier, EMBO Press, Emerald Publishing, European Respiratory Society, Frontiers, Future Science Group (FSG), Global Virus Network Healthcare Infection Society, Hindawi, IOP Publishing, JMIR Publications, Karger Publishers, F1000 Research Limited, The Lancet, Life Science Alliance, MDPI, Microbiology Society, New England Journal of Medicine (NEJM), Oxford University Press, PLOS, PNAS—Proceedings of the National Academy of Sciences of the USA, Rockefeller University Press (RUP), The Royal Society, SAGE Publishing, Science Journals—American Association for the Advancement of Science, Springer Nature, Taylor & Francis, WikiJournal User Group, Wiley, Wolters Kluwer." The author noted that the review was open to updates.

2.2.2 COVID-19 Clinical Features

COVID-19 is predominantly a respiratory illness and pulmonary appearances which constitute main presentations of the disease. COVID-19 infects the respiratory system but could affect other organs as reported in some studies. Renal dysfunction [14, 69], gastrointestinal complications [39], liver dysfunction [23], cardiac manifestations [75], mediastinal findings [58], neurological abnormalities, and haematological manifestations [51], are among the reported extrapulmonary features. Some of the clinical symptoms of COVID-19 are cough, expectoration, asthenia, dyspnoea, muscle soreness, dry throat, pharyngeal dryness and pharyngalgia, fever, poor appetite, shortness of breath, nausea, vomiting, nasal obstruction, and rhinorrhoea. According to a WHO report on COVID-19, the disease has no specific manifestation to note, and the patients' presentation can range from completely asymptomatic to severe pneumonia and death [63–65].

Some symptoms presented by patients include sore throat, fever, dry cough, aches, nasal congestion and in severe cases patients build up respiratory breakdown, various organ malfunction, acute respiratory distress syndrome and in the end death [9].

The symptoms of COVID-19 infection begin to appear 5–6 days subsequent to contracting it either from the droplet or close contact with an infected person. According to Wang et al. [60], the period between the beginning of symptom and demise ranges from 6 to 41 days depending on the age and immune system of the patient. The period is shorter among older people. General symptoms at the beginning of the disease include fatigue, sore throat, fever, dry cough, aches, nasal congestion, sputum production, diarrhea and in severe cases patients show respiratory dysfunctions, chronic breathing distress syndrome, manifold organ failure and eventual demise [9, 18]. Chest CT scan shows pneumonia-like and some other viral pneumonia.

Furthermore, it presents other symptoms like severe respiratory distress syndrome, acute cardiac injury, RNA anemia and incidence of grand-glass opacities which lead to death [18]. COVID-19 shows some unique clinical symptoms like targeting the lower airway that manifests in the form of sore throat, sneezing and rhinorrhea. In addition, the chest radiographs result in some cases possesses “infiltrate in the upper lobe of the lung” related to growing dyspnea with hypoxemia [18]. COVID-19 has become pandemic and rapid diagnosis is imperative to identify patients and carriers for possible isolation and treatment in order to curb the spread of the disease. Attempts have been made to diagnose the disease, but a number of them are slow and not accurate in that they often give false-negative and false-positive results.

2.2.3 Related Works on the Detection of COVID-19

Li et al. [27, 28] examined chest images for the diagnosis of COVID-19. High-Resolution Computed Tomography (HRCT) was implemented for the primary diagnosis of the virus infection. HRCT objectively evaluates lung lesions giving a better understanding of the pathogenesis of the disease. CT scans were taken with the following parameters: collimation of 5 mm; 512 × 512 matrix; 100–250 mAs; collimation of 5 mm; pitch of 1–1.5; and 120 kV. The images were reconstructed by high resolution and conventional algorithms. The experiments were repeated several times, running into days for each patient.

Furthermore, COVID-19 have overlapping imaging manifestation with other cases of pneumonia such as SARS, other tests like the nucleic acid tests of samples from the respiratory tract are necessary for an accurate diagnosis. Long et al. [30] evaluated the suitability of Computed Tomography (CT) and “real-time reverse-transcriptase-polymerase Chain Reaction (rRT-PCR).” Clinical experiment with life data was executed, and the results presented that CT examination outperforms that of rRT-PCR at 97.2% and 84.6% respectively. In [57], seven important AI applications for the novel COVID-19 were recognized that can perform vital roles in screening, analyzing, tracking, and prediction of patients. Application areas identified comprise quick discovery and prognosis of the infection, treatment monitoring, individuals contact tracing, projection of cases and mortality, treatments and vaccines engineering, lessening of healthcare workers assignment and deterrence of the disease by providing updated supportive information.

Raajan et al. [42] suggested the use of image-based detection approach for COVID-19 detection, noting observations on the accuracy, speed and reliability of Chest CT imaging approach in the diagnosing and testing of COVID-19, in contrast with the Real-time Reverse Transcription Polymerase Chain Reaction (RT-PCR) detection approach. The work has the primary objective of proposing a high-speed, accurate and very sensitive CT scan approach for the diagnosis of COVID-19. The study further gives credence to novel computer-aided diagnosis system in the detection of COVID-19 using Deep Convolution Neural Network. The ResNet-16 network architecture was adopted in the training and labelling the CT dataset. The trained ResNet-16 model was then used to effectively diagnose COVID-19 patients. In evaluating the model, the accuracy obtained was 95.09%, specificity obtained was 81.89%, while the sensitivity obtained was 100%. On speed of test, it was reported that after four tests, the CT scan using ResNet CNN model required a maximum of one hour for test as compared with the RT-PCR that would require 2–3 hours for each test.

In considering the fact that the results of COVID-19 tests take long time, within a range of 2 hours and two days and the limited number of RT-PCR test kits, Altan and Karasu [3] argued on the importance of applying another diagnostic approach and thus proposed a hybrid model that consists of two-dimensional (2D) curvelet transformation, Chaotic Salp Swarm Algorithm (CSSA) and deep learning scheme to detect patients that contracted COVID-19 pneumonia from X-ray images. The model developed applied 2D curvelet transformation on the images acquired from the patient's chest X-ray radiographs and then formed a feature vector based on the coefficients realized. The Chaotic Salp Swarm Algorithm was employed to optimize the coefficients in the feature matrix. Diagnosis of COVID-19 infections in patients was then done by using a trained deep learning model,EfficientNet-B0 model. The propose hybrid model for COVID-19 diagnosis, in the study therefore consists of a framework of data synthesis using image processing method, revolution of RGB into grayscale images, application of the two-dimensional curvelet transformation to every image, the training and testing segments of the EfficientNet-B0 deep learning model, along with the model evaluation stage. The accuracy of the EfficientNet-B0 model alone is 95.24%, its specificity is 96.05%, while the accuracy of the model developed by applying only the 2D curvelet transformation is 96.87%, and its specificity is 97.46%. Also, the hybrid model, in which the feature matrix is formed using optimal coefficients obtained from CSSA optimization technique has an accuracy of 99.69%, while its specificity is 99.81%.

In a study, Pu et al. [40] aimed to develop and test feasibility of software for the detection, quantification, and monitoring of progression of pneumonia cases that are accompanying COVID-19 disease from chest CT scans. To achieve this, two datasets were collected and used. The first dataset in the study contained 120 chest CT scans which was used in the training and testing of deep learning algorithms for the segmentation of the lung boundaries and main lung vessels. The second dataset consisted of 72 serial chest CT scans that were obtained from 24 patients diagnosed with confirmed COVID-19, which was used to develop and test the deep learning algorithms for the detection and quantification of the presence and progression of infiltrates that accompany COVID-19, in the pneumonic regions. The computerized scheme flowchart of the algorithm used captured four important aspects of the detection process, first, an automated segmentation of the lung boundary and vessel based on the U-Net framework deep learning technique; secondly, an elastic lung registration stage for registering lung boundary between two serial CT scans at different time points using a bidirectional elastic registration algorithm; thirdly, a computerized automated identification of COVID-19 disease of the pneumonitis regions, and lastly, a quantifiable valuation of disease progression subjectively rated by radiologists. Radiologists rated 95% accuracy of heatmaps at least "acceptable" for representing disease progression. This suggests the feasibility of using computer software to detect and quantify pneumonic regions associated with COVID-19 and to generate heatmaps that can be used to visualize and assess progression.

Li et al. [27, 28] in a study on using Artificial Intelligence for the detection of COVID-19 and Community-acquired Pneumonia developed a fully automatic three-dimensional deep learning framework for the discovery of COVID-19 disease from chest CT scan images and evaluated the performance of the framework. A deep learning model based on RestNet50 was developed and christened COVID-19 detection neural network (COVNet) for the extraction of visual characteristics from volumetric chest CT scan images in order to detect COVID-19 in such CT scan images. The CT scan images of community-acquired or viral pneumonia and some other non-pneumonia conditions were involved in order to evaluate how effective the model would be in the differentiation of these conditions from COVID-19 disease proper.

The chest CT scan datasets that was used were those collected from six medical centers from the month of August 2016 to the month of February 2020. The results of evaluation of the developed model show that the deep learning neural network was able to detect COVID-19 distinctly having to differentiate it from the community-acquired or viral pneumonia and some other non-pneumonia lung diseases from chest CT scan images. It detected COVID-19 on CT scan images with an AUC value of 0.96, and viral pneumonia on chest CT scan images with an AUC value of 0.95.

Dipayan et al. [15] proposed a deep learning-based Convolutional Neural Network (CNN) architecture called Truncated Inception Net. The posited model classified COVID-19 positive cases from combined Pneumonia and normal cases with an accuracy of 99.96% (AUC of 1.0). They employed six different types of datasets to validate their proposal by taking the chest X-rays (CXRs) from COVID-19 positive, Pneumonia positive, Tuberculosis positive, and normal cases into considration. They obtained an accuracy of 99.92% (AUC of 0.99) in predicting COVID-19 positive cases from combined Pneumonia, Tuberculosis, and healthy CXRs. They therefore concluded that the posited Truncated Inception Net would be effective in predicting COVID-19 positive cases using CXRs.

Alazab et al. [2] proposed VGG16, a deep convolutional neural network model to detect COVID-19 from the chest X-ray. Their dataset contained 128 images of both COVID-19 healthy and non-healthy persons. The dataset was augmented to become 1000 images, 500 of which are for healthy and the other half for non-healthy persons. The proposed system achieved a weighted average F-measure of 95% on non-augmented dataset and a weighted average F-measure of 99% when trained on an augmented dataset. Additionally, three forecasting methods namely: the prophet algorithm (PA), autoregressive integrated moving average (ARIMA) model, and long short-term memory neural network (LSTM) were adopted to predict the numbers of COVID-19 confirmations, recoveries, and deaths over the next 7 days. The prediction results exhibit promising performance and offer an average accuracy of 94.80 and 88.43% in Australia and Jordan, respectively. They therefore concluded that the proposed system can significantly help identify the most infected cities, and also revealed that coastal areas are heavily impacted by the COVID-19 spread as the number of cases is significantly higher in those areas than in non-coastal areas.

The work of Sharma [46] proposed lung Computed Tomography (CT) scan as the first screening test and an alternative to real-time reverse transcriptase-polymerase chain reaction (RT-PCR) for diagnosis COVID-19 patients. About 2200 CT scan images consisting or 800 COVID-19 patients, 600 other viral pneumonia patients and 800 healthy persons were collected and used to train the machine learning model. A fresh set of 600 CT images with 200 COVID-19, 150 other viral pneumonia and 250 healthy persons were used to test the model for the three cases. Both training and testing used the custom vision software based on Residual Neural Network (ResNet) architecture of Microsoft azure. The model achieved a high accuracy and it is fast as it requires no blood sample collection, no tests kits and the diagnosis could be done on the spot of the scan. The results obtained compared favourably with other models in literature with about 91% accuracy, 92.1% sensitivity, 90.29% specificity in classifying the CT scan images into COVID-19, viral pneumonia and healthy cases. The author also recommends inclusion of polymerase chain reaction (PCR) for final diagnosis for images that were wrongly classified.

In [50], a multi-objective differential evolution-based convolutional neural network was proposed for COVID-19 diagnosis from the chest CT scan images of suspected patients. The model was built to classify images as COVID-19 positive or COVID-19 negative, i.e. the images were classified into two, positive and negative cases of COVID-19. Convolution operator with 3 Kernel/filter and 2 strides was used to extract potential features, max pooling layer of size 2 kernel and 1 stride was used to minimize the spatial size of the convolved features and Rectified linear unit (ReLU) activation function was employed to study the complex functional mappings between inputs and output parameters. The model was implemented with MATLAB 2019a software with deep learning toolbox. The population size of 40 was varied at different ratio for training and testing, 20:80, 30:70, 40:60, 60:40, 70:30, 80:20 and 90:10 ratios were used for the experiment. The model's performance was compared with those of competing models CNN, ANFIS and ANN. The model outperformed other models with accuracy > 92% for all the data ratio divisions, it presented improved and consistent true positive and true negative values as well as had lower false negative and false positive values when compared with other models. The results also showed that the model outperformed other models with 2.0928% F-measure, about 1.8262% more in sensitivity, 1.6827% more specificity and 1.9276% more in Kappa statistics. It could be deduced from the experiment that multi-objective differential evolution-based convolutional neural network was suitable for real-time COVID-19 diagnosis from chest CT scan images.

A deep learning-based software called "uAI Intelligent Assistant Analysis System" was proposed by Zhang et al. [71, 72] to diagnose COVID-19. This AI was developed to assess COVID-19 by United Imaging Medical Technology Company Limited in China. The software consists of an adapted 3D convolutional Neural Network and a combined VB-Net with bottle neck structure. The system has the capability to quickly and accurately localize and quantify COVID-19 infection, comprising the volume of the infection in the lung, lung lobes and bronchopulmonary segments. The percentage of infections can be calculated to determine the seriousness of the disease and to define the anatomical pattern within the lung. The software used the values Hounsfield Unit histogram within the infection region to evaluate the ground glass opacity (GGO), solid and sub-solid components in the affected region and to classify them. A data set of 2460 chest CT scan images were used, 90% (2215) showed COVID-19 pneumonia in both lungs, 7% (167) showed unilateral pulmonary infection with 81 and in the right and left lung respectively, 84 had negative chest CT scan. In terms of lung appearance, 298 (12%) showed pure GGO, 778 (32%) showed GGO with sub-solid lesion and 1300 (53%) with GGO with solid and sub-solid lesion. Their results showed that elderly patients ($\geq$ 60 years) were more susceptible to COVID-19, in addition, the dorsal segment of the right lobe of the lung is the preferred site for the pneumonia, this could be attributed to the distinctive anatomic features of the lobar bronchus, the bronchus of the right lower lobe of the lung is straight and steep. It was reported that the model would aid in prognosis of COVID-19 in addition to determining the seriousness of the disease to guide in the treatment plans.

Statistical analysis using Linear regression, Multilayer perceptron and Vector autoregression techniques were explored in [53] to predict the occurrence and spread of COVID-19 infection. The impact of COVID-19 in India resulting from statistics of confirmed, death and recovered cases were used to predict the rates of infection, death and recovered cases on COVID-19 for the subsequent 69 days. Linear regression (LR) predicted death cases with 95% Confidence Interval indicating an increase in death rates and recovery rates in the future based on existing case data. Multilayer perceptron (MLP) predicted a reduction in the confirmed cases with a slow rate and fluctuation in the death and recovered cases with 95% confidence Interval. The Vector autoregression (VAR) model of order 10, with AIC optimize information criteria with constant and linear trend vector and 95% confidence interval for the confirmed, recovered and death cases also predicted for the period under consideration perfectly.

Tuncer et al. [56], presented an automated residual exemplar local binary pattern and Iterative RelieF-based COVID-19 detection method with chest X-ray images. The scheme involved 87 X-ray images with COVID-19 and 234 healthy X-ray images, preprocessing, feature extraction using residual exemplar local binary pattern (ResExLBP), feature selection with the aid of iterative ReliefF (IRF), and the classification stage. A Grayscale transformation was carried out on the input X-ray images while resizing them into 512×512 size. These input images were subsequently divided into 128×128 sized exemplars with the aid of the ResExLBP and features extracted from these input images and their exemplars using local binary pattern. Discriminative features were selected using IRF after the generated features were concatenated. The chosen features served as input to different classifiers implemented with varying modes of validation. Evaluation of the system was carried out with accuracy, sensitivity, specificity, confusion matrix, AUC value, and geometric mean. Classification result showed that the SVM gave an accuracy of 100% by outperforming other classifiers, while the decision tree gave the worst accuracy of 91%.

Xu et al. [67, 68] proposed an early screening model to differentiate COVID-19 pneumonia from IAVP and healthy cases via pulmonary computed tomography (CT) images using deep learning procedures. Initially, the CT images were preprocessed to mine the effective pulmonary regions, and multiple candidate image cubes were partitioned using a three-dimensional (3D) CNN segmentation model. This was achieved after the central image, gathered for further processing in accordance with the two adjacent partners of each cube. The study used 618 CT samples and had 86.7% overall accuracy.

A model for detection and classification of COVID-19, using convolutional neural network as feature extractor with Bayesian optimization and 3 machine learning algorithms as classifiers was proposed by Nour et al. [37]. A total of 2905 X-ray images with three classes (COVID-19, viral pneumonia and normal) from an open-access dataset that covers the posterior-to-anterior chest X-ray images was employed for investigation in the study. Implementation of the model was actualized by applying data augmentation like flipping and rotation on the COVID-19 database and Bayesian optimization algorithm to enhance the CNN hyperparameters. The proposed CNN model was trained from scratch and validated and confusion matrix with other metrics derivable from it, like accuracy, sensitivity, specificity, as evaluation parameters. The model yielded an accuracy of 98.97%, F-1 score of 95.75%, a sensitivity of 89.39%, and specificity of 99.75% with the SVM classifier, whereas KNN and decision tree resulted in 95.76% and 96.10% accuracies respectively.

Toğaçar et al. [55] developed a deep learning model for detection of COVID-19 utilizing fuzzy colour and social mimic optimization techniques for pre-processing and SVM as classifier. The study utilized COVID-19 chest images, normal chest images and pneumonia chest images. The dataset was reconstructed by way of preprocessing using fuzzy and stacking techniques. Training and validation of the model were accomplished on the three datasets using the MobileNetV2 and SqueezeNet deep learning models and classification was actualized using the support vector classifier. For this investigation, two openly available databases comprising COVID-19 images were consolidated upon, since COVID-19 is a novel infection and the quantity of images associated with the virus is low. A total of 458 images were used to implement the model. This total comprises 295 images in COVID-19 category, 65 images in the normal class and 98 X-ray images in the pneumonia category. The experiments were implemented in python and confusion matrix and other parameters derivable from it were used as performance metrics. It was observed that the SVM classifier obtained an accuracy of 99.27% with the proposed method.

Amrane et al. [4] adopted a genetic approach using a rapid virological diagnosis on sputum and nasopharyngeal samples from suspect patients. Two real-time RT-PCR systems by means of a "hydrolysis probe and the LightCycler Multiplex RNA Virus Master Kit" were used. The primary technique probes the envelope protein (E)-encoding gene and uses a synthetic RNA positive control. The subsequent system targets the spike protein-encoding gene (forward priming, reverse priming, and probe) and uses optimistic control methods for synthetic RNA.

Bai et al. [9] proposed the use of medical technology through the internet of things (IoT) to develop an intelligent diagnosis and treatment assistance program (nCapp). The proposed cloud-based IoT platform includes the basic IoT roles and has a core graphics processing unit (GPU). Cloud computing systems link existing electronic medical records, image archiving, image archiving and communication to assist in profound mining and smart diagnosis.

A review of different machine learning methods with their attendant challenges for predicting the number of confirmed cases of COVID-19 was performed by Ahmad et al. [1]. The study involved a comprehensive review of different articles that employed machine learning strategies to forecast number of confirmed cases of COVID-19 and came up with a nomenclature system that categorized these techniques into four broad groups. The research characterized four titles or classes to which each methodology can be associated, taking care to ensure each method was placed in the most related category. However, it was discovered that certain methods belonged to more than one category. The four themes are: data-based search queries, traditional regression of machine learning, network and social media analysis, and methods of deep learning regression. It was noted that the traditional regression method of machine learning is a supervised technique of machine learning, which approximates the relationship between a dependent variable and independent variables. The study also revealed that two approaches have been used in the prediction of confirmed cases of COVID-19 using regression methods and that Random Forests and Neural Networks fall under this group. The first approach is the time series analysis and the other in which the associations between confirmed instances of COVID-19 and the other factors such as dampness, temperature etc. are mined from the data and the relationships were utilized to forecast the number of confirmed cases with the new values of the factors. The study further reviewed that deep learning essentially is related to ANNs which simulated human brain and used its many hidden layers to make accurate predictions, whereas analysis comprises networks or graphs which consisted of nodes and edges utilized for social networks analysis, community detection, web mining, etc. Ultimately, the work pointed out that social media and internet queries have huge data embedded in them, which can be utilized to estimate the number of confirmed cases of COVID-19. The study was concluded by highlighting the challenges associated with the methodologies and suggestions to address them were as well presented.

A feasibility study was performed by Brinati et al. [11] on the detection of COVID-19 infections using machine learning methods with blood as sample. The essence of the study was to find a sound and cost effective substitute to the costly and scarce rRT-PCR reagent for discovering COVID-19 positive cases. The feasibility study was carried out using 279 cases randomly selected from the patients admitted into the IRCCS Ospedale San Raffaele clinic between February ending 2020 and the middle of March 2020. The study employed descriptive statistics like mean, median, standard deviation, skewness and curtosis as descriptive statistics for the features considered. Implementation was actualized with the standard Python data analysis framework, comprising pandas for data loading and pre-processing, scikit-learn for both pre-processing and the classifiers analysis and matplotlib for visualization purposes. Different machine learning classifiers like KNN, decision tree, random forest, SVMs, Naïve Bayes, Logistic regression and extremely randomized trees were used for classification and their results compared. The resulting models were evaluated on balanced accuracy, positive predictive value (PPV), sensitivity, accuracy and specificity. The highest accuracy obtained from the study was 86%, and as such, the resulting model presented a good substitute to the gold standard method which requires highly sophisticated laboratory and the costly and scarce rRT-PCR reagent for detection of COVID-19.

A review of the use of Artificial Intelligence techniques amidst the COVID-19 Pandemic was presented by Bansal et al. [10]. The study demonstrated that the role of machine learning strategies, which heavily rely on artificial intelligence, in the prediction and management of COVID-19 pandemic. Different aspects of management explored were outbreak detection, spread prediction, preventive strategies and vaccine development, early case detection and tracking, prognosis prediction and treatment development. Further, the study also highlighted the role of big data generation, data cleaning and standardization in building reliable prediction models. The review also emphasized that noise and other anomalies in data, which could result in outliers, leading to prejudiced outcome must be avoided by all means. After a comprehensive review of different machine learning tools in combating the scourge of COVID-19, it was concluded that machine learning approaches are fast, more flexible than the traditional methods, and are free from human intervention and prejudice in detecting positive cases of COVID-19.

Lokuge et al. [29] proposed an effective, rapid, and scalable surveillance approach to spot all residual COVID-19 community transmissions over exhaustive identification of each energetic spread chain. They combined efficiency and sensitivity to identify community transmission chains by monitoring of patients with primary care fever and cough, hospital cases or asymptomatic community members, using surveillance evaluation approaches in addition to mathematical modeling, varying testing capacities and prevalence of COVID-19 and non-COVID-19 fever and cough, and duplication quantity. The study results showed that screening all demonstrations of syndromic fever and cough primary care, in combination with thorough and meticulous case and contact identification and management, allows for the proper primary discovery and removal of COVID-19 community transmission. If the test capability is limited, interventions such as combining allow for increased case discovery, even given the sensitivity of the concentrated test.

Hyafil and Moriña [24] carried out an impact analysis of the lockdown on the evolution of COVID-19 epidemics in Spain. The study was to assess the effect of the measures that started in Spain to deal with the epidemic. The amount of cases and the influence of the imposed lockdown on the multiplicative quantity resulting in hospitalization reports were estimated. The projected instances displayed acute rise till the lockdown, followed by deceleration and then a reduction after the full lockdown was imposed. The basic reproduction ratio reduced meaningfully from 5.89 (95% CI: 5.46–7.09) before the lockdown to 0.48 (95% CI: 0.15–1.17) thereafter. The study opined that managing a pandemic in the magnitude of COVID-19 was very intricate and required timely decisions. The great modifications found in the rate of infestation displayed that being able to employ inclusive participations in the first phase was vital to reducing the effect of a possible transferrable threat. This study likewise stressed the significance of dependable up-to-date epidemiological facts to precisely measure the influence of Public Health guidelines on the virus-related outburst.

“A hybrid deterministic and stochastic formalism that allows for time-variable transmission rates and discovery probabilities modelling for COVID-19” was presented by Romero-Severson et al. [43]. The model was fitted using iterative particle filtering to case and death counts time series analysis of data obtained from 51 countries. The study established the fact of a declining spread rate in 42 among the 51 countries studied. Out of the 42 countries, 34 had a major proof for subcritical transmission rates, though the turndown in novel cases was moderately slow in contrast to the early development rates. The study recommended that the adoption of social distancing efforts to reduce the incidence of COVID-19 were efficient, although they could be strengthened and maintained in various regions to prevent more renaissance of the disease. The study also proposed other approaches to manage the virus prior to the relaxation of social distancing efforts.

Previous related works have achieved good performance results in terms of accuracy, however detection accuracies obtained in the previous approaches could be improved upon. The aim of this chapter therefore is to improve the accuracy of COVID-19 detection model by deploying Deep Transfer Learning Convolutional Neural Network to classify real-life COVID-19 dataset consisting of X-ray images. Further studies on efficient diagnosis and detection of the virus and vaccine development are continuing owing partly to the fact that the disease is new and available research efforts have not been able to effectively address the concerns. Therefore, in this chapter, a deep transfer learning framework for efficient identification, classification and provision of new insights for the diagnosis is presented. Also, the prediction of probable patients of the novel COVID-19 and related Viral Pneumonia using radiology scanned images of suspected patients are presented.

2.3 Methodology

This research is centered on classifying COVID-19 chest X-ray dataset using a Convolutional Neural Network (CNN). The CNN consisted of one or more convolution layers and one or more fully connected layers as in a standard multilayer neural network. COVID-19 Radiology Dataset (chest X-ray) for Annotation and Collaboration was collected from the Kaggle website. The collected data was preprocessed, where the median filter was used to restore the image under examination by reducing the effects of the acquisition degradations. In [33], various pre-processing and segmentation techniques were discussed. The median filter replaces every pixel value, including itself, with the mean value of its neighbours. Therefore the pixel values that are very different from those of their neighbors have been eliminated. Following the preprocessing of the image dataset, the images were sectioned by using a simulated annealing algorithm. Feature extraction and classification were done using CNN. The neural network-based convolutional segmentation was implemented in Jupyter Notebook using Python programming language, and the system was trained with sample datasets for the model to recognize and classify the coronavirus. The model generated could be used to develop a simple web-based application, where medical personnel handling COVID-19 tests can input new cases and quickly predict the presence of the coronavirus, with a very high level of accuracy.

2.3.1 Dataset Description

Researchers from Qatar University, Doha, Qatar and the University of Dhaka, Bangladesh together with collaborators from Pakistan and Malaysia and some medical doctors have collated a database of chest X-ray images for COVID-19 positive cases along with normal and viral pneumonia images. There were 219 COVID-19 healthy images in their latest publication, 1341 normal images and 1345 images with viral pneumonia [13]. The study selected 125 images from each category. Data augmentation was performed by setting the random image rotation to 15° in clockwise direction to ensure the model generalizes.

2.3.2 The VGGNet Architecture

The VGGNet that Simonyan and Zisserman [49] proposed is a convolutional neural network that performed very well in the 2014 ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The VGG-16 and VGG-19 are variants of the VGGNet Architecture. The network of the VGG-16 CNN has 13 convolutional layers (that is, 3 × 3 convolutional layers in blocks that are stacked on top of one another with growing depth). Two blocks house two 3 × 3 convolutional layers of the same setup in a sequential arrangement, while three blocks have three 3 × 3 convolutional layers of the same configuration in a sequential arrangement. Max pooling handles the reduction of the volume size of inputs at each layer. It further has two fully-connected layers, each with 4096 nodes and one fully-connected layer with 1000 nodes, and is followed by the SoftMax classifier, as shown in Fig. 2.1.

The network of the VGG-19 CNN has 16 convolutional layers (that is, 3 × 3 convolutional layers in blocks that are stacked on top of one another with growing depth). Two blocks house two 3 × 3 convolutional layers of the same setup in a sequential arrangement, while three blocks have four 3 × 3 convolutional layers of the same configuration in a sequential arrangement. Max pooling handles the reduction of the volume size of inputs at each layer. It further has two fully-connected

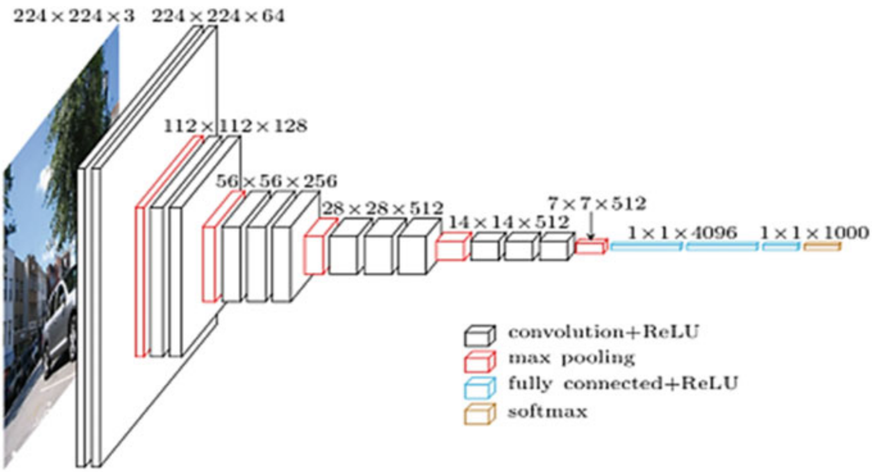

Fig. 2.1 A visualization of the VGG architecture. *Source* [17]

layers, each with 4096 nodes and one fully-connected layer with 1000 nodes, and is followed by the SoftMax classifier.

This chapter employed the VGG-16 and VGG-19 Convolutional Neural Networks (CNN) with Deep Transfer Learning (DTL) approach for COVID-19 detection. The Deep Transfer Learning (DTL) approach focused on the storage of weights that have been grown while unravelling some image classification tasks and then engaging it on a related task. Several DTL networks have been proposed, some of which include VGGNet [49], GoogleNet [54], ResNet [20], DenseNet [22] and Xception [12]. In this chapter, VGG-16 CNN and VGG-19 CNN, variants of the VGGNet were trained on the popular ImageNet images dataset. The VGG-16 and VGG-19 CNN were pre-trained deep neural networks for computer vision having 16 weight layers and 19 weight layers, respectively. They can be used as pre-trained models to help learn the distinguishing features in COVID-19 X-ray images with the aid of transfer learning approach and thus train DTL models for the detection of COVID-19 infection from X-ray images of patients.

As shown in the workflow in Figs. 2.2 and 2.3, to train the VGG-16 based Deep Transfer Learning model and VGG-19 based Deep Transfer Learning model for the detection of COVID-19, the VGG-16 CNN and VGG-19 CNN were used as pre-trained models respectively and were fine-tuned for COVID-19 detection based on the principles of transfer learning. In order to implement transfer learning with fine-tuning, the weights of the lower layers of the network, which learn very generic features from the pre-trained model served as feature extractors. The pre-trained model's lower layers weights were frozen and were therefore not updated through

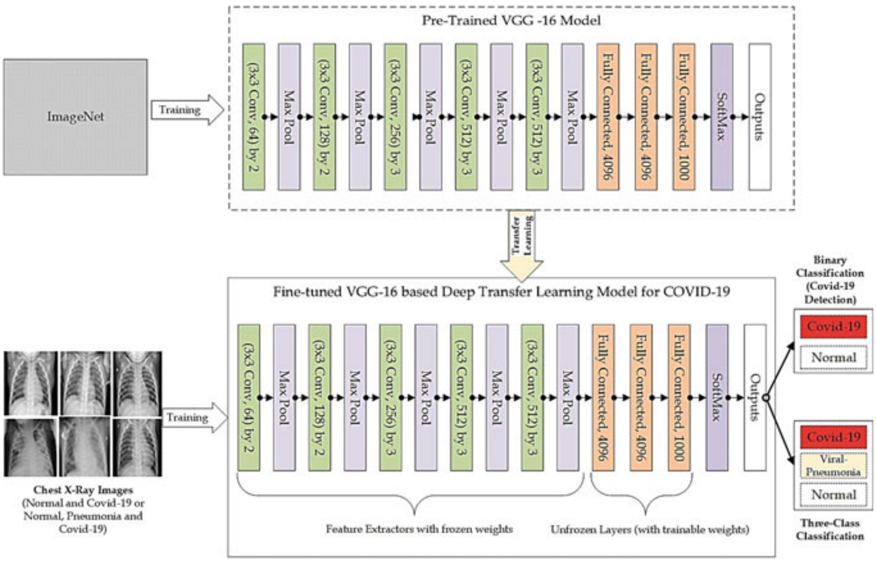

Fig. 2.2 The architectural workflow of the proposed fine-tuned VGG-16 based deep transfer learning model for COVID-19 detection

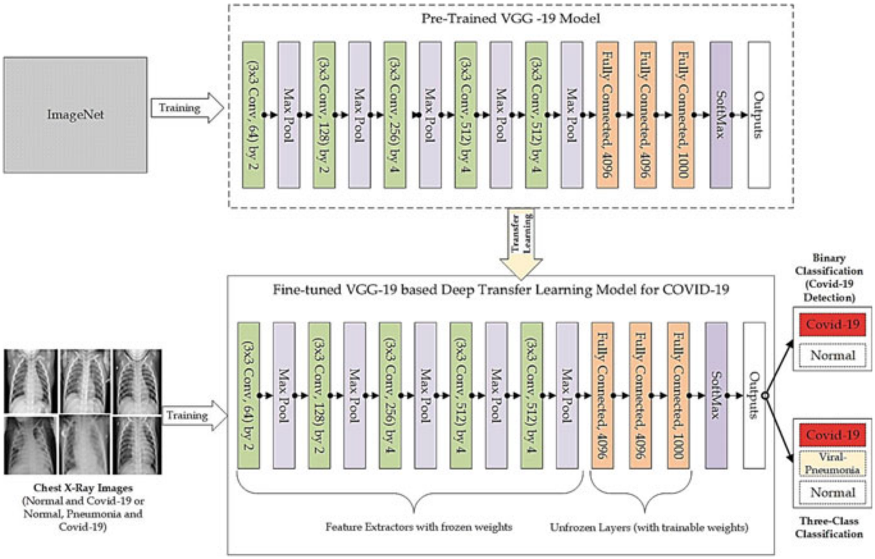

Fig. 2.3 The architectural workflow of the proposed fine-tuned VGG-19 based deep transfer learning model for COVID-19 Detection

the training process, thus not participating in the transfer-learning process. The higher layers of the pre-trained model were used for learning task-specific features from the COVID-19 images dataset. In this case, the higher layers of the pre-trained model were relaxed and thus made trainable or fine-tuned in which the weights of the layers were updated. Therefore, the layers were allowed to participate in the transfer-learning process. Each of these models ends with the SoftMax layer, which produces the outputs. Both the binary classification task and three-class classification scenarios were considered in the workflow, in which the DTL model determined the class of the chest X-ray images either as the COVID-19 category or Normal category in the binary classification and either as any of the COVID-19 category, Viral-Pneumonia category, or Normal category in the three-class classification.

2.4 Experimentation and Results

Two different experiments were performed to classify radiological X-ray images using Deep Transfer learning approaches. For the experiments, out of a total of 375 images that were used, 225 images were used to train the models, 75 images were used to perform validation and hyper-parameter tuning, and 75 images were used for testing in order to provide an unprejudiced assessment of a final model fit on the training dataset.

In the first experiment, a DTL model based on pre-trained VGG-16 model was trained in order to classify the X-ray images into three groups of COVID-19, Viral-Pneumonia or Normal; and also, to detect if X-ray images are simply of the class COVID-19 or Normal. The VGG-16 based DTL model summary, detailing the layers and parameters in each layer of the model is shown in Table 2.1. The fine-tuned VGG-16 based DTL model consists of 14,747,715 total parameters, with 33,027 of them made trainable while 14,714,688 are non-trainable. The model was trained on 40 epochs and with a batch size of 10, using Adams optimizer specifically for updates of weights, certain cross-entropy loss function with a learning rate of $1e^{-2}$. The performance of the proposed fine-tuned VGG-16 based DTL model was evaluated on 25% of the X-ray images.

The confusion matrix result of the binary classification task obtained from the VGG-16 based DTL model is shown in Table 2.2, while the confusion matrix result of the three-class classification task obtained from the VGG-16 based DTL model is shown in Table 2.3. Figure 2.4 illustrates the training loss and accuracy along with the validation loss and accuracy graphs of the proposed fine-tuned VGG-16 based

Table 2.1 The layers and layer parameters of the proposed fine-tuned VGG-16 based DTL model

	Layers	Layer's type	Shape of output	Number of trainable parameters
1	Convolution_1 of Block_1	Convolution 2D	[64, 224, 224]	1,792
2	Convolution_2 of Block_1	Convolution 2D	[64, 224, 224]	36,928
3	Convolution_1 of Block_2	Convolution 2D	[128, 112, 112]	73,856
4	Convolution_2 of Block_2	Convolution 2D	[128, 112, 112]	147,584
5	Convolution_1 of Block_3	Convolution 2D	[256, 56, 56]	295,168
6	Convolution_2 of Block_3	Convolution 2D	[256, 56, 56]	590,080
7	Convolution_3 of Block_3	Convolution 2D	[256, 56, 56]	590,080
8	Convolution_1 of Block_4	Convolution 2D	[512, 28, 28]	1,180,160
9	Convolution_2 of Block_4	Convolution 2D	[512, 28, 28]	2,359,808
10	Convolution_3 of Block_4	Convolution 2D	[512, 28, 28]	2,359,808
11	Convolution_1 of Block_5	Convolution 2D	[512, 14, 14]	2,359,808
12	Convolution_2 of Block_5	Convolution 2D	[512, 14, 14]	2,359,808
13	Convolution_3 of Block_5	Convolution 2D	[512, 14, 14]	2,359,808
14	Flatten	Flatten	[512]	0
15	Dense	Dense	[64]	32,832
16	Dense_1	Dense	[3]	195

Table 2.2 The confusion matrix of the binary classification task obtained from the fine-tuned VGG-16 based DTL

	COVID-19	Normal
COVID-19	22	1
Normal	0	27

Table 2.3 The confusion matrix of the three-class classification task obtained from the fine-tuned VGG-16 based DTL

	COVID-19	Normal	Viral pneumonia
COVID-19	23	0	0
Normal	0	25	2
Viral pneumonia	0	0	25

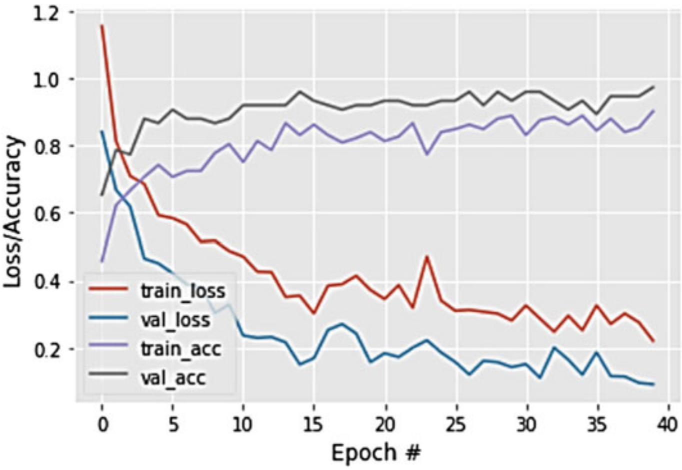

Fig. 2.4 The Training loss and accuracy with the validation loss and accuracy curves obtained for the fine-tuned VGG-16 based deep transfer learning model

DTL model. The precision, recall and F1-Score of the proposed fine-tuned VGG-16 based DTL model were also obtained for both binary and three-class classifications and shown in Tables 2.4 and 2.5.

It was observed from Fig. 2.4 that the validation and training losses were significantly high in the earlier epochs and then noticeably decreased as the training occured in more subsequent epochs. This sharp decrease in the loss values at the 40th epoch

Table 2.4 The precision, recall and F1-score obtained for the binary classification task using the fine-tuned VGG-16 based DTL model

	Precision	Recall	F1-score
COVID-19	1.00	0.96	0.98
Normal	0.96	1.00	0.98

Table 2.5 The precision, recall and F1-Score obtained for the three-class classification task using the fine-tuned VGG-16 based DTL model

	Precision	Recall	F1-score
COVID-19	1.00	1.00	1.00
Normal	1.00	0.93	0.96
Viral pneumonia	0.93	1.00	0.96

can be attributed to the fact that the fine-tuned VGG-16 based DTL model has been exposed to all the available X-ray images time and again during each of the epoch considered during training.

The accuracy obtained for the fine-tuned VGG-16 based DTL model was 97.33%, its sensitivity was 100% while its specificity stood at 92.59%. The obtained precision, recall and F1-Score metrics for the binary classification task and three-class classification task are given in Tables 2.4 and 2.5 respectively.

In the second experiment, a DTL model based on pre-trained VGG-19 model was trained in order to also classify X-ray images into three categories of COVID-19, Viral-Pneumonia or Normal; and also, to detect if X-ray images are simply of the class COVID-19 or Normal. Also, the VGG-19 based DTL model summary, detailing the layers and the parameters in each layer of the model is shown in Table 2.6. The fine-tuned VGG-19 based DTL model consists of 20,057,411 total parameters, with 33,027 of them made trainable while 20,024,384 are non-trainable. The model was trained on 40 epochs and with a batch size of 10, using Adams optimizer for the updates of weights, categorical cross-entropy loss function with a learning rate of $1e^{-1}$. The performance of the proposed fine-tuned VGG-19 based DTL model was evaluated on 25% of the X-ray images.

Table 2.6 The layers and layer parameters of the proposed fine-tuned VGG-19 based DTL model

	Layers	Layer's type	Shape of output	Number of trainable parameters
1	Convolution_1 of Block_1	Convolution 2D	[64, 224, 224]	1,792
2	Convolution_2 of Block_1	Convolution 2D	[64, 224, 224]	36,928
3	Convolution_1 of Block_2	Convolution 2D	[128, 112, 112]	73,856
4	Convolution_2 of Block_2	Convolution 2D	[128, 112, 112]	147,584
5	Convolution_1 of Block_3	Convolution 2D	[256, 56, 56]	295,168
6	Convolution_2 of Block_3	Convolution 2D	[256, 56, 56]	590,080
7	Convolution_3 of Block_3	Convolution 2D	[256, 56, 56]	590,080
8	Convolution_4 of Block_3	Convolution 2D	[256, 56, 56]	590,080
9	Convolution_1 of Block_4	Convolution 2D	[512, 28, 28]	1,180,160
10	Convolution_2 of Block_4	Convolution 2D	[512, 28, 28]	2,359,808
11	Convolution_3 of Block_4	Convolution 2D	[512, 28, 28]	2,359,808
12	Convolution_4 of Block_4	Convolution 2D	[512, 28, 28]	2,359,808
13	Convolution_1 of Block_5	Convolution 2D	[512, 14, 14]	2,359,808
14	Convolution_2 of Block_5	Convolution 2D	[512, 14, 14]	2,359,808
15	Convolution_3 of Block_5	Convolution 2D	[512, 14, 14]	2,359,808
16	Convolution_4 of Block_5	Convolution 2D	[512, 14, 14]	2,359,808
17	Flatten	Flatten	[512]	0
18	Dense	Dense	[64]	32,832
19	Dense_1	Dense	[3]	195

Table 2.7 The Confusion Matrix of the Binary classification task obtained from the fine-tuned VGG-19 based DTL

	COVID-19	Normal
COVID-19	21	2
Normal	0	27

The confusion matrix result of the binary classification task obtained from the fine-tuned VGG-19 based DTL model is shown in Table 2.7, while the confusion matrix result of the three-class classification task obtained from the fine-tuned VGG-19 based DTL model is shown in Table 2.8.

Figure 2.5 illustrates the training loss and accuracy along with the validation loss and accuracy graphs of the proposed fine-tuned VGG-19 based DTL model. The precision, recall and F1-Score of the proposed fine-tuned VGG-19 based DTL model were also obtained for both binary and three-class classifications as shown in Tables 2.9 and 2.10.

The same trend as of the fine-tuned VGG-16 based DTL model could be observed from Fig. 2.5 in that the validation and training losses were significantly high in the earlier epochs and then noticeably decreased as the training occured in more subsequent epochs. These sharp decreases in the loss values at the 40th epoch can

Table 2.8 The confusion matrix of the three-class classification task obtained from the fine-tuned VGG-19 based DTL

	COVID-19	Normal	Viral pneumonia
COVID-19	22	0	1
Normal	0	26	1
Viral pneumonia	5	1	19

Fig. 2.5 The training loss and accuracy with the validation loss and accuracy curves obtained for the fine-tuned VGG-19 based deep transfer learning model

Table 2.9 The precision, recall and F1-Score obtained for the Binary classification task using the fine-tuned VGG-19 based DTL model

	Precision	Recall	F1-score
COVID-19	1.00	0.91	0.95
Normal	0.93	1.00	0.96

Table 2.10 The precision, recall and F1-score obtained for the three-class classification task using the fine-tuned VGG-19 based DTL model

	Precision	Recall	F1-score
COVID-19	0.81	0.96	0.88
Normal	0.96	0.96	0.96
Viral Pneumonia	0.90	0.76	0.83

be attributed to the fact that the fine-tuned VGG-19 based DTL model has been exposed to all the available X-ray images over and over again during each of the epoch considered during training.

The accuracy obtained for the fine-tuned VGG-19 based DTL model was 89.33%, its sensitivity was 95.65% while its specificity stood at 96.30%. The obtained precision, recall and F1-Score metrics for the binary classification task and the three-class classification task are given in Tables 2.9 and 2.10 respectively.

It could be noted from the obtained confusion matrices and the computed performance evaluation metrics of the three-class classification task that the fine-tuned VGG-16 based deep transfer learning model classified COVID-19 well than the fine-tuned VGG-19 based deep transfer learning model. Based on this, tests were carried out on unlabeled images using the developed fine-tuned VGG-16 multi-classification model. This is in order to yield an unprejudiced evaluation of the final model fit on the training dataset. Some results of the tests are shown in Figs. 2.6, 2.7 and 2.8.

The output results of the tests as shown in Figs. 2.6, 2.7 and 2.8 show how the fine-tuned VGG-16 DTL model classified and detected each of the images as either "COVID-19", "Viral Pneumonia" or "Normal". The level of confidence in the model classification is also shown. Figure 2.6 shows the images that were detected as "COVID-19" along with the model's classification confidence accuracy values. Figure 2.7 shows the images that were detected as "Viral Pneumonia" along with the model's classification confidence accuracy values, while Fig. 2.8 shows the images that were detected as "Normal" along with the model's classification confidence accuracy values.

Out of the six sample images shown in Fig. 2.6, only one showed a lower level of confidence of 76.37% while others were above 94%. Similar results could be seen in Fig. 2.8 for Normal classification, where the lowest level of confidence was 78.92%. However, the lowest output for Viral Pneumonia was 96.21%, as shown in Fig. 2.7. These test results showed that the developed models were able to generalize and adapt to new unseen data that are outside the training and validation dataset. These test results are necessary to show the adaptability of the developed models when given any related data.

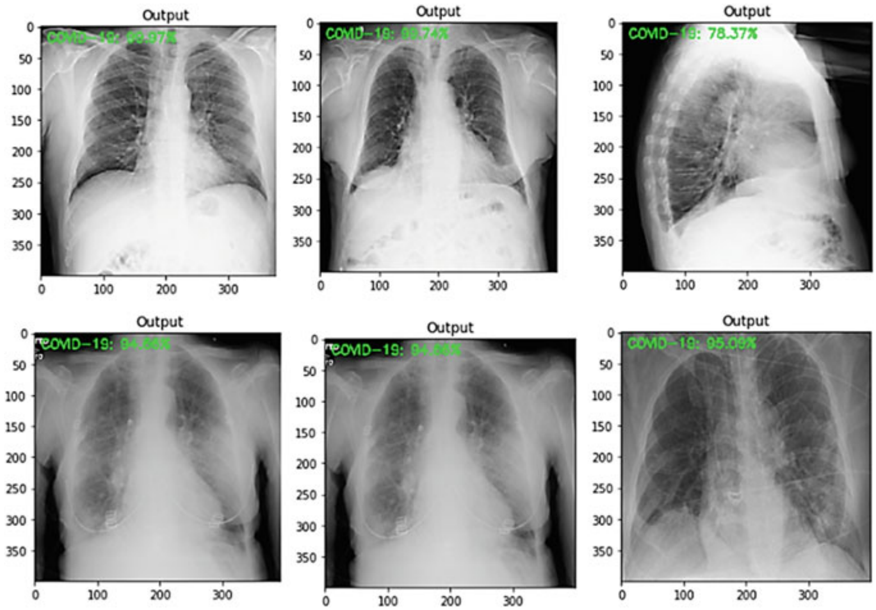

Fig. 2.6 COVID-19 sample test results with predicted level of confidence value

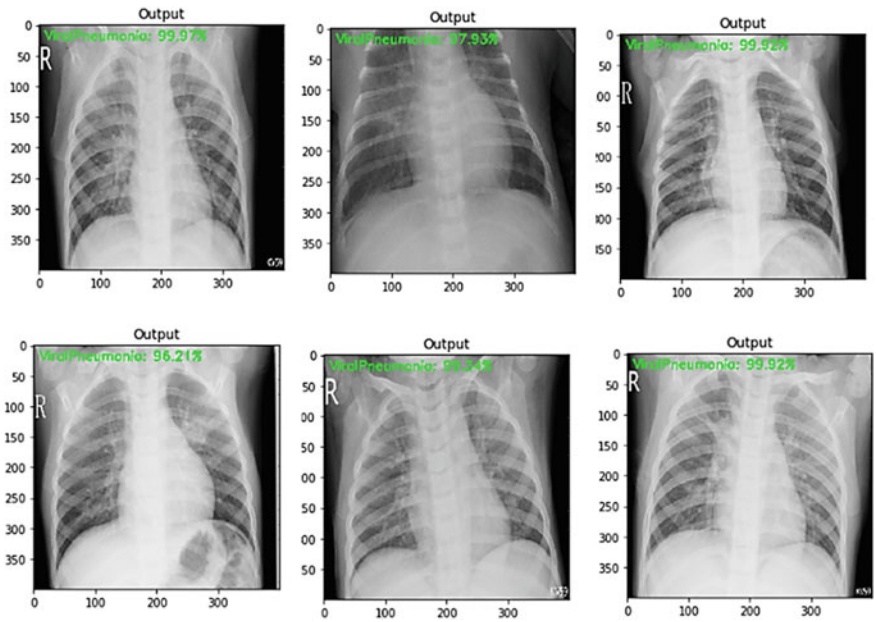

Fig. 2.7 Viral pneumonia sample test results with a predicted level of confidence value

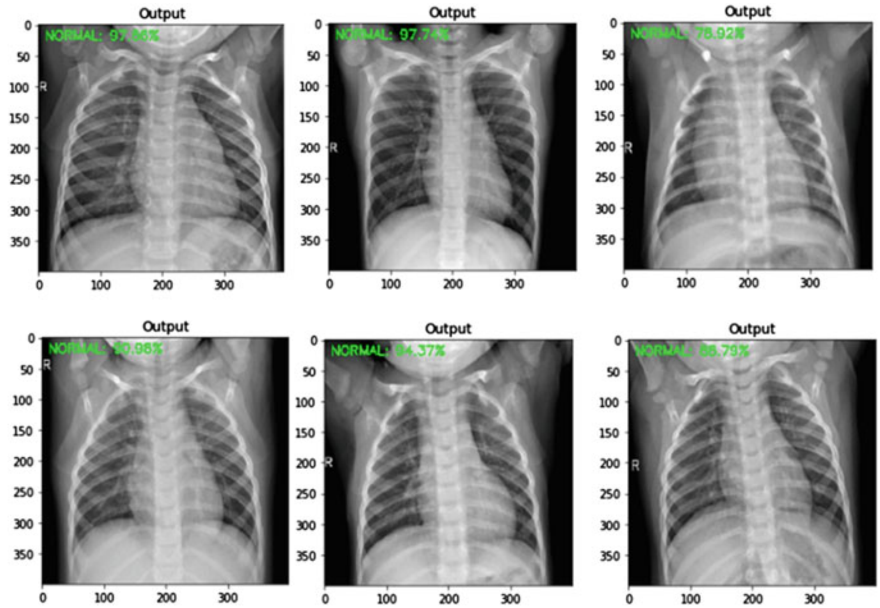

Fig. 2.8 Normal sample test results with predicted level of confidence value

2.4.1 Evaluation of Results

The findings obtained in this study were compared with twenty other current literature surveys. Few number of studies conducted prior to this study used twenty-five and fifty images in each class [21, 35, 45], while eight comparative reviews used imbalanced data (Table 2.7). Generally, there is a problem in modelling imbalanced data, which can lead to the inability of the model to generalize, or the model could be biased towards a class with the high number of data points. Hence, in this study, an equal value of data was used for each class, and this is believed to have contributed to increase in the accuracies of the proposed models. Because COVID-19 is a new disease, there are few X-ray images available to establish the automated diagnostic program. Data augmentation was performed by setting the random image rotation to 15° in clockwise direction to ensure the generalization of the models developed in this work. The proposed new models were based on fine-tuning VGG-16 and VGG-19 methods by constructing a new fully-connected layer head consisting of POOLING ⇒ FC ⇒ SOFTMAX layers and append it on top of VGG-16 and VGG-19, the CONV weights of VGG-16 and VGG-19 were then frozen, such that *only* the FC layer head was trained. The fine-tuned models gave better results when compared to other models that used ordinary pre-trained VGG-16 and VGG-19 [5], Asnaoui and Chawki [7]. Full results of the comparison with twenty other existing results from the literature are presented in Table 2.11. The proposed model outperformed all the twenty existing results in terms of accuracy.

Table 2.11 Comparison of the proposed COVID-19 diagnostic methods with other deep learning methods developed using radiology images

S. No.	Study	Type of images	Number of cases	Method used	Accuracy (%)
1	Apostolopoulos and Mpesiana [5]	Chest X-ray images	224 COVID-19 700 Pneumonia 504 Normal	VGG-19	93.48
2	Wang and Wong [61]	Chest X-ray images	53 COVID-19 5526 Normal 8066 Healthy	COVID-Net	92.4
3	Sethy and Behra [45]	Chest X-ray images	25 COVID-19 25 Normal	ResNet50 + SVM	95.38
4	Hemdan et al. [21]	Chest X-ray images	25 COVID-19(+) 25 Normal	COVIDX-Net	90.0
5	Narin et al. [35]	Chest X-ray images	50 COVID-19 50 Normal	Deep CNN ResNet-50	98.0
6	Ying et al. [52]	Chest CT scan images	777 COVID-19 708 Normal	DRE-Net	86.0
7	Wang et al. [62]	Chest CT scan images	195 COVID-19 258 Normal	M-Inception	82.9
8	Zheng et al. [74]	Chest CT scan images	313 COVID-19(+) 229 COVID-19(-)	UNet + 3D Deep Network	90.8
9	Xu et al. [67, 68]	Chest CT scan images	219 COVID-19 224 Viral pneumonia 75 Normal	ResNet	86.7
10	Ozturk et al. [38]	Chest X-ray images	125 COVID-19 500 Normal	DarkCovidNet	98.08
			125 COVID-19 500 Pneumonia 500 Normal		87.02

(continued)

Table 2.11 (continued)

S. No.	Study	Type of images	Number of cases	Method used	Accuracy (%)
11	Asnaoui and Chawki [7]	Chest X-ray and CT Scan	2780 bacterial pneumonia 1493 corona-virus 231 COVID-19 1583 Normal	Inception_Resnet_V2	92.18
				DensNet201	88.09
				Resnet50	87.54
				Mobilenet_V2	85.47
				Inception_V3	88.03
				VGG-16	74.84
				VGG-19	72.52
12	Raajan et al. [42]	Chest CT scan images	349 COVID-19 CT images of 216 patients and 463 non-COVID-19 CT images	ResNet-16	95.09
13	Pu et al. [40]	Chest CT scan images	120 chest CT scans and 72 serial chest CT scans from 24 COVID-19 patients	U-Net framework deep-learning technique	95
14	Li et al. [27, 28]	Chest CT scan images	4563 3D chest CT scan images from 3506 patients	A three-dimensional deep-learning framework based on RestNet50 (COVID-19 detection neural network)	0.96 AUC
15	Yoo et al. [70]	Chest X-ray images	240 images were used for the augmentation of 1216 images	Resnet18 model with PyTorch frame	95
16	Qianqian et al. [41]	Chest X-ray images	14,435 participants 2154 COVID-19 5874 Pneumonia 6434 Normal	Deep learning algorithm	95.0
17	Harsh et al. [19]	Kaggle's Chest X-Ray Images	192 COVID-19	VGG-16	88.0
				nCOVnet	97.0

(continued)

Table 2.11 (continued)

S. No.	Study	Type of images	Number of cases	Method used	Accuracy (%)
18	Shashank et al. [47]	https://github.com/ieee8023/covid-chestxray-dataset	181 COVID-19 with 364 chest X-ray images	VGG-19	96.3
19	Xu et al. [67, 68]	Chest X-ray images	618 Cases	CNN segmentation with Bayesian function	86.7%
20	Nour et al. [37]	Chest X-ray images	2905 Cases	CNN with Bayesian Optimization	98.97%
21	Proposed Study	Chest X-ray images	100 COVID-19(+) 100 Normal	VGG-16	**99.0**
				VGG-19	**99.0**
			100 COVID-19(+) 100 Viral Pneumonia 100 Normal	VGG-16	**97.3**
				VGG-19	**89.3**

2.5 Conclusion

Many researchers around the world are coordinating their efforts to gather data and develop solutions for COVID-19. Laboratory testing of suspicious cases characterized by long waiting times and an increasing rise in testing demand has been a major global bottleneck. To ameliorate this, rapid diagnostic test kits are being developed; most of which are currently undergoing clinical validation and therefore, are yet to be adopted for routine use. While waiting for results, this chapter proposes a solution of using Deep Learning Convolutional Neural Network Architecture to classify real-life COVID-19 dataset of chest X-ray images into a three-class classification scenario of COVID-19, Viral-Pneumonia or Normal categories. In this study, a Convolutional Neural Network was fine-tuned to instinctively prognose or detect COVID-19 using deep learning. A total of 300 images (100 COVID-19, 100 Viral Pneumonia and 100 Normal) were used to develop the models of which 225 was used to train the model, 75 was used for validation and to perform hyper-parameter tuning. Also, a total of 75 new images were used for testing the models (25 COVID-19, 25 Viral Pneumonia and 25 Normal). The proposed models were developed to provide accurate diagnostics for binary classification (COVID-19 and Normal) and multi-class classification (COVID-19, Viral Pneumonia and Normal). The fine-tuned VGG-16 and VGG-19 models both produced a classification accuracy of 99.00% for binary classes and 97.33% and 89.33% for multi-class cases respectively. Two experiments were performed where the VGG-16 and VGG-19 Convolutional Neural Networks (CNN) with Deep Transfer Learning (DTL) was implemented in Jupyter Notebook using Python programming language, and the result showed that the DTL model based on pre-trained VGG-16 model classified COVID-19 better than the VGG-19 based deep transfer learning model. The proposed model, in this work, also outperformed existing methods in terms of accuracy, although different publicly available dataset other than those used in the various related works have been used in this work. The findings have a high potential of increasing the prediction accuracy for coronavirus disease, which would be of immense benefit to the medical field and the entire human populace as it could help save many lives from untimely death. Finally, the publicly available image datasets of COVID-19 are limited at the moment, and this is a limitation in this research work. Future works would, therefore, consider increasing the volume of data used for the study and further hyper-parameter tweaking to get more accurate results.

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