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Taxonomy of COVID-19 Disease Radiology by using Convolutional Neural Networks

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Abstract

The viral illness known as coronavirus disease (COVID-19) is mostly caused by the SARS-CoV-2 virus. The majority of individuals who get the virus will have a mild to severe respiratory infection and achieve recovery without necessitating specialized medical intervention. Nevertheless, a portion of individuals will have severe illness and require medical intervention. Individuals who are advanced in age or possess pre-existing medical diseases such as cardiovascular disease, diabetes, chronic respiratory disease, or cancer have a higher propensity for the development of severe sickness. Individuals of all ages are susceptible to contracting COVID-19 and experiencing severe illness or mortality.

This research utilizes global datasets and employs deep learning techniques, namely Convolutional Neural Networks (CNNs), to enhance the obtained results. The model's validation is conducted using a Global dataset named "COVID-19Radiography" sourced from Kaggle. The performance of the model may be summarized as follows: during the training phase, the accuracy achieved was 100.0% and the loss metric was measured to be 0.0349. In the validation phase, the accuracy reached 99% and the loss metric was recorded as 0.0340. As a consequence, a model was developed and transformed into a graphical user interface program named "AzadCXR Covid19" with a focus on user-friendliness. Clinicians and radiologists possess the proficiency to effectively use and utilize chest X-ray (CXR) images for the purpose of diagnosing individuals with suspected cases of COVID-19.

Keywords: Deep Learning Techniques, CNNs, COVID-19 Radiography, Chest X-Ray (CXR)

1. Introduction

The ongoing epidemic of the novel coronavirus SARSCoV2, also known as coronavirus disease 2019 (previously 2019 nCoV), originated in the Hubei Province of the People's Republic of China and has since spread to several other countries. The declaration of a global health emergency was made by the WHO Emergency Committee on January 30, 2020, in response to a rise in case notification rates seen in both Chinese and international regions. The Johns Hopkins University website provides near-real time access to daily changes in the number of identified cases for monitoring purposes. Utilize the coronavirus as a primary source, with other sources. As of mid-February 2020, China exhibits the greatest rates of illness and mortality, whereas other Asian countries, Europe, and North America have notably lower rates.

Both animals and humans have the potential to contract coronaviruses, which are enveloped, positive-sense, single-stranded RNA viruses of considerable size. In 1966, Tyrell and Bynoe made the discovery of coronaviruses by isolating and cultivating the virus from individuals afflicted with ordinary colds [1]. The Latin term coronaviruses was given to this group of viruses due to their spherical shape, presence of a core shell, and surface projections resembling a solar corona, which is characterized by its crown-like appearance. The classification of coronaviruses encompasses four distinct categories, namely alpha, beta, gamma, and delta. It is widely believed that bats are the likely source of the alpha and beta coronaviruses, whereas the gamma and delta coronaviruses are hypothesized to have originated from pigs and birds, respectively. The genome exhibits variations in size ranging from 26 to 32 kilobase pairs.

The infection of lung alveolar epithelial cells by SARSCoV2 occurs by a process known as receptor-mediated endocytosis, wherein the angiotensin-converting enzyme II (ACE2) serves as the entry receptor. This mode of cellular entry is also used by other viruses. According to the findings of artificial intelligence, it is predicted that pharmaceutical interventions targeting

AP2-associated protein kinase 1 (AAK1) have the potential to hinder the process of viral entry into the intended host. The potential of baricitinib, a pharmaceutical used in the treatment of rheumatoid arthritis, has been suggested for its ability to impede viral replication due to its dual inhibition of AAK1 and Janus kinase [2]. Furthermore, remdesivir, a pharmaceutical compound that functions as an adenosine analogue and has inhibitory effects on viral proteins, has shown promising outcomes in a single patient throughout both *in vitro* and clinical experimental investigations [3-4]. The inhibition of viral infection is achieved by the elevation of endosomal pH by chloroquine. The reason for viral cell fusion is the need of a low pH environment. The impact of p38 mitogen-activated protein kinase (MAPK) activation on HCoV 229E replication has been shown [5]. The concurrent administration of lopinavir and ritonavir, two antiretroviral medications, demonstrated a substantial improvement in clinical outcomes among individuals diagnosed with SARSCoV. There is potential for the treatment of COVID-19 infections [6]. The treatment options that might be considered include the use of leronlimab, a humanized monoclonal antibody acting as a CCR5 antagonist, and an inhibitor of nucleoside RNA polymerase. Both of these pharmaceutical agents have shown the ability to enhance the likelihood of patient survival in individuals afflicted with a diverse array of potentially fatal viral illnesses [7].

2. Aim and Objectives

The objective of this research is to enhance the management of COVID-19. The proposed method utilizes a deep learning algorithm and transfer learning methodology to effectively differentiate between COVID-19 cases and non-COVID-19 instances. This approach aims to provide accurate infection detection by using a publicly available dataset. This study uses deep learning techniques on a publically accessible dataset to create, build, and assess the COVID19 Diagnosis application using chest X-ray (CXR) images. A Deep Learning model was built with the purpose of aiding radiologists and clinicians in the identification of COVID-19 patients via the analysis of chest X-rays. This initiative was undertaken in response to the scarcity of testing kits and the increasing number of daily cases. Develop an application with the purpose of facilitating the use of the model within the medical sector, therefore enabling radiologists and doctors to effectively differentiate instances of COVID-19 from regular cases.

3. Methodology

Perform a comprehensive systematic review to examine the efficacy of public health interventions in managing COVID-19, with an assessment of the effectiveness of deep learning methodologies in distinguishing COVID-19 cases from non-COVID-19 cases. Acquire a comprehensive global dataset pertaining to COVID-19, specifically focusing on chest X-ray (CXR) samples, from the Kaggle platform. Modify a pre-trained deep learning model. Train the model using global samples. Develop an application with a user-friendly interface to facilitate the use of the model within the medical domain.

4. Literature Review

The symptoms of acute respiratory distress syndrome (ARDS) were characterized by their severity, accompanied by several instances of organ failure. There is a growing body of evidence indicating a strong association between immunological characteristics and the progression of disease in individuals who have acquired viral infections. Patients with severe acute respiratory syndrome (SARS) have a significant decrease in peripheral T cell subsets [8]. Recovered patients exhibit a rapid reestablishment of peripheral T cell subsets, indicating that the number of peripheral T cells might be used as a dependable diagnostic tool for severe acute respiratory syndrome (SARS). Another study also found a same trend, whereby the immune system was shown to be weakened during the SARS outbreak. The numerical value provided by the user is 6. A separate investigation revealed a decrease in the quantity of natural killer (NK) cells in individuals diagnosed with Ebola in comparison to those who were in good health [9]. The levels of proinflammatory cytokines were shown to be elevated with the onset of symptoms associated with Ebola virus infection, while people who had recovered from the disease had decreased cytokine levels [10]. The finding of a link between immunological responses and COVID-19 has resulted in the recognition of immune variables as potential markers of the illness and prospective targets for the therapy of COVID-19. This work offers a thorough review of the immunological components of COVID-19, including an investigation into the likely mechanisms that drive immune changes generated by SARS-CoV-2, their influence on the progression of the illness, and their possible ramifications for the development of future treatments for COVID-19 [11]. In light of the emergence of the new coronavirus SARS-CoV-2, extensive scholarly investigations have been undertaken to ascertain effective diagnostic measures and identify individuals who have contracted the virus, hence facilitating the implementation of relevant interventions. Chest imaging is a pivotal component at this stage, since the use of CT scans and X-rays has shown efficacy in the identification of COVID-19 manifestations inside the pulmonary region. This study introduces deep learning models that use transfer learning techniques for the purpose of COVID-19 detection. Both X-ray and computed tomography (CT) images were used in order to assess the suggested methodologies [12]. The COVID-19 pandemic that occurred in 2020 has brought attention to the need of mobilizing all accessible resources in order to address and alleviate the profound impacts of unforeseen and rare disasters sometimes referred to as "Black Swan" occurrences. In pursuit of this objective, we conducted an inquiry into the potential use of technology for the purpose of aiding in the diagnosis of those afflicted with the virus. Therefore, a number of advanced pre-trained convolutional neural networks were assessed in terms of their efficacy in identifying individuals with infections based on chest X-Ray pictures. The dataset was constructed by combining publicly accessible X-ray pictures obtained from patients who were diagnosed with COVID-19, those with common bacterial pneumonia, and healthy individuals. In order to address the limited sample size, we used transfer learning, a technique that leverages pre-trained models to transmit extracted information to the model undergoing training. The experimental findings indicate that the classification performance of the top two models may achieve an accuracy rate of 95% [13].

5. Diagnosis of Covid-19

There are many methods for diagnosis Covid-19 as found as in the below:

1. The reverse transcription-polymerase chain reaction (RT-PCR) test is widely regarded as the most reliable method for diagnosing COVID-19. The test is designed to detect the presence of viral RNA in respiratory specimens, such as swabs taken from the nose or throat. The diagnostic test has a high degree of specificity and sensitivity, enabling the detection of the virus even in individuals who do not display symptoms. The reverse transcription polymerase chain reaction (RT-PCR) test is widely used on a global scale and is recognized as the primary diagnostic modality for COVID-19 [14]. In the below Fig 1 illustrated the mentioned test.

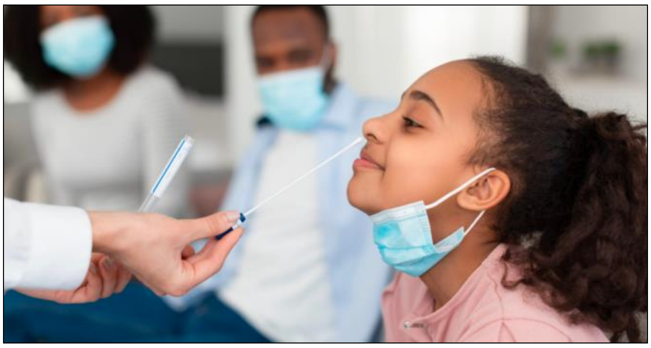

Fig 1: COVID-19 PCR TEST

2. The antigen test is designed to detect viral proteins present in respiratory samples. This test is characterized by a rapid turnaround time, with findings typically obtainable within a span of 15 to 30 minutes. The antigen test has lower sensitivity compared to the RT-PCR test and is susceptible to a higher likelihood of false-negative results, especially among those who do not have symptoms. Nevertheless, it is an invaluable instrument for rapid assessment and may be used in combination with further diagnostic examinations [15].
3. Imaging methods, including chest X-rays and CT scans, have shown their utility in providing valuable insights into the extent of lung involvement among individuals diagnosed with COVID-19. However, it is not recommended to use them as independent diagnostic tests for COVID-19 due to their inability to differentiate between COVID-19 and other respiratory illnesses. Fig. 2 illustrates a computed tomography (CT) scout image of a 28-year-old male patient diagnosed with COVID-19 [16]. In the below Fig 2 Illustrated the mentioned test.

Fig 2: The CT scout picture (a) does not display any identifiable abnormalities, whereas the enlarged axial image does. CT scan picture (b) illustrates a circular ground glass opacity situated in the outer region of the right lower lobe, while image (c) exhibits a subpleural nodule

6. Convolutional Neural Networks (CNNs)

The efficacy of Deep Learning as a computational approach has been widely acknowledged in recent decades due to its capacity to efficiently process and analyze large volumes of data. The use of hidden layers has garnered more attention compared to traditional approaches, especially within the field of pattern recognition. Convolutional Neural Networks (CNNs), also known as ConvNets, are a highly regarded category of deep neural networks within the domain of deep learning, particularly designed for the execution of Computer Vision tasks.

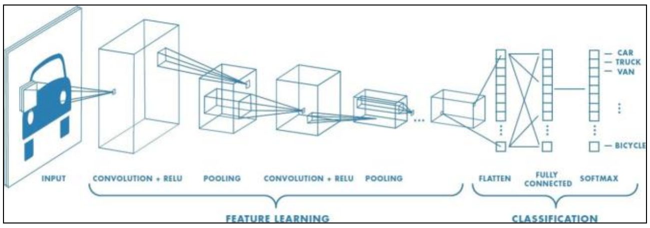

Fig 3: Convolutional Neural Networks (CNNs)

7. Training Dataset

In the conventional practice, the dataset is inputted into the deep learning algorithm for the purpose of training the model. The model undergoes several iterations on the identical dataset throughout each epoch inside the training set. The procedure is then replicated to acquire knowledge on the features of the data. The objective is to use the model for the purpose of making predictions on data that has not been seen before. Consequently, the forecasts are derived from the model's acquisition of knowledge via the training dataset [17].

8. Validation Dataset

During the training process, a separate subset of the dataset, known as the validation set, is used to assess and evaluate the performance of the model. This validation set is distinct from the training set. The aforementioned methodology facilitates the acquisition of data, enabling the developer to refine the hyperparameters. at the training process, the model undergoes training on the data included inside the training set at each epoch. Concurrently, the model is assessed using the data included inside the validation set. In order to ensure that the model does not overfit the training data, it is necessary to include a validation set. Overfitting is a phenomenon that arises when a model exhibits a high level of accuracy in classifying data inside the training set. However, it lacks the ability to accurately generalize and identify data that it has not been trained on [18].

9. Testing Dataset

The test dataset is used to assess the efficacy of the model after the completion of the training procedure. The differentiation between training and validation sets is separate from the topic under consideration. Before making predictions on unlabeled data in the test set, the model is subjected to a training and validation process utilizing the training and validation sets. It is essential to recognize that the test set should not be allocated as either the training or validation sets. Therefore, it is crucial to allocate appropriate labels to the two sets in a way that aids in the representation of the training metrics (such as accuracy and loss from each epoch), as seen in Fig 3. In this study, a publicly available collection of X-ray images depicting individuals diagnosed with pneumonia, COVID-19, and those in a healthy state was used. The Hold-out approach was used to divide the dataset into separate subgroups for training and evaluation purposes. This included the random selection of a sample subset for the purpose of training the model, while the remaining subset was allocated for the purpose of evaluating the model. The training procedure used a subset consisting of 80% of the samples from the dataset, while the remaining 20% were held aside for the purpose of evaluation. The preliminary findings derived from the constructed dataset revealed the existence of many outliers that had significantly distinct confidence levels compared to the remaining genuine positive cases. After careful examination of these specific cases, it was noted that they consisted of precise radiography pictures of the individual's thorax taken from a lateral viewpoint. The collection also includes a limited quantity of Magnetic Resonance photographs. The dataset contains a small number of images belonging to the two categories mentioned above. These images are exclusively associated with the COVID-19 class. Consequently, it becomes difficult for a model with a large number of parameters to effectively learn and apply the necessary properties for accurate categorization. Given the extensive use of frontal X-rays in medical establishments and their equivalent efficacy to other anatomical planes, it does not seem to provide a substantial constraint to confine the model's application just to the identification of frontal pictures. As a result, some photographs were finally excluded from both the training and testing stages. To ensure this, a preprocessing step was carried out to remove these images before initiating the training method.

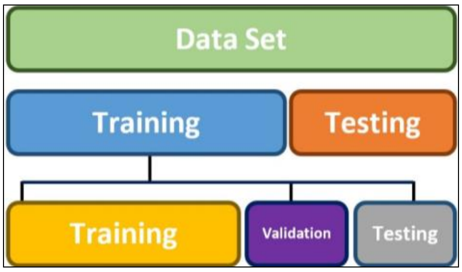

Fig 4: Dataset partitions

10. Structure for Data Processing

The study's architectural framework is derived from a VGG-16 model, which underwent training with Keras and TensorFlow. The preprocessing stage was conducted prior to the implementation of the model, and the ultimate classification was executed based on the confidence parameter derived from the training process. The subsequent steps are outlined as follows: The preprocessing of photographs is an essential stage in the study of images. The main dataset comprises radiographic pictures of the lungs representing people who exhibit normal health, those diagnosed with pneumonia, and individuals who have tested positive for COVID-19. However, it is crucial to refrain from including explicit images of individuals who have been confirmed to have contracted COVID-19 as a result of the failure to comply with the aforementioned guidelines. Additionally, the use of histogram equalization is applied as a means to handle photographs that demonstrate uniform qualities. The preprocessing step consists of two separate operations. The outcomes of the preprocessing methodology are shown in Fig 4. The process of acquiring knowledge, skills, and competencies through systematic instruction and practice, often the research entails the development of a VGG-16 model using TensorFlow and Keras. This model is augmented with a final inference layer to enable the training of a classification system that distinguishes between three classes: healthy, pneumonia, and COVID-19. The previously described level produces the model of a convolutional neural network. After the development of the model, the testing dataset is used to evaluate the effectiveness of the classification process, leading to the calculation of a confidence measure. The objective of this research is to assess the efficacy of Convolutional Neural Networks (CNNs) as a diagnostic tool by analyzing its performance. After the system architecture has been finalized, the dataset used for the development of the classification mechanism has been identified.

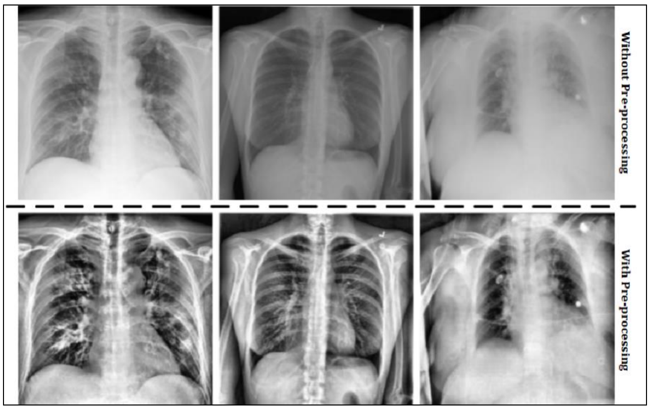

Fig 5: Preprocessing result

11. Model Evaluation Metrics

Various criteria are used in the evaluation of machine learning (ML) and deep learning (DL) models in academic literature. These measurements include precision, accuracy, sensitivity, and specificity. In this part, the assessment elements are introduced to the reader. The study starts with the inclusion of four distinct measurements:

1. True Positives (TP) refer to the quantity of samples that have been accurately classified as true when they are really true.
2. The true negative (TN) refers to the count of samples that have been correctly identified as false when they are really false.
3. A false positive (FP) refers to the count of samples that are incorrectly labeled as true when they are really false.
4. A false negative (FN) refers to the count of instances in which samples are erroneously labeled as negatives despite their genuine positive status [19-20].

Once the values for true negatives (TN), true positives (TP), false positives (FP), and false negatives (FN) have been obtained, performance metrics may be calculated using the following formulas. Accuracy is quantified by calculating the ratio of correct forecasts to the total number of available guesses. The calculation of accuracy is determined in the following manner.

Accuracy refers to the measure of accurate predictions in relation to the total number of estimations made. The formulation of accuracy is as follows.

$$Accurcy = \frac{TN + TP}{FN + TP + TN + FP} \tag{1}$$

The evaluation of performance in CNN designs often relies on the analysis of the confusion matrix as well as the accuracy and loss figures. The confusion matrix is used to evaluate and characterize the performance of a classification model. This feature enables the graphical representation of a model's performance.

12. Global Dataset

The data in this section was obtained from publicly available sources and repositories, specifically gathered from hospitals located in several nations. We obtained an equal number of samples, consisting of 250 healthy individuals and 250 individuals diagnosed with COVID-19, from the Kaggle repository. These samples were in the form of chest X-ray (CXR) pictures. The information was obtained from the COVID-19 Radiography database, which has been recognized as the recipient of the COVID-19 Dataset Award. The dataset comprises six distinct sources, including the RSNA Pneumonia Detection Challenge dataset, the Twitter COVID-19 CXR Dataset, the COVID-19 Image Data Collection, and the SIRM COVID-19 Database [21].

Table 1: Data details of global collection by using COVID-19 Radiography Database

Dataset	Class of Cases	No. Images
Covid-19 Radiography database	Covid-19	200
Covid-19 Radiography database	Normal	200

13. Classification of Dataset Samples

In this particular stage, the dataset was partitioned into training and validation sets in order to evaluate the performance of our model. According to the information shown in Table 2, the global datasets are divided into two subsets, namely the train and test data, with a distribution ratio of 70% and 30% respectively. This indicates that the global datasets consist of 350 samples, with 150 allocated for training and 150 for validation.

Table 2: Local and international dataset's train-to-test set ratio

Dataset	Validation		Trian	
	%	Number	%	Number
Global Dataset	25	100	75	300
Total		100		300

14. Result and Discussions

Evaluations Process

Fig 5 and 6 illustrate the performance of the VGG16 Model on the dataset we developed, which is derived from a global dataset. The graph illustrates a positive correlation between the number of epochs and the classification accuracy, indicating that an increase in the number of epochs leads to an improvement in accuracy. In contrast, the train and validation losses decrease as the number of epochs increases. The training loss of 0.0187 resulted in a training classification accuracy of 100%. Additionally, a validation accuracy of 95.33% was attained, accompanied with a validation loss of 0.1179.

Consequently, we obtained and illustrated the confusion matrix of our model's classification, as shown in Fig 7. The graphical representation illustrates that a mere 1 out of 75 photographs related to COVID-19 are categorized as normal, indicating a false positive outcome. In addition, it is worth noting that out of a total of 75 non-COVID-19 images, only 6 were classified as COVID-19, indicating a false negative rate.

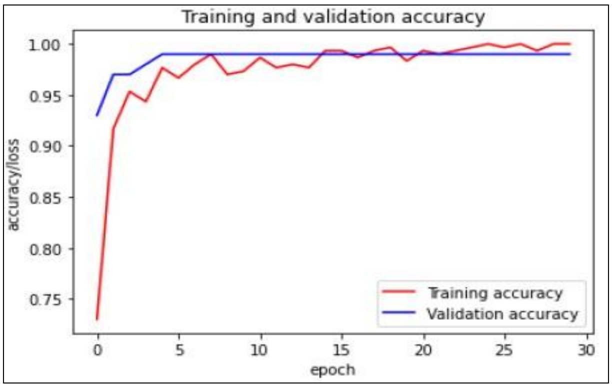

Fig 6: Training and validation curves for models' Global data accuracy

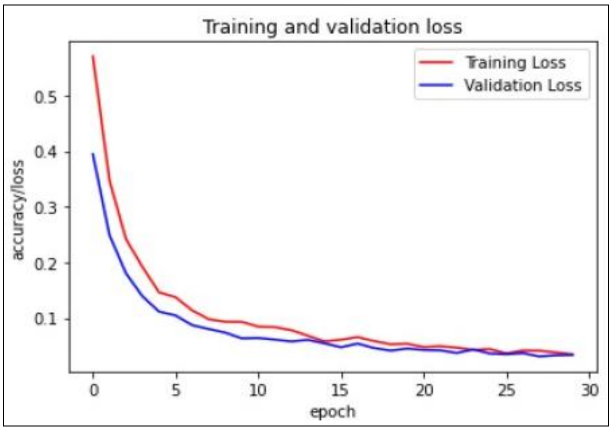

Fig 7: Curves of validation data and model training on global data

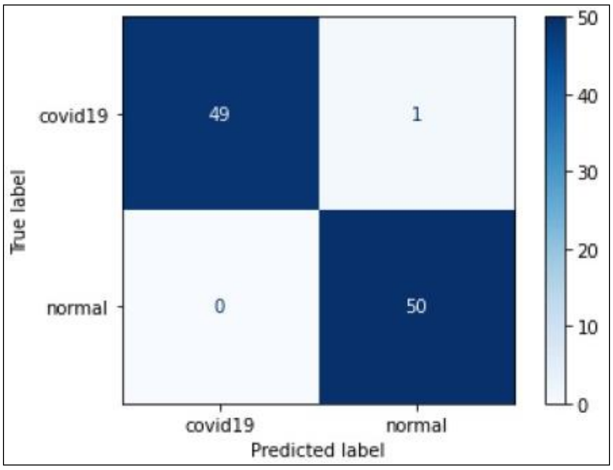

Fig 8: Confusion matrix of the model on the global dataset

Table 3: VGG16 parameter neural network

Model	VGG16
Epochs	30
Learning rate	0.0001
Convolution layer activation function	Relu
Output Layer activation	Sigmoid
The number neurons in the output layer	2
Type of optimizer function	Adam

Confusion Matrix Results

1. The concept of accuracy is of utmost importance in academic research and scholarly discourse. It refers to the accuracy of classification is determined by the number of samples that are properly categorized out of the total number of samples in the test set.

$$Accurcy = \frac{TN + TP}{FN + TP + TN + FP}, Accurcy = \frac{99}{100} = 0.99$$

2. The measure of precision specifically for the positive class. The true positive rate refers to the proportion of samples correctly classified as positive by the model, out of all the samples projected to be positive.

$$\Pr ecision = \frac{TP}{FP + TP}, \Pr ecision = \frac{49}{50} = 0.98$$

3. Recall pertaining to the positive class. The accuracy of accurately predicting samples belonging to the positive class, expressed as a ratio of the number of samples correctly predicted to the total number of samples actually belonging to the positive class.

$$\mathrm{Re}\,call = \frac{TP}{FN + TP}, \mathrm{Re}\,call = \frac{49}{49} = 1.0$$

4. The concept of specificity refers to the degree of detail or precision in a given context. It the accuracy of predicting samples in the negative class is determined by the number of accurately predicted negative samples in relation to the total number of negative samples in the dataset.

$$Specificity = \frac{TN}{TN + FP}, Specificity = \frac{50}{51} = 0.98$$

15. Results

In this chapter, the global data set was collected and then partitioned into training and validation sets. The global data set, which included 400 X-Ray pictures, was split so that 75% was allocated to the training set and 25% was allocated to the testing set. The model was assessed on the dataset considering many criteria, including the amount of data points, data categories, data partitioning, specifics of the confusion matrix, accuracy, and loss.

Using a comprehensive global dataset, the initial training classification achieved an accuracy of 98% after 20 epochs, accompanied by a training loss of 0.1435. Additionally, a validation accuracy of 94.76% was obtained, with a validation loss of 0.2254. However, upon increasing the number of epochs to 30, the model exhibited rapid learning, resulting in noticeable changes in accuracy. The classification accuracy has been achieved at a training level of 100%, accompanied with a training loss of 0.0349. Furthermore, we achieved a validation accuracy of 99.00% together with a validation loss of 0.0340. Hence, the findings indicated that increasing the number of epochs during model training resulted in higher prediction accuracy. This may be attributed to the enhanced training process and improved stability of the verification classification.

16. Comparison of the Studies of All Deep Learning Techniques Used in the Detection of COVID-19

This study has conducted a comprehensive evaluation of 22 research articles, aiming to support academics in their investigation and advancement of AI-driven knowledge-based systems for the purpose of detecting and diagnosing COVID-19. The studies have been classified according to the methodologies used for COVID-19 detection, namely: novel deep learning architecture, direct application of deep learning, transfer learning with tuning methodology, and transfer learning with feature extraction approach. The utilization of deep learning technology and the transfer of learning features has been found to yield enhanced accuracy, approximately 98%, when compared to other techniques. Moreover, this approach demonstrates greater stability in obtaining accurate results and exhibits a low error rate in disease prediction. VGG16 was selected as the preferred model among various convolutional neural network (CNN) models due to its superior performance.

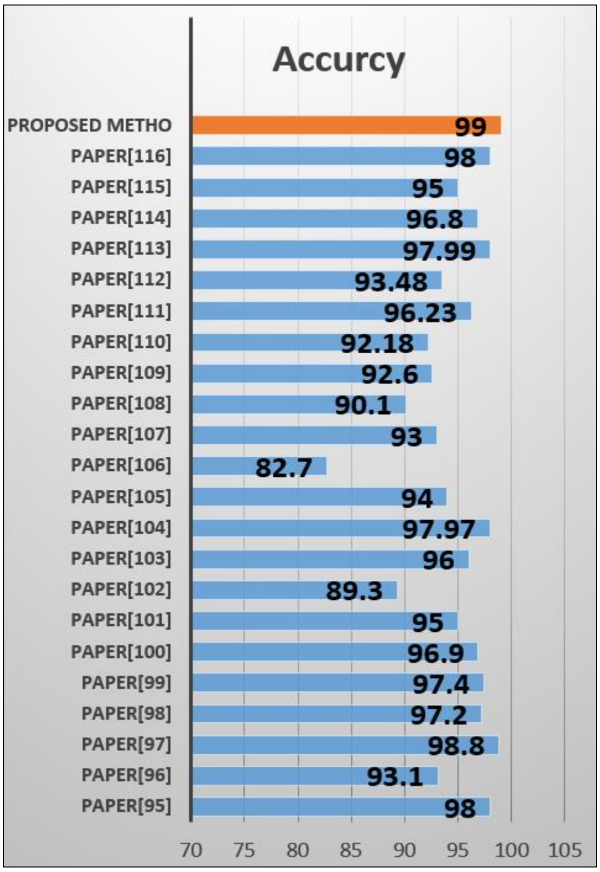

Fig 9: Research Analyses for Each Deep Learning Method

On a daily basis, the Covid-19 pandemic continues to spread. Hence, the primary objective of this study was to enhance comprehension of deep learning-based methodologies for COVID-19 identification by a comprehensive examination and analysis of prior research conducted in this domain. In order to provide a full overview of the various techniques, a total of 22 publications were examined and assessed. The aforementioned publications are sourced from reputable scientific databases. The use of deep learning algorithms for the identification of COVID-19: 1) A novel architecture for deep learning is proposed in this study. 2) The direct application of deep learning is used in this research. 3) A strategy for fine-tuning transfer learning is utilized in this investigation. 4) A technique for feature extraction in transfer learning is employed in this study. We conducted a comparative analysis of many contemporary techniques for each method.

17. Conclusion

The Coronavirus (COVID-19) first presents as a mild respiratory illness akin to the common cold, but may progress to a severe and potentially fatal disease. In situations characterized by the severity of the COVID-19 pandemic, the main objective is to mitigate the mortality rate. The use of artificial intelligence (AI) in the timely identification of COVID-19 leads to reduced death rates and enhanced recovery outcomes. The use of computer-aided methods for the automatic classification of chest X-Ray pictures has significant importance in the field of medical image analysis. The process of examining chest X-ray pictures at a microscopic level is both intricate and demanding in terms of time.

The objective of the research was to identify individuals with COVID-19 by using a deep learning strategy for classifying chest X-ray images. This approach demonstrated superior accuracy compared to other methods. This paper examines a collection of 22 studies that have used deep learning-based approaches for the identification of COVID-19. The COVID-19 detection algorithms that are based on deep learning use feature extraction using transfer learning. A thorough examination indicated that the majority of models had accuracy performance scores within the range of 80.8% to 98%.

Moreover, the process of training deep neural networks with limited datasets might lead to overfitting and impede the ability to generalize. The VGG16 convolutional neural network (CNN) model is used in order to achieve both efficient implementation and superior performance. The approach used in this study involves the utilization of transfer learning, namely the direct employment of a pre-trained model, to extract deep features from chest X-ray (CXR) pictures. These images were obtained from a worldwide dataset available on Kaggle. The current DL models used for the detection of COVID-19 in radiography pictures shown considerable promise, suggesting that DL has significant untapped potential and may assume a more substantial role in mitigating the impact of this pandemic.

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