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Transfer Learning for Image Classification of COVID-19 Using Chest Radiographs

Muhammad Ashad Baloch[1], Hamza Jabbar[1], Imran Khurshid[1], Abdul Majid Soomro[1], Sadaqat Ali Ramay[1] and Rana Kamran Ayub[1]

[1]Department of Computer Science, National College of Business Administration & Economics, Multan, Pakistan.
*Corresponding Author: Muhammad Ashad Baloch. Email: ashad5765@gmail.com.

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Abstract: Globally Health crisis has been arising after the flare-up of COVID-19 that enormously affect the routine, how people assess the world, and their daily life matters. Our perception is threaded by the evaluation of illness and the patterns of bearing COVID-19 symptoms. RT-PCR Real-Time Polymerase Chain Reaction is regarded as one of the most extensively used procedures for diagnosing Covid-19 illness. This strategy is deemed to be uneconomical in terms of both time and money. Moreover, there are high chances of false negatives in these testing kits. To cope with these issues, radiologists usually employ Chest X-Rays with Pneumonia infection for the early detection of Covid-19 diseases. However, the diagnosis of this disease through manual analysis is considered to be a time-consuming and costly task. Protection measures were put in place to stop the COVID-19 virus from spreading by isolating humans from the item, which is the polar opposite of human social interaction. What impact will the current outbreak have on machine learning in terms of global risks, social isolation, and physical along with cognitive threats? In this study, there is a significant need to apply machine learning algorithms that have already been taught to automate the entire diagnosis procedure to deal with the challenges highlighted. In this article, we use the Resnet-50 model on the COVID-19 dataset. Our Dataset contains 6,432 Chest-Xray images. The total number of images for Pneumonia is 4,273, 576 images are related to COVID-19 patients, and, the other 1,583 images are normal chest X-ray images. By using Resnet-50 our experiment result has shown outstanding accuracy as compared to other algorithms. Our proposed model(Resnet-50) has been able to detect patients related to COVID-19, and Pneumonia with 96% accuracy.

Keywords: Convolution Neural Network, Image processing, ResNet50, Transfer Learning.

1. Introduction

The coronavirus (COVID-19) is considered to be one of the common viral infections that have proliferated globally in recent years. This viral disease became a substantial reason for the high mortality rate and also originated a global pandemic. However, this could not be considered a verified fact [1, 2]. A high temperature, a dry hacking cough, drowsiness, and a loss of taste are among the most common symptoms of COVID-19. Some of the less common symptoms that may appear are headaches, diarrhea, and conjunctivitis. These symptoms may or may not occur together. The disease, in its most severe forms, can cause pneumonia, difficulty breathing, failure of many organs, and ultimately death. Due to the exponential increase in the numbers of daily cases that are reported, medical institutions are teetering on the edge of collapse even in the most technologically advanced nations [3]. The World Health Organization (WHO) announced the pandemic status of this disease on February 11, 2020 [4]. In the middle of the 1960s, the coronavirus was recognized as a human disease-causing agent. It is capable of infecting humans as well as numerous animal species (including birds and mammals). Two coronaviruses that infect animals have evolved and caused human outbreaks since 2002. 2003 saw the discovery of the SARS-CoV (Severe Acute

Respiratory Syndrome Coronavirus) in southern China, and 2012 saw the discovery of the MERS-CoV (Middle East Respiratory Syndrome Coronavirus) in Saudi Arabia. Both of these coronaviruses have been linked to serious respiratory conditions in people. Coronaviruses, which are infectious to animals, was shown to be the root cause of both of these outbreaks [5]. We are currently in the midst of a war against one of the most devastating pandemics in the annals of humankind, which is taking place in the globe in which we currently reside. When the virus has progressed to the lungs, an opacity on the chest X-ray that looks like ground glass can be detected as a result of fibrosis in the lungs. This occurs when the infection has reached the lungs. There are considerable variations between the X-ray images of a person who is sick and the X-ray images of a person who is not infected. Because of these discrepancies, artificial intelligence algorithms can be applied to detect whether or not an infection is present and how serious it is [6].

The respiratory condition known as coronavirus infection is caused by a viral infection that most usually produces some of the following symptoms: 1) difficulty breathing, 2) coughing, 3) sore throat, 4) fever, 5) nasal blockage, 6) exhaustion, 7) pains, and 8) loss of taste [7, 8]. These symptoms could be visible within about 14 to 15 days of contamination[9]. The infected patients' saliva and respiratory secretions could be responsible for the transmission of the virus to other people. As a result, isolating sick people from their social networks is an essential component in preventing the further spread of this viral infection. The majority of the symptoms that are seen in people who have been infected with covid-19 are quite similar to those that are seen in patients who have another common chest disease known as pneumonia. Because of the similarities between the two diseases, it can be challenging for medical professionals to differentiate between the two conditions accurately and exactly. As a result, there is a significant demand for a method that can automatically differentiate between those who have pneumonia and others who do not have either pneumonia or corona.

The diagnosis of these mentioned diseases at an early stage could assist in controlling their rapid spread. In general, RT-PCR is considered to be one of the most widely employed methods for Covid-19 illness diagnosis. The drawback of this method is that it is considered to be non-economic in terms of time and cost i.e., testing kits are expensive and the time required for diagnosis is 6-9 hours [10]. Moreover, there are high chances of false negatives in these testing kits. To cope with these issues, different radiology-based medical imaging modalities (i.e., 1) X-Ray and 2) CT-scan) have been deployed for the early recognition of these viral diseases [11]. For our thesis, we want to make use of chest X-rays to diagnose the occurrence of the aforementioned chest disorders. Computer-aided diagnosis, which is more commonly referred to as CADx, is currently being utilized in a wide number of medical sectors for objectives including detection as well as diagnosis. The diagnostic accuracy and reliability of CADx's services are improved by the application of various methods based on artificial intelligence. These developments have been made possible by recent advancements in machine learning [12]. The design of CNN is one of the most common and effective methods for diagnosing COVID-19 from digital photos. several publications have highlighted recent contributions to the compilation of datasets to train models for COVID-19 identification [13].

Even though some studies have shown that CT may be used to diagnose pneumonia caused by COVID-19, it is not a good idea to use CT as a screening tool for COVID-19 since it is both expensive and puts patients at risk of radiation exposure6. In contrast, chest X-ray imaging, which is also commonly referred to as CXR due to its common usage, is routinely utilized for screening due to its low cost. The presence of COVID-19 pneumonia in a patient is indicated by the following features on the CXR: CXR abnormalities might be seen in both the upper and lower zones, and both sides of the lungs could be affected; nevertheless, pleural effusion was an extremely uncommon finding7. When it comes to diagnosing lung diseases, a chest X-ray (also known as a CXR) is typically not as useful as a chest computed tomography (CT) scan. When compared to a chest CT scan, a chest X-ray can be further challenging to use when attempting to diagnose COVID-19 pneumonia [14]. Currently, a technique that is known as converse transcriptase polymerase chain response is used to detect COVID-19. This technique is more generally referred to by its abbreviation, which is RT-PCR. When compared to other techniques, this one does not have a particularly high level of sensitivity when it comes to identifying the virus in its earlier stages. As a direct result of this, it is imperative that an alternative method of diagnosis that is more efficient be developed [15].

Utilizing radiation imaging from a chest X-ray to carry out an analysis of a patient's lungs is one of the best helpful and significant procedures that can be carried out in the fight against COVID-19. This procedure is one of the most beneficial and significant procedures that can be carried out. With the use of this analysis, it will be possible to establish whether or not the patient has COVID-19. The ability to determine whether or not the patient is infected with COVID-19 is aided by this information. It is going to be one of the steps that will help determine whether or not the patient has COVID-19, and this test right here is going to be that step. It is one of the procedures that will be performed to determine whether or not the patient has COVID-19. The results of various deep learning-based artificial intelligence (AI) techniques show that chest X-ray and CT images are useful for identifying COVID-19-infected individuals and may significantly improve detection accuracy. These findings were discovered as a result of the development of these methodologies. This information was derived from the outcomes of the AI methods, hence those outcomes served as the source material for this information. The researchers used 121 patients who had symptoms to examine the impact of the COVID-19 infection on chest CT imaging. They found that around 65% of patients still had a normal CT despite having more clinical indications later on, such as consolidation, and linear opacities as well as bilateral. They also found that this later came with additional clinical signs. The findings of this investigation were summarized and discussed in an article that was submitted to the journal Clinical Infectious Diseases. This knowledge was gathered by analyzing the medical records of 121 patients who, at the time of their examinations, had symptoms that were consistent with having been infected by the virus. The researchers [16] examined the sympathy of chest CT in addition to viral nucleic acid assay to associate the results produced by reference point approaches. According to the findings of the clinical studies, CT and RT-PCR have a sensitivity of 98% and 7%, respectively, when it comes to diagnosing COVID-19 infection. This was shown by the comparison of the two methods. They presented a successful method to control the SARS-CoV-2-like illness that they discovered after conducting an exhaustive investigation and providing a quantitative analysis of the efficacy of contact tracing and the isolation of cases. In addition, they reported that they were able to contain the illness. They devised a model of stochastic transmission to be successful in reaching this objective.

In the event of catastrophic occurrences such as the COVID-19 pandemic, it is impossible to prevent the breakdown of the health-care system from occurring. This is because there are not sufficient hospital beds or medical experts to meet the demand for health services at the same time. Furthermore, COVID-19 is an extremely contagious disease, and anyone working in the medical field, namely nurses and physicians, are at the greatest risk of becoming infected with it. The early diagnosis of pneumonia is of critical significance, not only to facilitate the patient's speedy recovery but also to reduce the rate of the epidemic's progression through the use of isolation precautions [17]. Researchers have been looking into many other options for determining whether or not someone has COVID-19. Images obtained from chest x-rays, also known as CXRs, are frequently used for diagnosing, evaluating, and monitoring the most prevalent respiratory and lung infections [18]. CT scans, which are among the most cutting-edge imaging techniques available today, play a significant role in the process of diagnosing COVID-19. Because of this issue, the application of computer-aided detection and diagnosis (CADD) must be made to support radiologists in the process of diagnosis and cut down on the overcapacity of a sizeable number of COVID-19 patients. It has been thoroughly examined using a variety of research approaches, including feature extraction, feature learning, and many others. The historical perspective of image diagnostic systems has been well investigated. The purpose of these inquiries was to gain a deeper comprehension of the thinking that went into the design of these systems in the very beginning. Researchers whose primary concentration is machine learning and computer scientists play an essential role during this period, which coincides with the proliferation of COVID-19 across the entire world. Deep learning is currently regarded as one of the most significant breakthroughs in the field of artificial intelligence that has occurred to date. After that, it extracts the data from the photographs, starting with the images themselves [19]. The researchers want to see if deep neural networks built from scratch outperform VGG19 and ResNet-50 in diagnostic accuracy. The answer is simply due to restricted computational resources. We tested three public chest X-ray datasets to solve this issue. These datasets comprised CheXpert from Stanford University, NIH, and Kaggle pneumonia chest X-ray images. VGG-19 and ResNet-50, trained from scratch via chest x-ray images, were compared to our updated CNN models [20]. One of the more recent breakthroughs in deep learning (DL) is the convolutional neural network, also known as CNN. CNN, which stands for "convolutional neural network," has a wide variety of applications in computer vision. It has also made it possible for a new generation of CAD-like tools to be developed for a wide range of medical imaging instruments. This has opened up a lot of doors [5]. Research is now being conducted into the use of deep learning (DL) methods for chest X-rays for COVID-19 classification. Specifically developed the concept of an open-source platform for deep convolutional neural networks and gave it the name COVIDNet. Using chest radiography images as its primary data source, this platform was developed expressly to identify COVID-19 cases. They claimed that COVIDNet is capable of reaching good sensitivity for COVID-19 cases, with a sensitivity of 80% or more [21].

In order to find this problem, a lot of work has gone into making computer-aided detection or diagnosis (CAD) systems that use medical image processing and machine learning. The goal of these schemes is to automatically figure out what a disease looks like and give radiologists useful tools to help them make decisions that will help them find COVID-19-infected pneumonia faster or better. Recent studies have shown that using deep learning algorithms to build CAD schemes instead of segmenting suspicious ROIs and hand-crafting image features is more efficient and reliable than using traditional machine learning techniques. On a chest X-ray, it's hard to find and distinguish subtle patterns of illness related to pneumonia or areas of interest (ROIs). Also, it is hard to tell these patterns apart from each other. Researchers have recently put out a large number of studies that describe different deep learning models that can find COVID-19 cases and put them into groups. Some deep learning convolution neural network (CNN) models have been used on CT images, but most research has focused on using CNN models on the images of chest X-ray to find COVID-19 patients and put them into groups. They are made by putting together a number of CNN models that have already been made (like Resnet50, MobileNetV2, CoroNet, and Xception + Resnet50V2) and a few CNN models that have been made specifically for certain tasks (such as Dark CovidNet, COVID-Net, and COVIDX-Net). The amount of COVID-19 patients in these studies ranged from 25 to 224, and the total amount of cases ranged from 50 to 11,302 people. The reported sensitivity was successful in locating between 70.0 and 98.0 percent of COVID-19 cases [22]. Healthcare systems in every region of the world are actively working to expand the availability of COVID-19 testing facilities in their respective regions. The identification and isolation of sick persons will ultimately result in a reduction in the rate at which the disease is spreading across the population [23], which will be achieved by testing a greater number of people. Having something readily available does not, however, ensure that it is trustworthy simply because it is accessible. At this point in time, the governments' greatest source of concern is the existence of false negative test results [24].This indicates that the results of the test for the individual who is sick came back negative. These individuals have a much increased risk of unintentionally transmitting the virus to other persons. The publication of test findings that are erroneous has the effect of hampering the measures being made to comprise the further transfer of the virus. It is impossible to forecast the effect that this concern will have on the safety of persons who work in the public and health sectors because there are no reports that are either clear or consistent on these test performance aspects. It is difficult to make educated guesses about the sensitivity of these tests [24].Deep learning, also known (Basu, 2020) technology that aims to learn from raw data in order to automatically find the representations that are necessary for detection or classification. This is the technique's purpose. When it comes to medical imaging, it use the pixel values of the images themselves as the input rather than the attributes that have been obtained or chosen. As a result, it can avoid mistakes that require human involvement, such as incorrect segmentation and/or subsequent feature extraction. The usage of convolutional neural networks, commonly referred to as CNNs, is one of the most common deep learning applications. ImageNet, which was held in 2012, was the initial step toward the breakthrough that CNNs finally accomplished. This competition has almost no object detecting false positives. Artificial intelligence algorithms and clinical and radionics features from chest X-rays will help programmers discover COVID-19 in any country with X-ray facilities. AI algorithms are predicted to greatly aid COVID-19 diagnosis. (ML) and (DL) detect abnormalities and extract critical components of changed lung parenchyma quickly, automatically, and effectively. ML and DL are abbreviations [25].

2. Literature Review

In the past few years, many of the existing deep learning-based techniques have been employed for the diagnosis of different diseases using Chest X-Rays. As this modality incorporates less ionizing radiations, therefore it is usually preferred over Computed Tomography (CT) modality [26]. Some of the recent literature studies related to our domain of interest have been analyzed in the subsequent section. In [27], a novel deep CNN model has been trained from scratch over Chest X-Ray based imaging dataset i.e., for diagnosing Covid-19 infection. The training of presented model has been done over 13,975 training instances, while the final achieved accuracy by the model is 98.9%. Author of this study [28], has presented another novel deep CNN named as COVIDX-Net for the diagnosis of patients infected from Corona infection. For the training of proposed model Chest X-Ray based imaging dataset have been deployed, which incorporates a total of 25 infected and 50 normal patient's X-Ray scans. The final accuracy that has been obtained by the presented COVIDX-Net is 91%. In another study [29], author has utilized a transfer learning-based approach for the detection of corona infected patients. Author has used pre-trained ResNet-50 model as a feature extractor, while the resultant set of extracted features are fed to machine learning based SVM classifier for the final training and classification. The accuracy of proposed model is 95.34%.

A comparative analysis of eight distinct pre-trained architectures have been performed by [30] for diagnosing Corona infection. For the training and evaluation of these utilized models a dataset of 5856 X-Ray scans have been utilized. The results of this analysis have depicted that the best achieved accuracy is 96% by the Inception-V3 and MobileNet-V2.

In [31], author has introduced a data augmentation method for the expanding the size of dataset by applying transformations over input images. The main motive of author is to perceive covid-19 using Chest X-Rays by the implication of transfer learning-based approach. To perform the mentioned classification task, four distinct well-known transfer learning based deep models have been utilized i.e., including Dense-Net-201, AlexNet, ResNEt-18 and SqueezeNet. The best performance has been achieved by the SqueezeNet, which is 98.3%.

The research (Nishio et al., 2020) was developed and validated a computer-aided diagnosis (CXDx) system to classify chest X-ray (CXR) images into COVID-19 pneumonia, non-COPD, and healthy categories. Two public datasets yielded 1248 CXR pictures. This included 500 CXR images of healthy samples, 215 CXR images of COVID-19 bacterial meningitis patients, and 533 CXR images of other pneumonia patients. In the proposed CADx system, VGG16 was employed as a pre-trained model, and new data was added by combining the mixup methodology and the conventional approach. Other types of models that had previously been trained competed, and the VGG16-based model was matched against them. Methods that contributed only one type of data, or none at all, were also considered. The training, validation, and test sets were divided during the process of building and testing the CADx system. A sample set of 125 CXR images was used to assess accuracy in three separate categories. The CAD method demonstrated an accuracy of 83.6% when comparing patients with COVID-19 pneumonia, non-COVID-19 infection, and healthy individuals. More than 90% of cases were determined to be caused with COVID-19 infection. When compared to adopting only one sort of data augmentation method or none at all, the mix-up strategy and the traditional way showed to be the more useful alternative. Creating a viable CADx classification scheme for the three-category classification was another accomplishment of this project. The public can get the source files for our CADx system for COVID-19.

The World Health Organization declared the December 2019 Wuhan coronavirus (COVID-19) pandemic (WHO). It harms people, public health, and the global economy. Doctors must now find coronavirus (COVID-19). Polymerase Chain Reaction, antigens, and antibodies can detect the virus, but they have pros and downsides that affect how long it takes, how accurate the results are, how much the test costs, and how well it matches the infection phase. Since there are no accurate automated toolkits, accurate, rapid, and cheap standalone diagnostic tools are needed. Thus this paper's [32] Key contribution more automated approach for detecting and diagnosing COVID-19 in chest X-ray and CT images by using pre-trained deep-learning CNN architectures. The editors of Computers in Radiology have chosen to publish this article. The main idea is to use the structure of their convolutional neural network as well as the weights that it has learned through dealing with large data sets like ImageNet. In addition, a change to ResNet50 is being investigated in order to determine whether or not a patient has COVID. The three new layers created by this update are named Conversion, Batch Normalization, and Activation Relu. These layers were added to the ResNet50 design to improve its ability to discriminate attributes and extract information from them. A significant amount of testing is performed utilizing COVID-19 chest X-ray and computed tomography scan pictures to see how well the proposed model operates. Experiments have demonstrated that the suggested alteration, known as injected layers, can enhance diagnosis accuracy to

97.7% for CT datasets and 97.1% for X-ray datasets, which is a higher percentage than can be reached with any other approach.

Chest X-rays have been crucial in the testing and diagnosis of the recent COVID-19 pandemic. Since there are only a limited number of labeled medical images, the automatic classification of these images into positive and negative cases remains the greatest obstacle to surmount before they can be used regularly for disease diagnosis and tracking. To classify COVID-19 chest X-ray pictures, they developed a transfer learning process with two publically accessible chest X-ray datasets (1, 2). The classifier separates pneumonia and COVID-19-induced lung inflammation with precision (normal). As the feature extractor, they employed a variety of pre-trained convolution backbones, with the VGG16, ResNet50, and EfficientNetB0 achieving overall detection accuracies of 90%, 94.3 percent, and 96.7 percent, respectively. To generate and supplement the underrepresented COVID-19 class, researchers trained a Cycle GAN, a generative adversarial system. To illustrate their points, they utilized a technique known as gradient class activation mapping. Using this strategy, input photos having predictive importance are highlighted. In addition, these images can be utilized to monitor the progression of the disease as it affects different regions of the lungs. Using five cross-validation, the researchers in [17] established three distinct binary classifications with a total of four classes: COVID-19, normal (healthy), viral pneumonia, and bacterial pneumonia. The pre-trained ResNet50 model outperformed the other four models in classification accuracy (Dataset-1 accuracy is 96.1%, for Dataset-2 accuracy is 99.5%, and for Dataset-3 accuracy is 99.7%). Performance data supported these findings.

In [18] study, Researchers classified COVID-19 into three classes: pneumonia, normal, and COVID-19. This improved classification problem comprehension. We now know how to fix it. The researchers created a new classification method to present their findings. This method combines deep convolutional neural network with manually selected features. It has three parts. In the first module, they use ResNet-50 to transfer learn from preprocessed images. This generates a 2048-feature vector. The second module creates a pool of manually selected frequency- and texture-based characteristics. Principal component analysis selects 64 traits from 252 attributes (PCA). A feed-forward neural network then retrieves 16 properties. The last module creates the categorization model. This module combines features from the first and second modules and sends them to a dense layer and softmax layer. The module creates the categorization model. The Mendeley and Kaggle Chest X-Ray Datasets were used for pneumonia and normal cases, but four independent public sources provided COVID-19 patient photos. Anyone can use these photos. The model is tested using a 10-fold cross-validation. This improves judgement. The model's classification accuracy was 0.974 0.02, with sensitivity of 0.987 0.05, 0.963 0.05, and 0.973 0.04 at the 95% confidence interval for COVID-19, normal, and pneumonia classes, respectively. Data informed these conclusions. A separate chest X-ray cohort confirmed the model, which had a 0.979% classification accuracy. This helped determine the model's efficacy. The suggested framework outperforms state-of-the-art approaches in precision and sensitivity. Gradient-weighted Class Activation Mapping records gradient-based localizations because medical professionals need interpretable data (Grad-CAM). Conclusion: Grad-CAM localizations can be used to analyse data across several cohorts and provide clinical evidence. Medical imaging requires segmentation to interpret X-ray images. Segmentation helps identify an image's key elements. CT scans, X-rays, ultrasonography, and other imaging methods allow doctors to observe a patient's organs and structures without surgery. Training a deep convolutional neural network (CNN) from scratch requires a lot of labelled training data, processing time, and experience to validate if the network converges. Fine-tuning a convolutional neural network (CNN) trained on many labelled medical datasets can improve its outcomes.. This is a viable other option to examine. In this [20] particular piece of research, a contrast was drawn between models that had previously been trained, such as VGG-19 and ResNet-50, and models that had been trained entirely from scratch. In order to reduce the amount of overfitting, data augmentation and dropout regularization were utilized. Iyke-Net is a CNN that was trained from scratch, and the results of our investigation showed that the fine-tuned pre-trained models were roughly equivalent to it in terms of their recall, which was 92.03%. Finding a procedure that is reliable for diagnosing COVID-19 illness is of the utmost significance. Finding those who are infected with COVID-19 as quickly as possible is absolutely necessary in order to stop the infection from dissemination to other people. In this study, we proposed a method that is based on deep learning and has the ability to differentiate between people who have COVID-19 disease and those who have viral pneumonia, bacterial pneumonia, or who are healthy (normal) instances. This method can be used to diagnose COVID-19 disease in patients, as well as other types of pneumonia. Deep transfer learning is the kind of education that is utilised in this method of learning. In our testing, we used both binary and multi-class datasets, and those datasets can be divided into the following groups, depending on the type of data they contain: (i) A total of 728 X-ray images were obtained, 224 of which showed confirmed cases of the COVID-19 disease, whereas the other 504 demonstrated normal circumstances. (ii) A collection of 1428 X-ray images, including 504 pictures showing normal conditions, 224 showing COVID-19 disease, and 700 showing pneumonia caused by common bacteria. (iii) A collection of 1442 X-ray images, including 504 shots portraying normal conditions, 714 images revealing verified bacterial and viral pneumonia, 224 photos indicating confirmed case of COVID-19 illness, and finally 504 photos depicting normal conditions. (iv) A pool of 5232 X-ray photos, of which it was established that 1345 had viral pneumonia, 1346 had normal conditions, and 1358 had bacterial pneumonia. In this paper, (Hira et al., 2021) employed nine different convolutional neural network-based architectures. These architectures were named as follows: GoogleNet, AlexNet, Se-ResNet-50, ResNet-50, DenseNet121, Inception V4, Inception ResNet V2, Inception ResNeXt-50, and Se-ResNeXt-50. According to the findings of experiments, the Se-ResNeXt-50 model has the highest classification accuracy of all the transfer learning models, with a score of 99.32% for the binary class and 97.55% is for multi class.

In [33] study, impartial fine-tuned learning (transfer learning) in various cutting-edge deep learning approaches was accomplished using random oversampling and a weighted class loss function approach. Inception-v3, Baseline ResNet Inception ResNet-v2, NASNet-Large and DenseNet169 are some of these methods. These approaches were used to implement binary classification (such as normal cases and COVID-19 cases), as well as multi-class classification (as normal case, pneumonia, and COVID-19) When evaluating the effectiveness of the models, accuracy, precision, recall, and loss rates, as well as the area under the curve, are the primary metrics that are considered (AUC). According to the findings of the tests, the amount of success that can be achieved by any model is contingent on the conditions that are present. On the other hand, the performance of NASNet-Large was superior to that of both older topologies and methods that were developed more recently. This article has been updated to include a picture that depicts how COVID-19 is categorized, as well as what it seems to be in CXR images and how that determination is made. In addition, the text has been modified to include new information. Coronavirus Infection 2019 (COVID-19) is causing havoc in many parts of the world and putting a significant amount of strain on the medical workforce as well as the infrastructure of health care facilities in a number of different countries. Examining a patient's lungs by producing chest X-rays and CT scans with the help of radiation imaging is one of the most effective and significant strategies for treating the COVID-19 virus. In this paper [16], a technique for classifying and detecting COVID-19 is developed with the use of five deep learning models that are associated with the keras framework. InceptionResNetV2, ResNet50, transfer learning , Xception, and pre-trained VGGNet16 are some of the models that fall into this category. CNN and SVM provides two benchmark methods for comparison through the classification–detection methodologies founded on the performance indicators, which include recall, precision, F1 scores, classification accuracy, confusion matrix and 3 different categories of AUC. These benchmark methods are compared to the classification–recognition approaches built on the performance indicators. The classification and detection strategies can be evaluated based on how well certain performance metrics fare (Area Under Curve). The maximum degree of categorization accuracy, founded on 5857 chest X-rays and 767 chest CT scans, is 84%, whereas the lowest level, 75%, is the level seen the most frequently. This demonstrates that the deep learning procedures that are linked with keras are what makes COVID-19-assisted detection more accurate and efficient. In order to put a stop to the spread of an illness throughout a community, it is necessary to do testing on a sizeable number of individuals. The real-time polymerase chain reaction (real-time PCR) is a diagnostic method that is becoming increasingly popular and is used to screen for a wide variety of disorders. On the other hand, due to the growing number of instances in which test results are erroneous, it is now possible to study other techniques of testing. Chest X-rays images of patients who have COVID-19 have been found to be a major alternative indicator, as was discovered through screening for COVID-19. However, another aspect that influences accuracy is the amount of information one has in the field of radiology. If the physician has access to a diagnostic recommender system that can aid them in examining the lung images of their patients, then it will be much simpler for them to make a diagnosis. This is because the system will help them examine the photos of their patients' lungs. The application of Deep Learning techniques [24], in particular Convolutional Neural Networks, has proven successful in the classification of medical pictures (CNN). Different types of X-rays images of chest were utilized in the diagnostic process of COVID-19 in order to test four distinct deep CNN architectures. These models have already been trained using the ImageNet database at some point in the past. This means that they do not need to train with a very large amount of weights because their weights have already been trained. They have previously trained their weights. It was found out that architectures based on CNN might be applied in order to appropriately diagnose COVID-19 sickness. It is essential to investigate a straightforward screening method for COVID-19 that makes use of radiological images like chest X-rays. This is because PCR tests produce a high number of false negatives, and there is a growing need to screen millions of possible cases of COVID-19, also known as "novel coronavirus." As a result, it is essential to investigate a screening method for COVID-19 that makes use of radiological images. In this circumstance, machine learning (ML) and deep learning (DL) offer methodologies that are speedy, automated, and effective for discovering anomalies and extracting crucial characteristics of the transformed lung parenchyma. It is possible that some signatures of the COVID-19 virus are associated with these anomalies and extracted traits. On the other hand, the COVID-19 datasets that are currently available do not offer sufficient information to properly train deep neural networks. Therefore, [25] has developed a novel concept that they refer to as "domain extension transfer learning" (DETL). On a large chest X-ray dataset that is intended to separate images into four groups—normal, pneumonia, other disease, and Covid-19—they apply DETL, which contains a deep convolutional neural network that has already been trained. The four groups that the dataset is intended to split images into are: normal, pneumonia, other disease, and Covid-19. Because of this, we are able to swiftly categorise the photographs. A 5-fold cross validation is performed in order to ascertain whether or not chest X-rays may be utilized in the process of diagnosing COVID-19. The preliminary findings appear to be encouraging, and it would be fascinating to find out whether or not those conclusions hold up when applied to data sets that are larger and more diversified. On the basis of the measurements that were carried out, the overall accuracy was calculated to be 90.13 0.14. They employed the concept of Gradient Class Activation Map, which is also known as Grad-CAM, to pinpoint the regions of interest where the model spent more of its attention during classifying. This allowed them to find the regions of interest. As a result of this, we were able to evaluate the degree of transparency exhibited by the COVID-19 detection. The existence of a meaningful connection between this and clinical data was validated by the opinions of a number of additional authorities. For the goal of assessing COVID-19 patients, particularly for the purpose of resolving overcapacity concerns in emergency departments and urgent care centers, it has been proved that the information collected from chest X-rays is quite promising. In the context of artificial intelligence (AI), the utilization of deep learning (DL) techniques as a high-performance classifier plays a pivotal character in disease diagnostic through the utilization of chest X-rays. This is because AI is better able to comprehend complicated patterns in a shorter amount of time compared to more conventional ways. This study will examine the fine tuning of CNNs that have been pre-trained to classify COVID-19 utilizing chest X-rays as the data source. This study aims to gain a deeper understanding of COVID-19. This is due to the fact that a substantial number of brand-new DL models have been created specifically with this objective in mind. If fine-tuned pre-trained CNNs are capable of giving classification results that are equivalent to, or even superior to, those given by other, that are extra sophisticated CNNs, formerly the use of Artificial intelligence based methods for recognizing COVID-19 should be seriously examined. According to Pham (2021), using data from chest X-rays will make it possible to be more efficient and save money. In order to carry out our 2-class and 3-class classification tasks employing three public chest X-ray databases, three pre-trained CNNs were chosen and fine-tuned without the utilization of any additional data augmentation. This was done in order to save time. This was done to ensure that accurate findings were obtained, thus that's why it was done. These particular CNNs are referred to by their respective names, such as AlexNet, GoogleNet, and SqueezeNet. When compared to DL models that were produced more recently [34], the three pre-trained CNNs exhibited results that were much more accurate in terms of categorization. Among the results that can be measured are sensitivity , accuracy, precision , specificity, the F1 score, and the area below the receiver-operating-characteristic curve. Other possible outcomes include: When it comes to pre-trained deep learning models, GoogleNet, SqueezeNet model and AlexNet require the minimum amount of training time due to their superior architectures. However, if the appropriate selection of training parameters is made, it is feasible to generate fantastic classification results without making use of the capabilities afforded by these networks for data augmentation. This is the case so long as the selection of training parameters is made appropriately. This contributes to the critical need for yoking the pandemic. This adds to the critical necessity to gain control of the pandemic as quickly as possible. Because of this, it is even more urgent than before to get the epidemic under control as soon as humanly possible. This helps address the urgent need for steps to be taken in order to contain the outbreak. A chest X-ray is the initial imaging test that is performed to determine whether or not a person has COVID-19 disease. During this examination, we will be focusing on the chest area. When it comes to the recognition and categorization of images, the application of convolutional neural networks, more commonly referred to as CNNs, has been shown to be beneficial. This is because it is quite simple to identify and make use of large-scale annotated image collections. This has led to this result. Categorizing medical images, on the other hand, remains one of the most difficult components of medical diagnosis. This is due to the fact that there aren't that many medical photographs that have been categorized. Pre-trained model is an efficient strategy that may offer a potential way out by moving familiarity from general object identification tasks to domain particular activities. This shifting of knowledge is accomplished through the process of transfer. Thanks to transfer learning, this problem has a potential answer. We validate and make use of a deep convolutional neural network (CNN) that we term Decompose, Transfer, and Compose (DeTraC) in this research [35] to classify COVID-19 chest X-ray images. DeTraC is able to handle any unexpected occurrences that may occur inside the picture collection by employing a class decomposition technique to investigate the location of the class boundaries. The findings of the testing indicated that DeTraC was able to identify COVID-19 cases within a massive collection of photographs amassed from medical facilities situated in every region of the world. When it comes to discovering COVID-19 on X-rays obtained from normal persons as well as patients with severe acute respiratory syndrome, DeTraC exhibited an accuracy of 93.1% and a sensitivity of 100%.

The most popular method for discovering novel coronaviruses such as COVID-19 is called real-time polymerase chain reaction (RT-PCR) (RT-PCR). However, RT-PCR kits can be quite pricey, and it can take anywhere from 6 to 9 hours to determine whether or not a patient has an infection. The sensitivity of RT-PCR is lower than that of other tests, which means that it frequently produces false negatives. Imaging methods using radiation, such as chest X-rays and computed tomography (CT), are utilised in the process of locating and diagnosing COVID-19. This action is taken in order to solve the situation. This [36] paper says that chest X-rays are better than CT scans. X-ray machines are available in most hospitals, which is why this is the case. The cost of purchasing an X-ray machine is significantly lower than the cost of purchasing a CT scan machine. X-rays emit less ionising radiation than CT scans, making them a more prudent choice for medical imaging. With chest X-rays, it is possible to identify certain radiological signals that are caused by COVID-19. To accomplish this, radiologists must examine these signatures. However, it is quite time-consuming and prone to errors in execution. Therefore, there is a requirement to mechanisemechanize of analysing chest X-rays. Using approaches based on deep learning, chest X-rays can be automatically read, which might potentially reduce the amount of time required. These strategies can be used to train network weights on datasets of any size, ranging from extremely large to very tiny. In addition, they can be utilized in the process of fine-tuning the weights of previously trained networks. Nevertheless, chest X-rays can only be performed to a limited extent utilizing these methods. Using the extreme version of the Inception (Xception) model, the fundamental purpose of this study is to build an automated deep transfer learning-based methods for diagnosing COVID-19 infection in chest X-rays. This will be accomplished. Extensive comparisons demonstrate that the proposed model operates significantly more effectively than the ones that are currently available in the market.

3. Methodology

In this study, we used the appropriate data preparation to evaluate the COVID-19 Diseases patient dataset for COVID-19 Pneumonia. In the first phase of preprocessing, we observed the color, size, image noise, and illumination effects then, machine-learning models (Resnet-50) have been trained on the patient dataset. Predictions are made using the mentioned algorithm. Each phase has been described in better detail below.

The proposed scheme contains six main steps and some sub-steps. A flow chart of our methodology is shown in Figure 1.

3.1 Data set Collection

We collect this Dataset from GitHub and its name is Chest Covid19 Pneumonia. (Github: chest-x-ray-covid19-pneumonia). The corona virus dataset comprises of corona features (Pneumonia infection, sore throat evidence in x-ray, breath issues etc.).Our Dataset contains 6,432 Chest-Xray images. The total number of images for Pneumonia is 4,273, 576 images are related to COVID-19 patients, and, the other 1,583 images are normal chest X-ray images. Figure 02 demonstrates the details of a dataset.

We have used a publicly available Chest Covid19 Pneumonia imaging dataset for performing the training and evaluation of our proposed approach. This dataset is named as Augmented Covid-19 X-Ray imaging dataset that has been published online on March 26, 2020 [37]. The mentioned dataset is a combined version of two online available chest X-Rays based datasets i.e., 1) Covid Chest X-Ray dataset (GitHub - Ieee8023/Covid-Chestxray-Dataset) and 2) Chest X-Ray images (Pneumonia) dataset [37]. The first dataset is taken from a public repository of X-Ray and Chest CT-Scan images dedicated to different viral diseases. The data in this repo has been obtained from different public sources as well as from different hospitals. Images of this dataset are available in jpg format.

Table 1. Covid-19 dataset Detail

Sr. No	Category	Records
1	Normal Personal	1,583
2	A person with Pneumonia disease	4,273
3	A person with COVID-19 disease	576
		Total: **6,432**

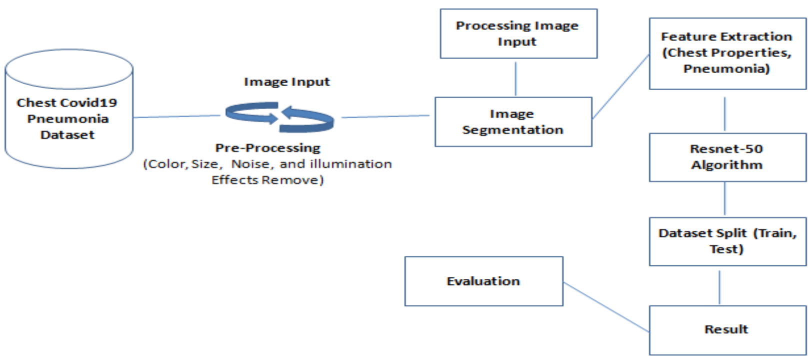

Figure 1. Proposed Methodology

3.2 Data Set Description

There have been numerous disagreements over the description of COVID19 Disease information in prior studies. As previously established, there are multiple different types of metadata employed in past studies. We have utilized the two metadata shown below

While incorporating a total of 6,432 images of patients infected with Pneumonia and normal people. This dataset is also available in .jpeg format in three different directories i.e., for training, validation, and testing of the model.

The gathered version of these two datasets is available on the Mendeley website, which has been categorized into two directories. One directory incorporates images of Covid patients, while the other incorporates non-Covid Patients' images. A sample image of normal and infected Pneumonia patients has been given in the Figure 2 below.

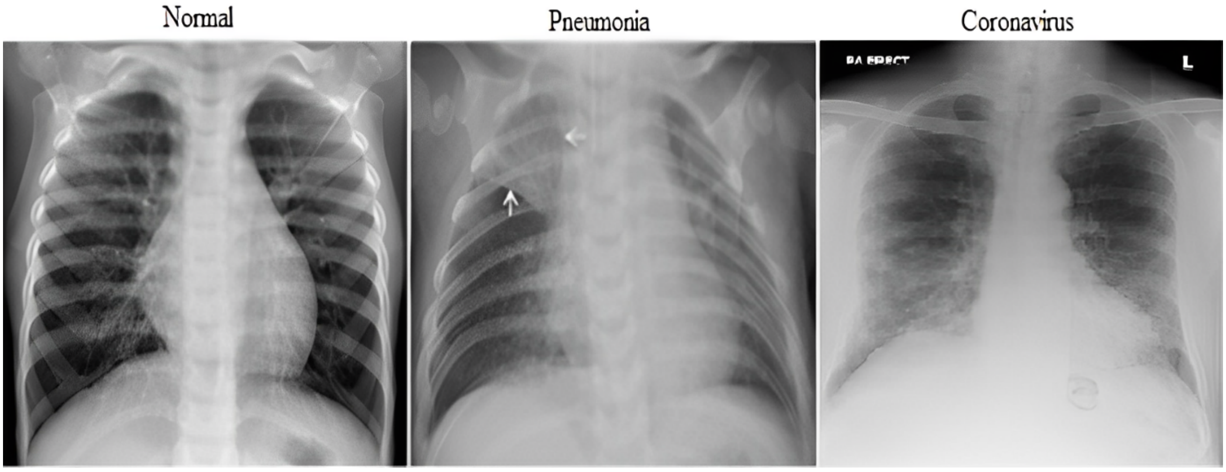

Figure 2. Sample Chest X-Ray images of Normal and Pneumonia infected patient

3.3 Preprocessing

This stage requires identifying image color blurriness, image illumination, image size disorder, and another factor for each chest x-ray of a dataset. Below, Figure 3 shows some images for the mentioned issues.

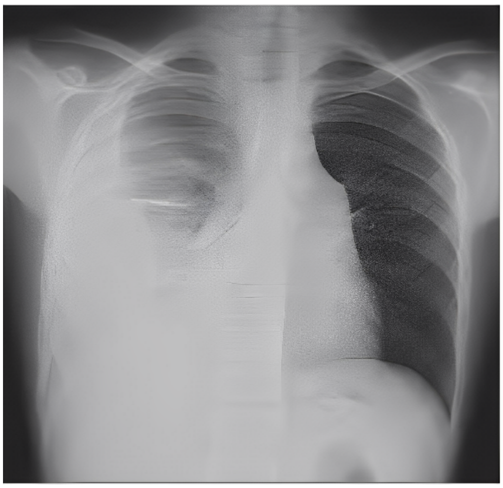

Figure 3. Example of Blurr Image in Dataset

Figure 4, is showing that there are some images in our dataset with disordered pixels. So it needs to apply pre-processing steps before processing steps. For that cause, we have used the machine learning model to smooth and clear images.

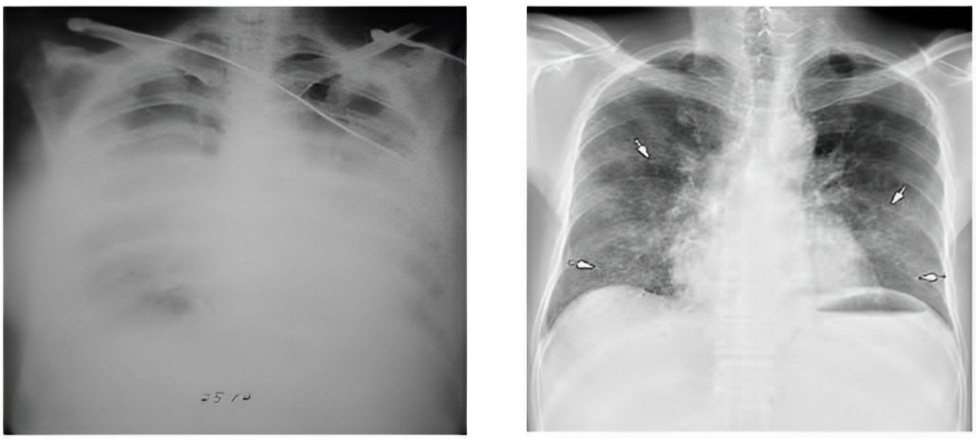

Figure 4. Before and After Pre-processing Steps

This section gets rid of any noise, makes the image smoother, and resizes any images that need to be changed. In this process, RGB photos are changed to greyscale images, and the contrast of an image is boosted to a certain degree. Photographs of fruit captured using a variety of cameras and cameras of varying quality are included in our collection. These images include images taken with mobile devices, images with noisy backgrounds, and other variations. As a result, it is necessary to employ various methods such as calming, the elimination of noise, and others. It will be useful for the forthcoming procedures.

3.4 Data Analysis

This is the next stage that we will take; in order to illustrate, demonstrate, describe, and condense our dataset as well as recognize patterns, we have employed a methodical strategy as well as statistical and conceptual tools.

3.5 Image Segmentation

Segmentation is used for partitioning an image into various Parts

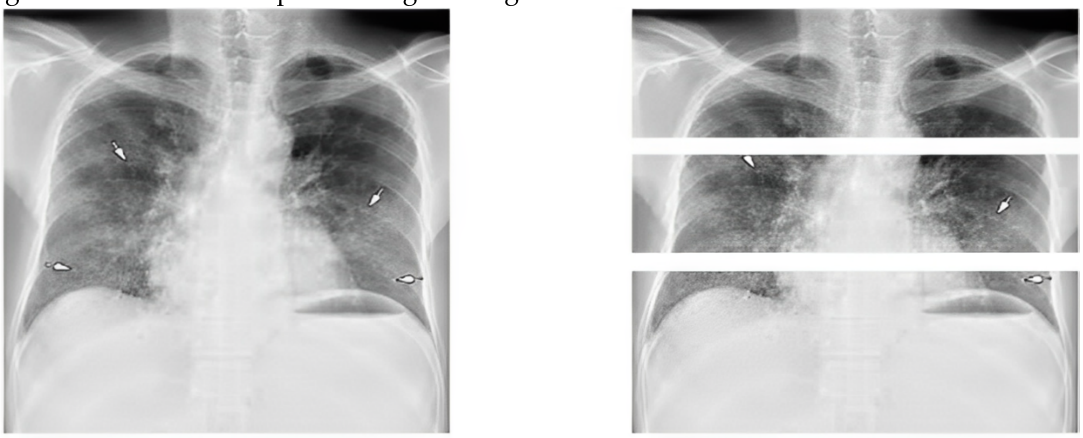

Figure 5. Sample of Image Segmentation

3.6 Feature Extraction

This portion is used to gather attributes such as color (Pneumonia infection person, COVID-19 patient, and Normal person), chest condition, and form, which reduce the resources required to explain a huge number of data prior to the classification of the corona patient chest image.

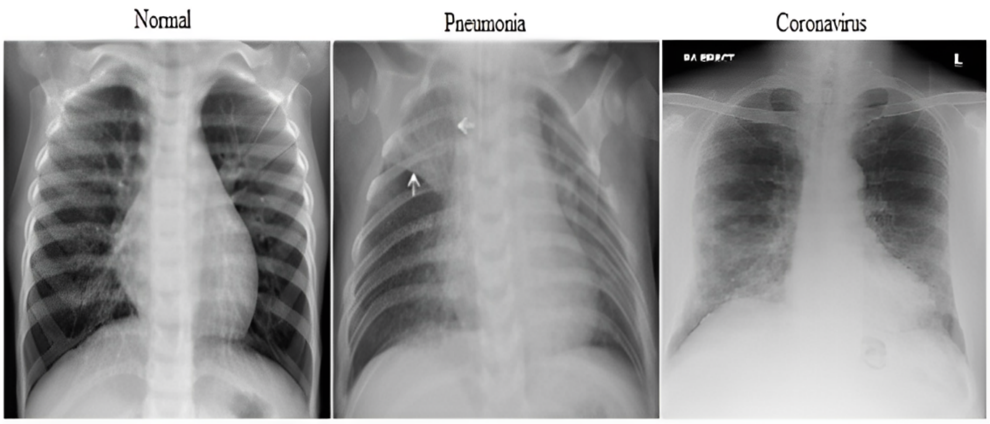

Figure 6. Sample of Normal, Pneumonia, and COVID-19 Patient chest x-ray

3.7 Classification Model ResNet-50 (CNN)

ResNet is an example of a specific kind of convolutional neural network. Its name stands for "Residual Network" (CNN). ResNet-50 was a weighted network that had fifty layers in total. By utilizing the idea of shortcut connections, it offered an original strategy for adding more convolutional layers to a CNN without triggering the vanishing gradient problem. This was made possible by to the innovation. A conventional network can be transformed into a residual network by utilizing shortcut connections, which "skip over" certain layers. The ResNet-50 model may be used to machines; if we train a model using a database, then it is not essential to retrain all of the models from scratch in order to adapt them to a new dataset that is comparable to the previous one. Both ImageNet and CIFAR-10 provide a collection of photos that can be used to teach a model how to identify images. Therefore, it is highly encouraging if we can reduce the amount of time spent training a model (given that this process might take a significant amount of time) by beginning to use the weights of a model that has already been trained. The ResNet-50 model is currently undergoing the process of transfer learning, which includes all that we require to also construct a model on our own.

The architecture of ResNet is based on two fundamental principles of design. To begin, regardless of the dimensions of the final feature map, the identical quantity of filters will be applied to each of the layers. Second, if the size of the feature map is cut in half, it will require twice as many filters in order to keep the same level of time complexity in each layer.

The 50-layer ResNet architecture includes the following elements, as shown in the table below:

1. A convolution of kernels with a dimension of 7 by 7 and 64 additional kernels, all separated by a stride of 2.
2. A layer that maximizes pooling and has a stride size of 2.
3. Add another nine layers, including a convolution layer with a kernel size of 33,64, one with 11,64 kernels, and a third with 11,256 kernels. This pattern of three layers is repeated thrice.
4. 12 more layers, with 1×1,128 kernels, 3×3,128 kernels, and 1×1,512 kernels, iterated 4 times..
5. 18 further layers, each with a core count of 11,256, followed by cores of 33,256 and 11,1024, iterated six times.
6. Nine further layers, each having a core count of either 1,512, 3,512, or 1,2048, iterated three times (up to this point the network has 50 layers).
7. An average pooling, then a fully connected layer with 1000 nodes that uses the softmax activation function, and finally, an average pooling again.

3.8 Hyper-parameter (Database)

Chest-x-ray-covid19-pneumonia is a dataset with 6,432: 32x32, 40x32, and 30x37 x-ray images grouped in 3 classes, 1,583 images are related to health person, 4,273 images for pneumonia patient, and 576 images belong to corona patients. We have the RELU activation function of each dataset, which will allow us to determine which of our training dataset's hyper parameters are the most optimal. Through the training stage of the model, the relu activation function was used to make the dataset's edges smoother. Random images were also fed into the model. Change the value of epochs such that it reads 2. Tables 03 and 04 display the details of our assigned model parameters for both the training dataset and the testing dataset respectively.

Table 2. ResNet-50 Model Training Hyper parameter

Identifiers	**Values**
Learning Rate	0.01
Activation Function	Relu
Bach Size	64
Epochs Size	2
Shuffle	True

Table 3. ResNet-50 Model Testing Hyper parameter

Identifiers	**Values**
Learning Rate	0.01
Activation Function	Relu

Bach Size	64
Epochs Size	2
Shuffle	False

3.9 Model Training ResNet-50 (CNN)

To execute the complete experiment for the grouping of COVID-19 using chest radiographs with pneumonia infect, we will first train a baseline model. Then, we will conduct more tests to examine the effect that altering the hyperparameters has on the model's overall performance. As shown in figure 11, our train model achieves val_accuracy 97%.

3.9.1 Robustness increase by Purifying Training Dataset

The image is trimmed in order to help eliminate the influence of outliers or data points on the tails, which may unjustly affect the traditional mean. This is accomplished by removing these points from the image. For that, we have to use a function with the name of trim. In this function, we have divided the training dataset with the original data frame via the use of the unique class label. After we group all data into their corresponding classes and then check the size of the sample with the max_size allow. If sample_count size is greater than max_size then trim train dataset size. Else append the sample to train the dataset sample.

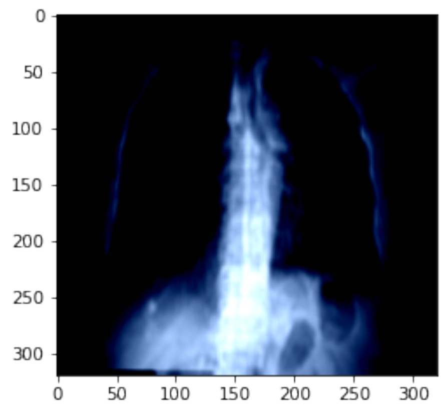

Figure 7. Purified Image

3.9.2 Split Dataset Training & Testing

We have utilized the Scikit package for the data splitting process, and through the assistance of header file split in train test and 80:20 ratio we spit this dataset successfully.The total number of images for the training dataset is 5,144 (Pneumonia: 3,418, Normal: 1,266, Corona: 460), and for testing 1,288 (Pneumonia: 855, Normal: 317, Corona: 116). We have also found out the average image height which is 721.152, and the average width is 702.528.

```
Train set:
--------------------------------------------------
PNEUMONIA_TRAIN=3418
NORMAL_TRAIN=1266
COVID19_TRAIN=460

Test set:
---------------------------------------------------
PNEUMONIA_TEST=855
NORMAL_TEST=317
COVID19_TEST=116
```

Figure 8. Split Dataset into Train and Test Group

3.9.3 Model Training

Figure 9, 10 is showing that our model successfully learns the difference between a Pneumonia patient image x-ray, a Normal person chest x-ray, and a Corona patient image chest x-ray with the highest accuracy of 97%.

```
Epoch 1 / 30
1 0.0001
Duration: 212s, Train Loss: 1.7488, Train Acc: 0.9056, Val Loss: 0.7164, Val Acc: 0.9573
Epoch 2 / 30
2 9.6667e-05
Duration: 204s, Train Loss: 0.7206, Train Acc: 0.9619, Val Loss: 0.4948, Val Acc: 0.9696
Epoch 3 / 30
3 9.333400000000001e-05
Duration: 205s, Train Loss: 0.5883, Train Acc: 0.9686, Val Loss: 0.6330, Val Acc: 0.9514
Epoch 4 / 30
4 9.000100000000001e-05
Duration: 204s, Train Loss: 0.4825, Train Acc: 0.9739, Val Loss: 0.5714, Val Acc: 0.9495
Epoch 5 / 30
5 8.6668e-05
Duration: 203s, Train Loss: 0.4577, Train Acc: 0.9775, Val Loss: 0.3957, Val Acc: 0.9709
Epoch 6 / 30
6 8.333500000000001e-05
Duration: 205s, Train Loss: 0.3841, Train Acc: 0.9833, Val Loss: 0.3342, Val Acc: 0.9747
Epoch 7 / 30
7 8.0002e-05
Duration: 204s, Train Loss: 0.3023, Train Acc: 0.9883, Val Loss: 0.3803, Val Acc: 0.9728
Epoch 8 / 30
8 7.666900000000001e-05
Duration: 205s, Train Loss: 0.3810, Train Acc: 0.9806, Val Loss: 0.4067, Val Acc: 0.9644
Epoch 9 / 30
9 7.3336e-05
Duration: 203s, Train Loss: 0.3024, Train Acc: 0.9864, Val Loss: 0.3458, Val Acc: 0.9747
Total Time:1844s
```

Figure 9. Model Training Result

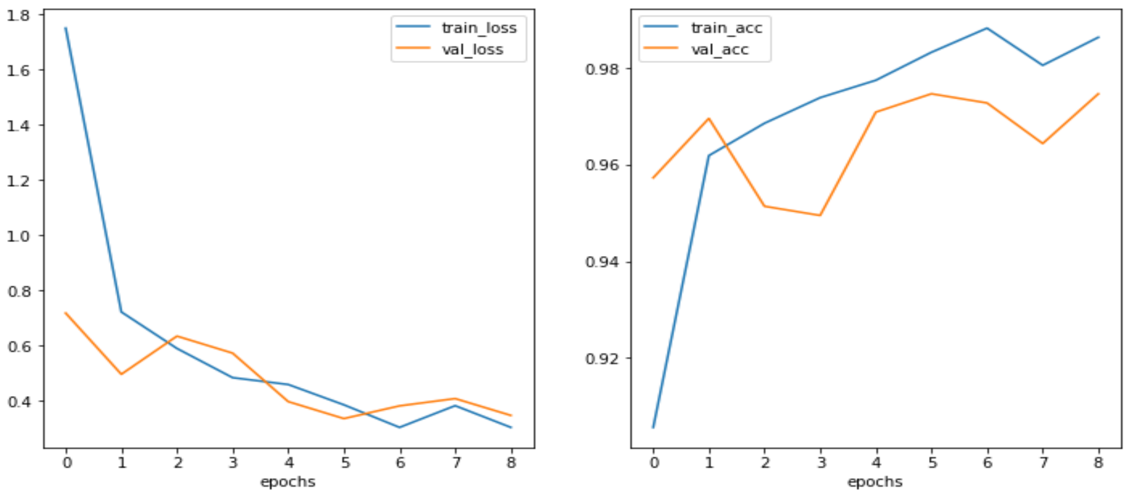

Figure 10. Model Training Loss Result

3.9.4 Model Testing

Figure 11 is showing that our train model will be able to predict corona disease via the use of chest x-ray with pneumonia infection with 96.20% accuracy.

```
Accuracy of the network on the test images: 97.44
Precision: 0.9835
 Sensitivity: 0.9825
 F1-score: 0.9830
 Specificity: 0.9495,
971 317
```

Figure 11. Model Testing Result

4. Result and Discussion

4.1 Confusion Metrics Expression

Used confusion matrix to present the performance of a ResNet-50 (CNN) algorithm.

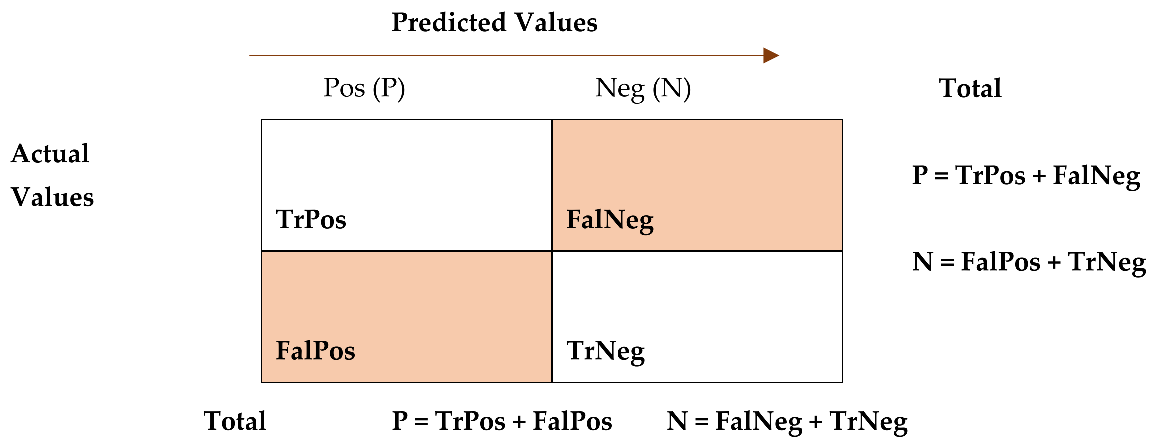

Figure 12. Confusion Matrix ResNet-50 (CNN)

For the validation of the Resnet-50 model, we used the Confusion matrix. The prediction rate of the proposed image processing model is 96.45% to 98.18% higher. Model performance Comparisons between corona patient detection are evaluated. Figure 12, it is verifying that the proposed image processing model work better for detecting covid disease in term of Precision, Accuracy, Recall, and F1-score.

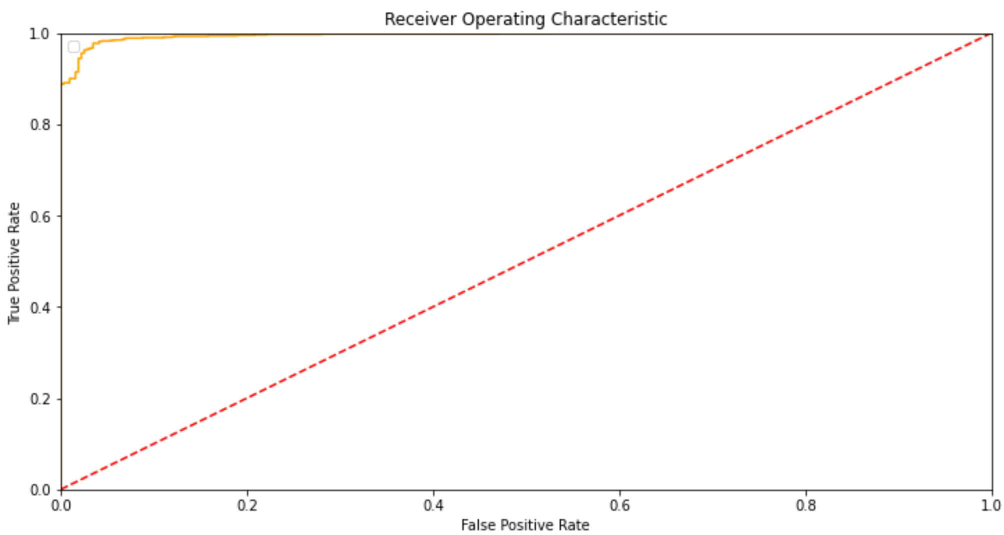

Figure 13. True Positive Rate and False Negative Rate

4.2 Discussion

Our methodical analysis establishes the worth of machine learning forecasting models for the development of health management solutions as well as the simplicity and efficiency of COVID-19 prediction. disease using data set component analytics. Our study presents the findings from a number of data visualizations, particularly as they relate to pneumonia infection and the Corona Outcome. To find the best accurate machine learning algorithm, we applied a number of algorithms to a dataset. We might need to determine a publication's statistically significant effects based on our findings.

Our results demonstrate the relationship between COVID-19 disease symptoms such as headache, cough, fever, etc. and test pneumonia. Comparing Residual Network - 50 to certain other Machine Learning approaches, it has shown greater accuracy for forecasting COVID19 Disease. The Resnet-50 approach has to be improved, though. Publication bias is the name for this tendency. Although a number of factors suggest that bias is unlikely to have a large impact, it is difficult to completely rule it out in study.

5. Conclusion

Our Dataset has undergone several statistical analyses. Residual Network -50 was examined. Residual Network operated admirably, as we discovered. We have created an algorithm for autonomous healthcare management that uses pneumonia infection to predict COVID19 disease in patients. In no time, patients suffering with COVID-19 Disease will be saved thanks to our suggested model. For the purpose of identifying the patient's most concerning COVID19 Disease features, various statistical analysis techniques have been used with dataset attributes (Pneumonia, Normal, and COVID-19). Our predictive technology will help medical professionals accurately diagnose COVID19 disease.

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