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Residual Learning Model-Based Classification of COVID-19 Using Chest Radiographs

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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. Further the estimation of illness and the patterns of carrying COVID-19 symptoms threads our sense. 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. So, protection produces took

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place to control the spread of the COVID-19 virus via social distancing which holds back humans from the thing, which is the natural opposite of human social life. Due to this outbreak, what will be the role of Machine learning in our life in the context of global threats, social distance, and physical as well as mental threats. In this research, there is a considerable need to automate the whole diagnosis task to cope with mentioned problems via the use of pre-trained machine learning algorithms such as Resnet-50.
Keywords: Deep Learning, COVID-19, Chest-Xray, Residual Learning, Classification

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 (Abdelli et al., 2021; Boopathi et al., 2020). 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, diarrhoea, 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 rise in the number of daily cases that are reported, medical institutions are teetering on the edge of collapse even in the most technologically advanced nations (Gupta et al., 2021). The World Health Organization (WHO) announced the pandemic status of this disease on February 11, 2020. (Kumar, 2020). In the middle of the 1960s, the coronavirus was recognised as a human disease-causing

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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, were shown to be the root cause of both of these outbreaks (Misra et al., 2020). 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 (Shelke et al., 2021).

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 (Landry et al., 2020; Sharifi-Razavi et al., 2020). These symptoms could be visible within about 14 to 15 days of contamination (MM et al., 2022). The infected patients' saliva and respiratory secretions could be responsible for the transmission of

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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 the diagnosis of Covid-19 disease. 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 (Xie et al., 2020). 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 detection of these viral diseases (Ng et al., 2020). For the purposes of our thesis, we want to make use of chest X-rays in order to diagnose the presence of the aforementioned chest disorders. Computer-aided diagnosis, which is more commonly referred to as CADx, is currently being utilised 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

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application of various methods based on artificial intelligence. These developments have been made possible by recent advancements in machine learning. (Nishio et al., 2020). The design of convolutional neural networks is one of the most common and successful methods for diagnosing COVID-19 from digital photos. a number of publications have highlighted recent contributions to the compilation of datasets to train models for COVID-19 identification. (Zebin & Rezvy, 2021).

Even though a number of 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 utilised 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 more challenging to use when attempting to diagnose COVID-19 pneumonia. (Nishio et al., 2020). Currently, a technique that is known as reverse transcriptase polymerase chain reaction is used to diagnose 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.

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As a direct result of this, it is imperative that an alternative method of diagnosis that is more efficient be developed (Punn & Agarwal, 2021).

The main contribution of this work as follows:

- The proposed automated approach for the diagnosis of Pneumonia and Coronavirus diseases using advanced image analysis techniques has the potential to significantly transform current diagnostic practices. By reducing the need for manual scrutiny and analysis of Chest X-ray scans, radiologists can save valuable time that is traditionally spent on reviewing and interpreting images. This allows them to focus on other critical aspects of patient care, potentially increasing overall efficiency within medical settings. The automation of image analysis not only accelerates the diagnostic process but also ensures more consistent results, which is especially crucial in busy healthcare environments where time is a key factor.
- Furthermore, the automation of disease detection could drastically reduce the likelihood of human errors caused by factors such as fatigue, distraction, or misconceptions. Manual diagnosis, which often requires extended periods of concentration and interpretation of complex visual patterns, is susceptible to misdiagnosis or overlooked symptoms. By leveraging an automated system, which can continuously scan and analyze X-rays with high precision, the potential for diagnostic errors is minimized. This increased accuracy could ultimately lead to more timely and reliable diagnoses, improving patient outcomes, especially in emergency or resource-constrained settings where quick decision-making is critical.

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- In addition to enhancing diagnostic accuracy, the implementation of an automated diagnostic system could also lead to substantial cost savings. The costs associated with manual diagnosis include not only the fees for medical practitioners but also the time spent on administrative tasks, follow-up consultations, and potential re-examinations. By automating the analysis process, these costs could be significantly reduced, making healthcare more affordable and accessible. Moreover, the automation could reduce the need for multiple rounds of testing or repeat visits to healthcare providers, further optimizing healthcare delivery and patient care.
- The integration of AI-driven systems into the diagnostic workflow offers the possibility to streamline processes, improve the accuracy of diagnosis, and reduce operational costs. This approach is particularly advantageous in areas with a shortage of skilled medical professionals or in situations where rapid diagnostics are crucial, such as during a pandemic. By enhancing the diagnostic workflow with automated solutions, healthcare systems could deliver faster, more efficient, and cost-effective care to a broader population, ultimately advancing public health outcomes.

Related Work

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 (Singh et al., 2020). Some of the recent literature studies related to our domain of interest have been

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analyzed in the subsequent section. In (Wang et al., 2020), 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 (Hemdan et al., 2020), 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(*P. Sethi et al, 2020*), author has utilized a transfer learning-based approach for the detection of corona infected patients. Author has used pretrained 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 proposed scheme has achieved an accuracy of 95.34%.

A comparative analysis of eight distinct pretrained architectures have been performed by(El Asnaoui et al., 2021)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 (Chowdhury et al., 2020), 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 detect covid-19 using Chest X-Rays by the implication of transfer learning-based approach. To perform the mentioned

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classification task, four distinct well-known transfer learning based deep models have been utilized i.e., including Dense-Net-201, AlexNet, ResNEt-18 andSqueezeNet. 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 contained 215 CXR photos of COVID-19 pneumonia patients, 533 CXR images of pneumonia patients other than COVID-19, and 500 CXR photographs of healthy samples. VGG16 was used as a pre-trained model in the proposed CADx system, and new data was contributed using a mixture of the mixup methodology and the traditional method. 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. When all three groups were compared, the CAD technique had an accuracy of 83.6% between patients with COVID-19 pneumonia, non-COVID-19 pneumonia, and healthy people. COVID-19 pneumonia was found to be the cause in more than 90% of cases. 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. Finally, this study was effective in constructing a useful CADx classification system for the

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three-category classification. The source code for our CADx system for COVID-19 is available to the public.

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 (Elpeltagy & Sallam, 2021) 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 utilising 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,

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which is a higher percentage than can be reached with any other approach.

Methodology

Putting an end to COVID-19, Disease has become a necessity. The quality of data-driven health management for predicting COVID-19 Disease can enhance the overall research and safety process, thereby ensuring that many individuals can lead healthy lives. Thus, Machine Learning (ML) enters the picture. We will employ ML algorithms to forecast COVID19 Disease, as ML generates accurate and straightforward predictions.

We have analyzed the COVID19 Disease patient dataset Chest Covid19 Pneumonia with the appropriate data preprocessing. In the preprocessing phase, we examined the color, size, image noise, and illumination effects Then, machine learning models with the name Resnet-50 were trained and implemented. Predictions are made using the mentioned algorithm. Each stage is described in greater detail below. The proposed method consists of six main steps and some sub-steps. COVID19 Disease. Figure 01 shows the flow chart of our methodology.

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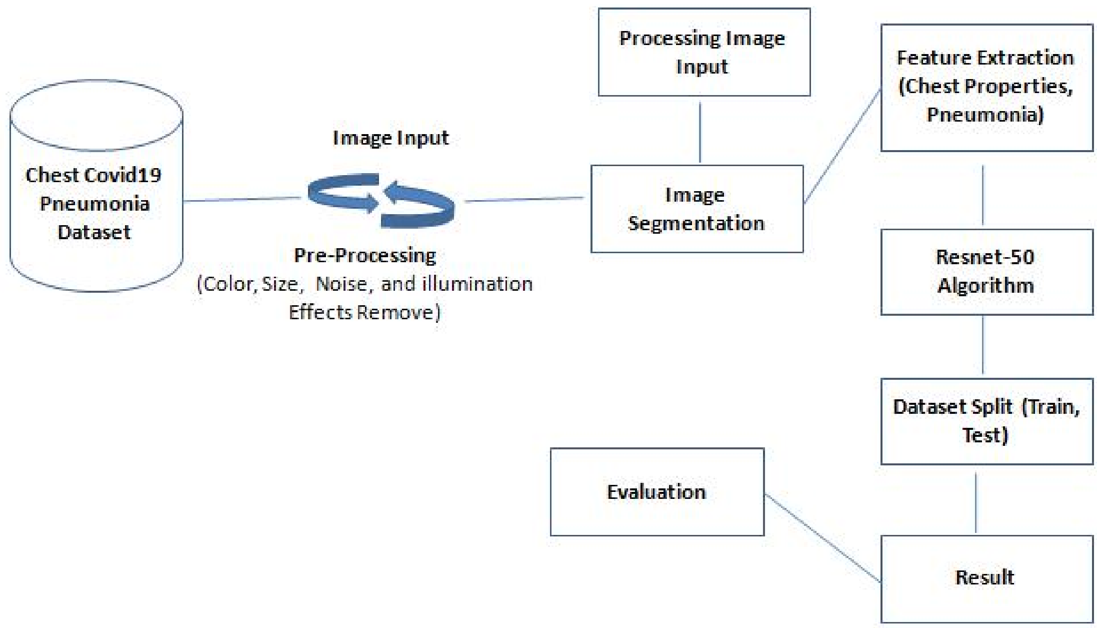

Figure 1. Proposed Methodology

Dataset Collection

We obtained the Dataset from GitHub; its name is Chest Covid19 Pneumonia. (Github: chest-x-ray-covid19-pneumonia). The corona disease dataset includes 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 (Alqudah & Qazan, 2020). 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 (Alqudah

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& Qazan, 2020). 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 2: 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**	

Dataset 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 below.

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

Pre-Processing

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. 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

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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.

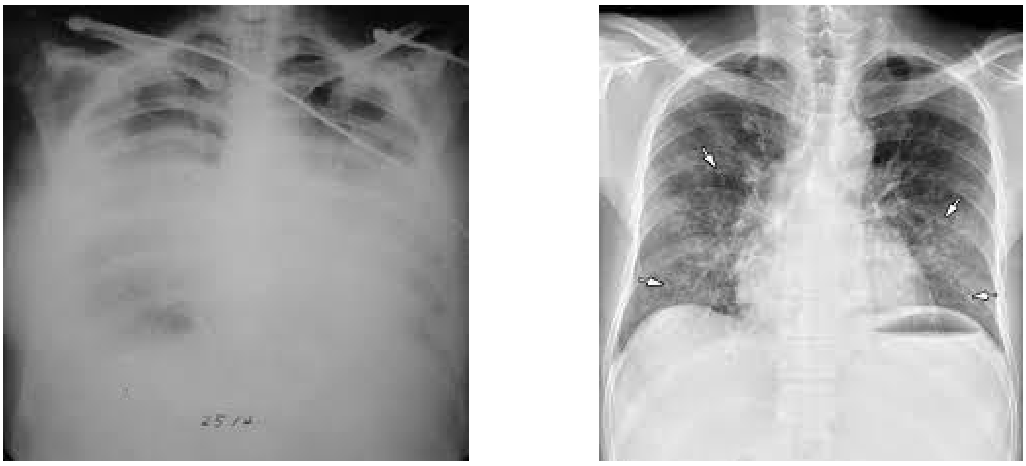

Figure 4 Before and After Pre-processing Steps

Results and Implementation

This describes the system's methodology result. An essential component of this chapter is the technique for predicting COVID-19 illness. In this inquiry, we have employed several comparisons to COVID19 symptoms to analyze and learn about distinct flare-up characteristics.

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.

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Image Pre-Processing

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.

Image Segmentation

Segmentation is used for partitioning an image into various Parts

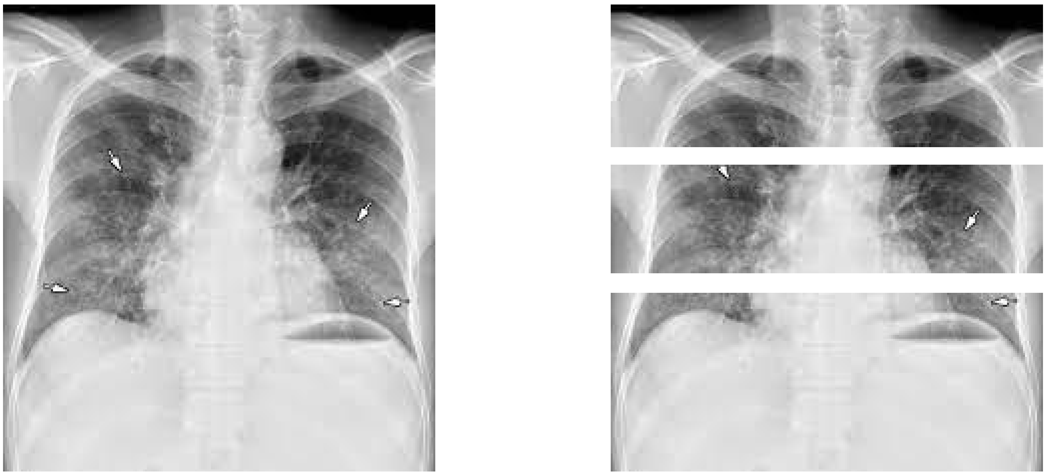

Figure 5 Sample of Image Segmentation

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

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explain a huge amount 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

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

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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.

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Materials & Methods ResNet-50 (CNN)

The first thing we do is import the libraries needed with the line of code below.

1. Tensorflow
2. Numpy
3. Torchvision Transforms

```
import numpy as np
import torchvision.transforms as transforms
```

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

Figure 7 Pre-require Libraries

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.

Hyper-parameter for Residual Network

We have the RELU activation function of each dataset, which will allow us to determine which of our training dataset's hyperparameters are the most optimal. During the training phase 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 3 Hyper parameter for ResNet-50 Model Training

Identifiers	Values
Learning Rate	0.01
Activation Function	Relu

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Bach Size	64
Epochs Size	2
Shuffle	True

Table 4: Hyper parameter for ResNet-50 Model Testing

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

Model Training ResNet-50 (CNN)

To execute the complete experiment for the classification 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%.

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. The

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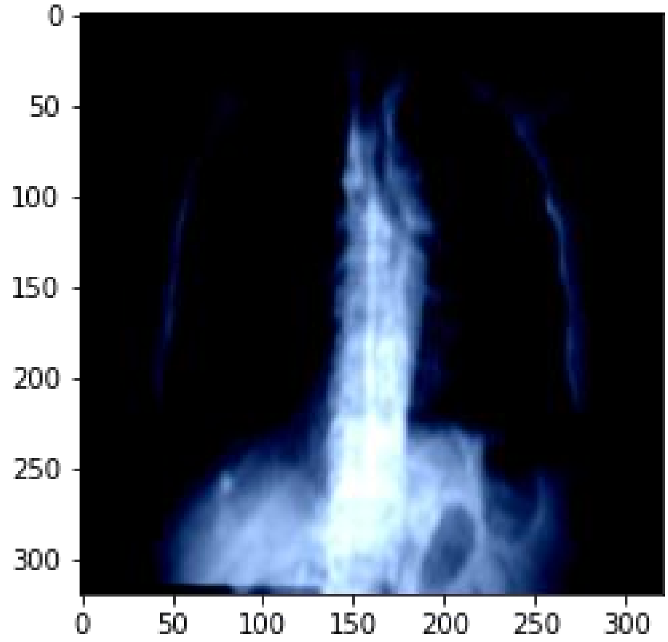

Figure 8 Purified Image

Split Dataset Training & Testing

We have utilized the Scikit package for the data splitting process, and with the assistance of the train test split header file, we have successfully split the dataset into 80:20 ratios.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 9 Split Dataset into Train and Test Group

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Figure 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 10 Model Training Result

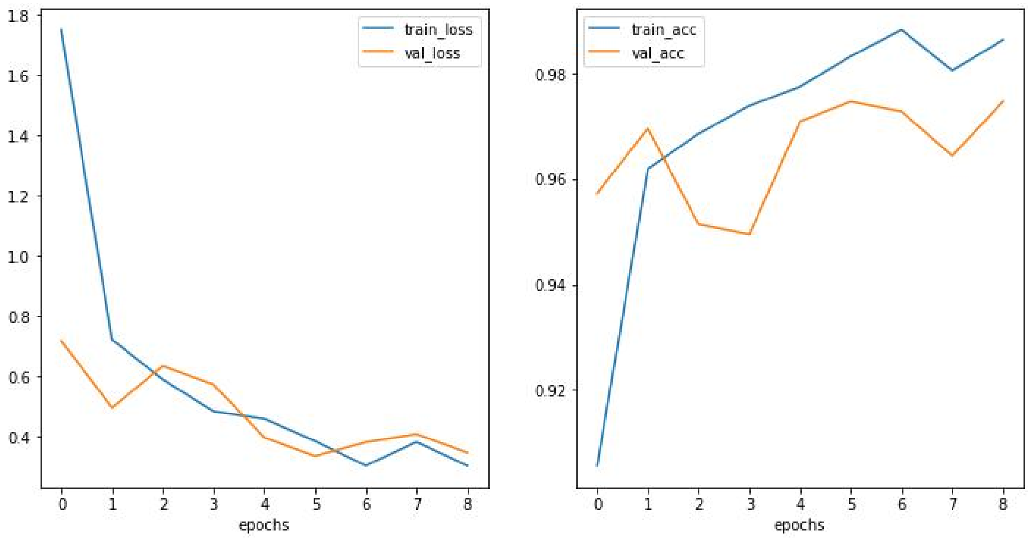

Figure 11 Model Training Loss Result

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Figure 12 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 12 Model Testing Result

Evaluation

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

Predicted Values

Actual Value	Pos (P)	Neg (N)	Total
	TrPos	**FalNeg**	**P = TrPos + FalNeg**
	FalPos	**TrNeg**	**N = FalPos + TrNeg**
Total	**P = TrPos + FalPos**	**N = FalNeg + TrNeg**	

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 13, it is verifying that the proposed image processing model work better for detecting covid disease in term of Precision, Accuracy, Recall, and F1-score.

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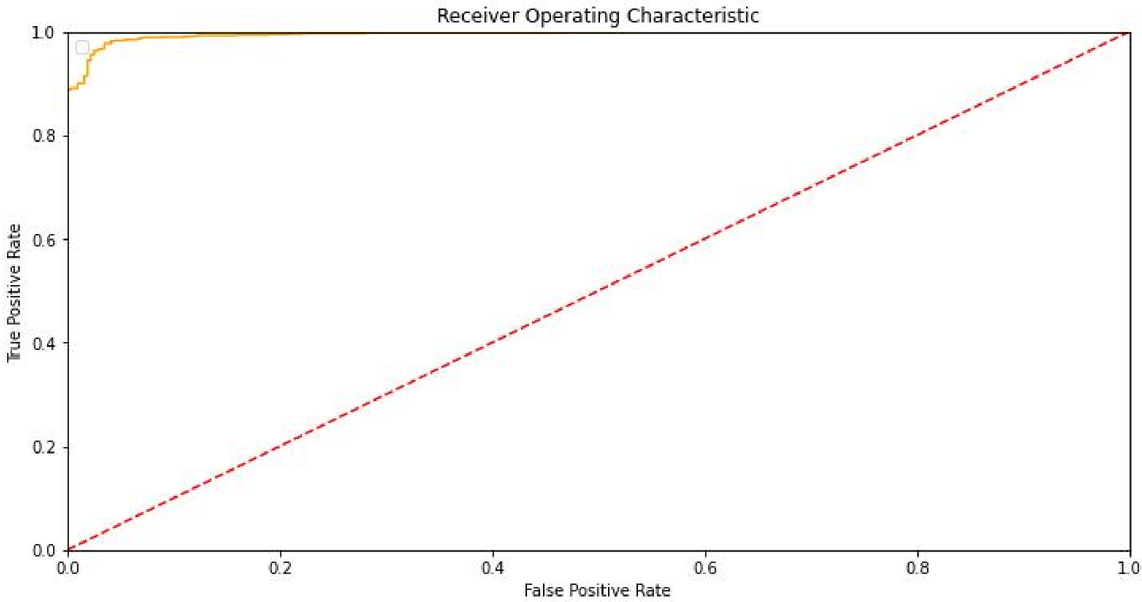

Figure 13 True Positive Rate and False Negative Rate

Discussion

Our systematic examination demonstrates the value of Machine Learning prediction algorithms for the construction of health management systems and the ease and speed of COVID-19 prediction. Disease via component analyses of data sets. Our study summarizes the outcomes of several data visualizations, particularly pneumonia infection concerning the Corona Result. We have applied many Machine Learning algorithms to a dataset to identify the most accurate algorithm. Based on our findings, we may need to identify statistically significant effects of a particular publication. Our findings illustrate the correlation between Test pneumonia and Headache, Cough, Fever, etc. for COVID-19 Disease. Residual Network - 50 has demonstrated superior performance in predicting COVID19 Disease compared to other Machine Learning techniques. However, the Resnet-50 method needs further development. This tendency is known as publication

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bias. It is challenging to exclude bias in research, although many variables indicate that it is unlikely to be significant.

Conclusion and Future Direction

Multiple statistical methodologies have been applied to our Dataset. We tested Residual Network -50. We found that Residual Network performed well. We have developed an autonomous healthcare management algorithm for predicting COVID19 Disease in patients via the use of pneumonia infection. Our proposed model will help save patients from COVID-19 Disease well no time. We have applied different types of statistical analysis using dataset attributes (Pneumonia, Normal, and COVID-19) to identify the patient's most alarming COVID19 Disease characteristics. Our predictive algorithm will aid doctors and clinicians in identifying COVID19 Disease accurately. Future research should investigate which corona type will have the most impact on human health relative to the others and what creates this kind. In addition to the Cluster Heat Map model, several types of models have been validated. Regardless, additional model applicability must still be validated. In addition, future research must study the optimal intensity of Pneumonia infection to prevent COVID-19 Disease.

Reference

1. A. Choudhury and D. Gupta, *A Survey on Medical Diagnosis of Diabetes Using Machine Learning*. Springer Singapore. doi: 10.1007/978-981-13-1280-9.
2. Khan, S. R., Raza, A., Shahzad, I., & Ijaz, H. M. (2024). Deep transfer CNNs models performance evaluation using unbalanced histopathological breast cancer dataset. Lahore Garrison University Research Journal of Computer Science and Information Technology, 8(1).

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

3. Bilal, Omair, Asif Raza, and Ghazanfar Ali. "A Contemporary Secure Microservices Discovery Architecture with Service Tags for Smart City Infrastructures." VFAST Transactions on Software Engineering 12, no. 1 (2024): 79-92.
4. S. Abhari, S. R. N. Kalhori, M. Ebrahimi, and H. Hasannejadasl, "Artificial Intelligence Applications in Type 2 Diabetes Mellitus Care : Focus on Machine Learning Methods," vol. 25, no. 4, pp. 248–261, 2019.
5. H. Kaur and V. Kumari, "Predictive Modelling and Analytics for Diabetes using a Machine Learning Approach," *Appl. Comput. Informatics*, no. December, 2018, doi: 10.1016/j.aci.2018.12.004.
6. I. M. Ibrahim and A. M. Abdulazeez, "The Role of Machine Learning Algorithms for Diagnosing Diseases," vol. 02, no. 01, pp. 10–19, 2021, doi: 10.38094/jastt20179.
7. A. Mujumdar and V. Vaidehi, "ScienceDirect ScienceDirect ScienceDirect ScienceDirect Diabetes Prediction using Machine Learning Aishwarya Mujumdar Diabetes Prediction using Machine Learning Aishwarya Mujumdar Aishwarya," *Procedia Comput. Sci.*, vol. 165, pp. 292–299, 2019, doi: 10.1016/j.procs.2020.01.047.
8. S. Brian and R. R. B. Pharmd, "Prediction of Nephropathy in Type 2 Diabetes: An Analysis of the ACCORD Trial applying Machine Learning Techniques," no. 317, doi: 10.1111/cts.12647.
9. Faruque, "Performance Analysis of Machine Learning Techniques to Predict Diabetes Mellitus," *2019 Int. Conf. Electr. Comput. Commun. Eng.*, pp. 1–4, 2019.
10. Asif, S., Wenhui, Y., ur-Rehman, S., ul-ain, Q., Amjad, K., Yueyang, Y., ... & Awais, M. (2024). Advancements and Prospects of Machine Learning in Medical Diagnostics: Unveiling the Future of Diagnostic Precision. Archives of Computational Methods in

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

Engineering, 1-31.

11. Asif, S., Zhao, M., Li, Y., Tang, F., Ur Rehman Khan, S., & Zhu, Y. (2024). AI-Based Approaches for the Diagnosis of Mpox: Challenges and Future Prospects. Archives of Computational Methods in Engineering, 1-33.
12. J. Li *et al.*, "International Journal of Medical Informatics Establishment of noninvasive diabetes risk prediction model based on tongue features and machine learning techniques," *Int. J. Med. Inform.*, vol. 149, no. August 2020, p. 104429, 2021, doi: 10.1016/j.ijmedinf.2021.104429.
13. S. G. Azevedo *et al.*, "System-Independent Characterization of Materials Using Dual-Energy Computed Tomography," *IEEE Trans. Nucl. Sci.*, vol. 63, no. 2, pp. 341–350, 2016, doi: 10.1109/TNS.2016.2514364.
14. B. Pranto, S. M. Mehnaz, E. B. Mahid, and I. M. Sadman, "Evaluating Machine Learning Methods for Predicting Diabetes among Female Patients in Bangladesh," 2020, doi: 10.3390/info11080374.
15. Shahzad, I., Khan, S. U. R., Waseem, A., Abideen, Z. U., & Liu, J. (2024). Enhancing ASD classification through hybrid attention-based learning of facial features. Signal, Image and Video Processing, 1-14.
16. A. T. Nagi, N. Ayesha, M. J. Awan, and R. Javed, "A Comparison of Two-Stage Classifier Algorithm with Ensemble Techniques On Detection of Diabetic Retinopathy," pp. 9–12, 2021.
17. H. Lu, S. Uddin, F. Hajati, M. Ali, and M. Matloob, "A patient network-based machine learning model for disease prediction: The case of type 2 diabetes mellitus," 2021.
18. Y. Sun and D. Zhang, "Machine Learning Techniques for

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

Screening and Diagnosis of Diabetes: a Survey," vol. 3651, pp. 872–880, 2019.

19. B. G. Choi, S. Rha, S. W. Kim, J. H. Kang, J. Y. Park, and Y. Noh, "Machine Learning for the Prediction of New-Onset Diabetes Mellitus during 5-Year Follow-up in Non-Diabetic Patients with Cardiovascular Risks," vol. 60, no. 2, pp. 191–199, 2019.

20. Khan, S.U.R.; Raza, A.;Waqas, M.; Zia, M.A.R. Efficient and Accurate Image Classification Via Spatial Pyramid Matching and SURF Sparse Coding. Lahore Garrison Univ. Res. J. Comput. Sci. Inf. Technol. 2023, 7, 10–23.

21. Farooq, M.U.; Beg, M.O. Bigdata analysis of stack overflow for energy consumption of android framework. In Proceedings of the 2019 International Conference on Innovative Computing (ICIC), Lahore, Pakistan, 1–2 November 2019; pp. 1–9.

22. F. Farrokhi *et al.*, "Investigating risk factors and predicting complications in deep brain stimulation surgery with machine learning algorithms," *World Neurosurg.*, 2019, doi: 10.1016/j.wneu.2019.10.063.

23. L. Math and R. Fatima, "Adaptive machine learning classification for diabetic retinopathy," 2020.

24. Farooq, M. U., Khan, S. U. R., & Beg, M. O. (2019, November). Melta: A method level energy estimation technique for android development. In 2019 International Conference on Innovative Computing (ICIC) (pp. 1-10). IEEE.

25. Khan, S. U. R., & Asif, S. (2024). Oral cancer detection using feature-level fusion and novel self-attention mechanisms. Biomedical Signal Processing and Control, 95, 106437.

26. Raza, A.; Meeran, M.T.; Bilhaj, U. Enhancing Breast Cancer Detection through Thermal Imaging and Customized 2D CNN

Spectrum of Engineering Sciences
Online ISSN
3007-3138
Print ISSN
3007-312X
SPECTRUM OF ENGINEERING SCIENCES

Classifiers. VFAST Trans. Softw. Eng. 2023, 11, 80–92.

27. Dai, Q., Ishfaque, M., Khan, S. U. R., Luo, Y. L., Lei, Y., Zhang, B., & Zhou, W. (2024). Image classification for sub-surface crack identification in concrete dam based on borehole CCTV images using deep dense hybrid model. Stochastic Environmental Research and Risk Assessment, 1-18.
28. Khan, S.U.R.; Asif, S.; Bilal, O.; Ali, S. Deep hybrid model for Mpox disease diagnosis from skin lesion images. Int. J. Imaging Syst. Technol. 2024, 34, e23044.
29. Khan, S.U.R.; Zhao, M.; Asif, S.; Chen, X.; Zhu, Y. GLNET: Global–local CNN's-based informed model for detection of breast cancer categories from histopathological slides. J. Supercomput. 2023, 80, 7316–7348.
30. Khan, S.U.R.; Zhao, M.; Asif, S.; Chen, X. Hybrid-NET: A fusion of DenseNet169 and advanced machine learning classifiers for enhanced brain tumor diagnosis. Int. J. Imaging Syst. Technol. 2024, 34, e22975.
31. IoannisKavakiotis, Olga Tsave, Athanasios Salifoglou, and NicosMaglaveras, "Machine Learning and Data Mining Methods in Diabetes Research", Computational and Structural Biotechnology Journal, vol. 15, pp. 104– 116, 2017
32. Khan, U. S., & Khan, S. U. R. (2024). Boost diagnostic performance in retinal disease classification utilizing deep ensemble classifiers based on OCT. Multimedia Tools and Applications, 1-21.
33. Khan, M. A., Khan, S. U. R., Haider, S. Z. Q., Khan, S. A., & Bilal, O. (2024). Evolving knowledge representation learning with the dynamic asymmetric embedding model. Evolving Systems, 1-16.
34. Raza, A., & Meeran, M. T. (2019). Routine of encryption in

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

cognitive radio network. Mehran University Research Journal of Engineering & Technology, 38(3), 609-618.

35. Al-Khasawneh, M. A., Raza, A., Khan, S. U. R., & Khan, Z. (2024). Stock Market Trend Prediction Using Deep Learning Approach. Computational Economics, 1-32.

36. Khan, U. S., Ishfaque, M., Khan, S. U. R., Xu, F., Chen, L., & Lei, Y. (2024). Comparative analysis of twelve transfer learning models for the prediction and crack detection in concrete dams, based on borehole images. Frontiers of Structural and Civil Engineering, 1-17.

37. Hekmat, A., Zhang, Z., Ur Rehman Khan, S., Shad, I., & Bilal, O. (2025). An attention-fused architecture for brain tumor diagnosis. Biomedical Signal Processing and Control, 101, 107221. https://doi.org/https://doi.org/10.1016/j.bspc.2024.107221