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BAYESIAN OPTIMIZATION-BASED DIAGNOSIS OF COVID-19 CHEST X-RAYS -AI PERSPECTIVE

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Keywords:

Covid-19, Artificial intelligence, prediction, Generative models

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ABSTRACT: Coronavirus is the deadliest disease globally, and no efficient treatment has been established. The prognosis of illnesses caused by virus outbreaks is a severe medical process that demands a large amount of accurate data comprised of many factors to produce an appropriate analysis. We have researched and analyzed the factors that might affect humans and increase the chances of infection with Covid-19. One of them is the breathing symptoms directly affecting the lungs and chest. To analyze the factors, we have used traditional machine learning and deep learning models to classify and predict the chances of a human getting infected with different SARs variants. So, we used a Cyclic Generative Adversarial Networks (CGANs) model, Convolutional Neural Networks (CNNs), to generate, predict and classify the Covid-19 occurrence through chest x-rays and other attributes like Diabetes and Hypertension. These models are deployed to the cloud with appropriate hypermeter tuning to use the result in real time. This paper proposed CGANs and CNNs, which automatically use ADAM, RMSprop and Bayesian optimizers to identify chest X-ray COVID-19 pneumonia images. Then, using extracted features has increased the performance of the proposed technique. The experiments suggest that the presented ADAM method fits RMSprop and Bayesian optimization achieves better accuracy. Within proposed algorithms, Bayesian optimization effectively predicts the diagnosis of covid-19 patients.

INTRODUCTION: In late 2019, the initial occurrence of Coronavirus (COVID-19) in China was recognized. An epidemic was identified as PHE Public Health Emergency) in Feb 2020 and an epidemic in Mar 2020 by the WHO. More than 183,431,558 COVID-19 cases have been reported in over 220 countries since May 2020 and more than 3,971,671 deaths have been recorded. Approximately 169,939,955 have been recovered [1].

QUICK RESPONSE CODE

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Primary care provides physicians with essential decision-making assistance using available images, including Chest X-rays (CXR). The significant benefit of CXR compared to computed tomography (CT) ensure rapid assessment and inexpensive and straightforward configuration with patients in isolation. The detection precision of CXR for identifying COVID-19 was thus poor compared to CT (radiographic assessment exactness).

This is incredibly complex to handle patients with mild symptoms at the early stage of COVID-19. This generates more inconsistency in radiologists' intra- and inter-observer data reading as assessment tools might be subtle. Consequently, a computer-aided diagnosis methodology is necessary to effectively assist radiologists in choosing to target COVID-19 [2].

The standard methods for COVID-19 are currently utilized for molecular and antigen testing in the clinic, typically with a plain CXR. The assessment is integrated to decrease the substantial number of possible negatives of such testing and confirm the prevalence and severity of the infection. The outcomes are now accessible as the process is free of inaccuracies, and radiologists probably approve of CXR interpretation due to its complexities. This study analyses a variety of deep learning-based neural network algorithms in order to provide adequate diagnosis validation.

The Artificial intelligence algorithms and CXR-associated clinical and radiomic features [3-5] are of enormous value in implementing vast identification initiatives performed in any nation where the radiograms have access to diagnostic kits and help in the fundamental analysis of COVID-19. In this situation, ML (Machine-Learning) and DL (Deep Learning) algorithms provide quick, autonomous, and efficient techniques for detecting anomalies and extracting essential characteristics of the modified pulmonary parenchyma that may connect to certain COVID-19 factors. The Chest X-rays analysis analyzes them in a predictive way to classify and predict the Covid-19 disease. The CXR approach to determine them in a prediction of the Covid-19 infection. GANs are computational structures that employ two computational models competing against one another (thus the "adversarial") to develop novel, synthesized data samples that can pass for real-world data. They are commonly utilized in image and video creation and voice formation. GANs' generated interpretations are utilized in various uses, for example, image restoration, semantic image editing, transfer of style, image super-resolution, and classifying.

The motivation of GAN is 1. Dynamic modeling 2. Problems with sensory loss functions 3. Quantification in dimensional space 4. Approaches to determine the taxonomic classification. The Adam Optimization Algorithm was recently used for deep learning methods in computer vision and natural languages, an extension of the stochastic gradient descent. Adam further uses the related topic in avoidance gradients instead of adjusting the variable training data depending on the average mean as in RMSProp. The RMSprop optimizer controls the upward direction of irregularities. Thus, an algorithm can take better measures to converge quicker in the downward motion to enhance the learning rate. Bayesian reasoning intends 'reduced error' with far more data than these techniques use to constantly evaluate the models of absolute likelihood in every after-fitness function assessment. Bayesian optimization strategies are incredibly effective since their aptitude level selects long-term hyperparameters. The fundamental concept is to choose the nearest hyperparameters to consider the goal feature fewer.

The spending time choosing further hyper-parameters is inconsistent, similar to the time consumed in the goal function. Bayesian methodologies can identify significantly improved configurations than random search in a few iterations by analyzing hyperparameters that seem more probable from prior results [6]. CXR is a simple, inexpensive diagnostic process, accessible and easy to assist in assessing persistent Coronavirus. The key objective is to evaluate and use CXR technology to predict disease seriousness, recurrence, and virus development in Coronavirus patients. The remaining paper is organized. The background on diagnostic procedures in Section 2 is presented. Section 3 The data set and technique utilized summarise the experimental setup and results in Sections 3 and 4. The discussions on the proposed method are shown in Section 5. Section 6 concludes the remark and section 7 describes the future research.

Related Work: Evaluating the accuracy of admission of CXR during a reducing phase of pandemics: identifying specific CXR characteristics exclusively related to COVID-19 contamination. Ground glass opacification, consolidation, reticular nodular opacity, excavation nodes, pneumothorax, pulmonary edema, congestion, and cardiac enlargement have been studied in each CXR. The practical applications of each CXR have been determined. Pulmonary abnormalities are common, focal or diffuse, central or peripheric in either the highest or lowest percentages. Then radiotherapists evaluated whether the COVID-19 virus was probable in CXRs. A prognostic score has been pragmatic to persistent with Coronavirus and is associated with the consequences [7]. CXR outcomes can also resemble the opacity of the ground glass and peripheral and bidirectional consolidations reported in CT scans [8, 9]. Compared with RT-PCR testing, COVID-19 identified with CXRs can produce insufficient sensitivity [10]. Where CXRs potentially recognize irregularities, many situations were reported negative by the RT-PCR investigations for those patients. In this case, the RT-PCR diagnosis cannot be replaced by CXRs but can be employed in both techniques to minimize global stress on healthcare services. CXR is considering an indication of pneumonia with better accuracy for patient screening. Also, the evacuation may expand by differentiating bacterial from viral pneumonia to save RT-PCR resources significantly. Bioinspired AI algorithms and deep learning approaches have significantly improved several domains [11–14]. It has been widely used during a disease outbreak for automatic recognition of body temperatures, mask identification, social distance observations, and strain analysis of RNA. Techniques have constantly been applied to optimize COVID-19 classifications of CXR diagnostics.

NCoV-19 is detected using the Support Vector Machine [15] and X-ray images for feature selection. Mined the intense characteristics of CNN prototypes, and everyone sequentially uses ResNet50 plus SVM in the Classification model. Computed tomography that used the VB-Net DL model is predicted in COVID-19 [16]. For evaluation, they utilized 300 images and 250 images. The diagnosis of Covid-19 has been made more accurate. A methodology for infectious diseases pathogen pneumonia Identification nCoV-19 [17] in CT pulmonary images utilizing deep learning methods. The Classification algorithm has enhanced the precision of CT scans.

The Xception and VGG16 CNN model demonstrates an early screening system [18]. The evaluations demonstrate that the VGG16 network is superior to the Xception System. The VGG16 system is far more efficient than the Xception model in categorizing CXR images. Pre-trained ConvNet models [19] Indicated for the classification of healthy and pathological CXR pneumonia, such as ResNet50, DenseNet-121, Xception, VGG-16, and DensNet-169, integrating separators made by various classes KNN (K-nearest neighbor), SVM, NB (Naïve Bayes) and RF (Random Forest) classification algorithms.

Diagnosis methods based on AI can be effective for appropriate patient care. Several investigations in literature have been described based on these techniques, although there are only significant analyses. Convolutional Neural Network (CNN) developed seven algorithms, including the VGG19 and Google MobileNet, developed CNN (Convolutional Neural Network) to evaluate Coronavirus in chest X-ray images [23]. For the diagnosis of COVID-19, an innovative (multiple input deep convolutional attention network) MIDCAN model [24] was developed. The MIDCAN technique outperforms eight cutting-edge methods. Employing the CBAM (convolutional block attention module), end-to-end MIDCAN. The authors show that combining different modalities yields better outcomes than utilizing a single mode. Also, show how CBAM may aid in enhancing diagnostic accuracy. An innovative PZM-DSSAE (pseudo-Zernike moment-deep-stacked sparse autoencoder system) is used for virus detection.

The authors were the first to use PZM to analyze COVID-19 images. Two enhancements are made: DSSAE is utilized as the classification model, and (ii) diverse data augmenting is used to generalize the classification technique [25].

METHODOLOGY: Individuals with COVID-19 who are considered becoming contaminated must understand once they have received proper treatment, self-isolation, and information about continuous interaction. A proper COVID-19 identification needs a laboratory test for samples in the snout and pharynx. This test needs a specific kit and a report for at least one day. That is inaccurate but might require an additional RT-PCR or a separate diagnostic test. The respiratory disease is COVID-19. Physicians can diagnose COVID-19 complications using CXR to anticipate RT-PCR outcomes or with a negative RT-PCR consequence and COVID-19 indicators [20].

Pneumonia Classification

1. Bacterial Pneumonia

2. Viral Pneumonia

3. Aspiration Pneumonia

Bacterial pneumonia is the most common due to the bacteria getting into the throat or lungs. Bacterial pneumonia generally results in focal lobar consolidation, which means lobes of the lungs are filled with pus or bacterial fluids, resulting in shortness of breath. Viral pneumonia is perhaps considered the most dangerous type of pneumonia as it is causing due to Influenza A or Influenza B, which are the deadliest viruses. They spread in the lungs in an interstitial pattern, so the time taken to come out of the infection might be longer than Bacterial and it may even have side effects on the other organs. Aspiration Pneumonia is caused by people's body fluids getting inside the lungs. It is rare but might be dangerous if precaution is not taken at the early stages.

CNNs: It is a method of the supervised machine learning algorithm. It comprises fully connected layers at the start of the system, accompanied by a neural net. The number of hidden layers, filters, max pool, and optimizations differs from one use case.

Convolutional neural networks are mainly used to do tasks such as image classification. The convolutional layer takes a filter and applies convolution operation on the image based on the filter size and stride. A max-pooling layer then follows this. Multiple filters are used. The convolutional filters are used for feature selection and dimensionality reduction.

Then, random weights are fed with the data processed by the Convolutional layer in a neural network with multiple hidden layers. The random weights are adjusted to minimize the error by backtracking. The backtracking is repeated until a good enough accuracy has been attained.

Convolutional Neural Network consists of

1. Filter
2. Max Pooling Layer
3. Activation Function

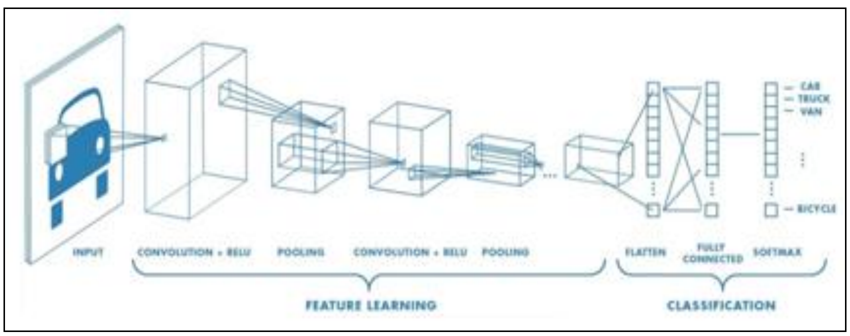

FIG. 1: FRAMEWORK OF CNN

Generative Adversarial Networks (GANs): The base concept of Generative Adversarial Networks is to train two Neural Networks to contest each other where one's gain is the latter's loss. Giving specific data to train, the algorithm learns to generate new data with the exact statistics of the training set. It was formerly anticipated as a generative model for unsupervised learning. GANs come under semi-supervised learning, supervised learning and reinforcement learning. Generative Adversarial Networks have two Neural Networks. Formerly a generator which at first is a data space of random noise. The latter is a discriminator or a classifier used to classify the data passed on to it. The discriminator's basic principle is to detect fake images generated by Generator. The Generator's basic principle is to generate images that the discriminator classifies as actual images.

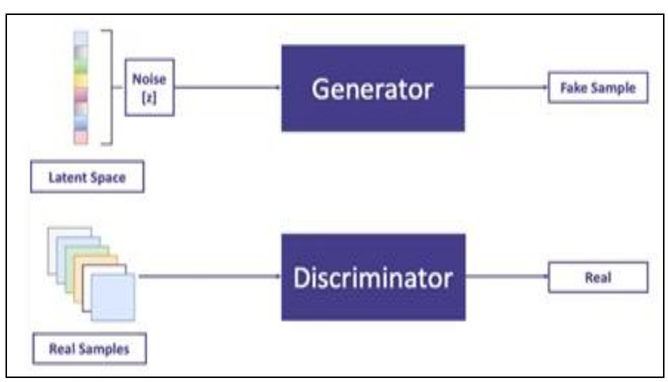

FIG. 2: FRAMEWORK OF GAN

Optimization Techniques: As optimization techniques for detecting COVID-infected x-rays from other pneumonia images, deep CNN and GAN are used by ADAM and RMSprop. There is a discussion of ADAM algorithms [21] and RMSprop [22]. Also, Bayesian optimization uses CNN and GAN to detect identities of infectious chest x-ray pictures of COVID-19.

IMPLEMENTATION RESULTS: A group of investigators created a method for training a CNN with a dataset of over 79 500 X-Ray pictures derived from various sources, with around 8,500 Coronavirus samples. Three parameters with 3 distinct pre-processing approaches have been completed to assess and analyze the predictions. The research outlines the initial stages in developing an automated diagnostic methodology that uses pulmonary X-ray images to distinguish between normal, infection and COVID-19 categories.

The objective was to see how well the data changes the outcomes and makes them more explainable. Similarly, a comprehensive investigation of many variability concerns that may jeopardize the process and its impacts are being carried out.

For implementation purposes, we collected a dataset from Kaggle. The data is divided into three files: training, testing and validation, subdirectories for every image classification (Chest infections). There are 5,863 JPEG X-Ray images and two classifications (Pneumonia/Normal).

For analysis of X-ray images, using three steps to design.

1. Data Cleaning and Segmentation
2. Data Generation and Augmentation
3. Model training and Validation

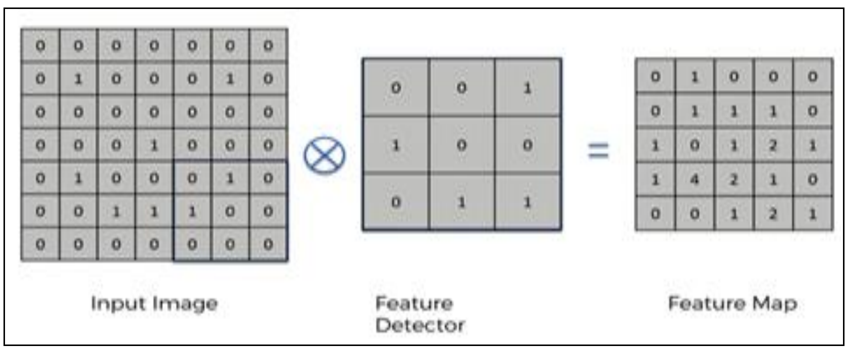

FIG. 3: CXR IMAGE FEATURE MAPPING

Data Cleaning and Data Segmentation: The implementation purpose used Kaggle API to get data from the Kaggle website where the data is presented. We have used visualization techniques using matplotlib and seaborn packages in python to view and study the data. Generative Adversarial Networks (GANs) are used to generate samples for the training to improve our validation accuracy at the production level. Generative Adversarial Networks use two systems, *i.e.*, a Generator. Which generates fake data learning from a classifier and a Discriminator, a classifier used to classify whether the data passed on to it is fake or real. Generators initially aim to create a fake image that looks approximately real and gets to be classified as an actual image by the discriminator.

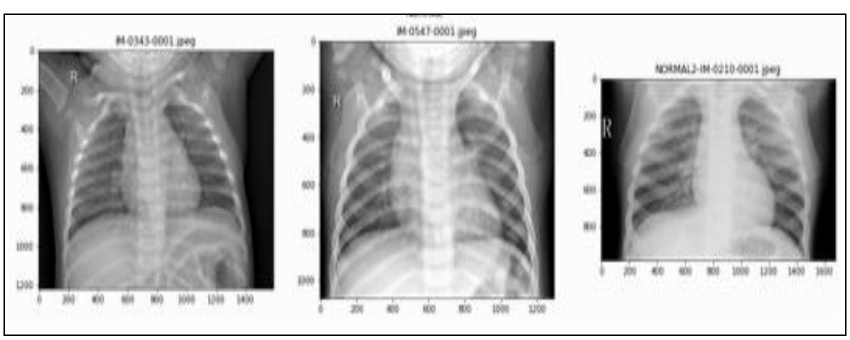

FIG. 4: THE STANDARD CHEST X-RAY IMAGES

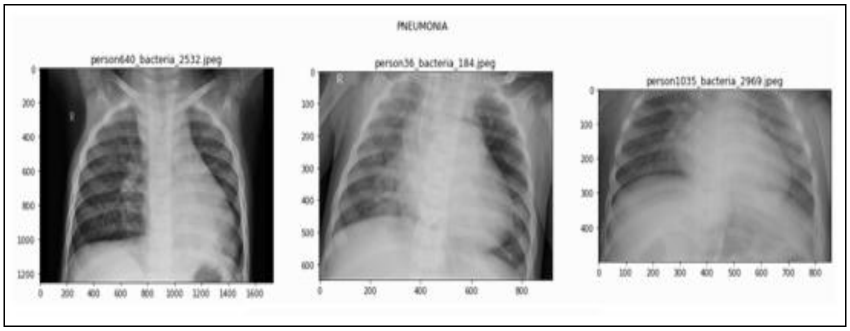

FIG. 5: THE PNEUMONIA CHEST X-RAY IMAGES

There are differences in the rib cage shape of the patient with pneumonia compared to the standard chest from the images. Somehow the x-ray returns a more precise image of an average person, and a foggy image is infected. Also, the normal chest is symmetric between the right and left parts. Know the case: The physician interprets the x-ray by checking for white lung areas that lead to pneumonia. This examination also determines whether you have any influenza issues, including infections or pulmonary edema (fluid surrounding the lungs). [Source] Infections are a significant illness. Bacterial meningitis, infectious pneumonia, mycobacterium pneumonia, and bacteria and fungi pneumonia are possibilities. This data consists of influenza samples in the first two categories.

We have taken three categories of data

1. Normal Lungs
2. Bacterial Pneumococcal Lungs
3. Viral Pneumococcal lungs

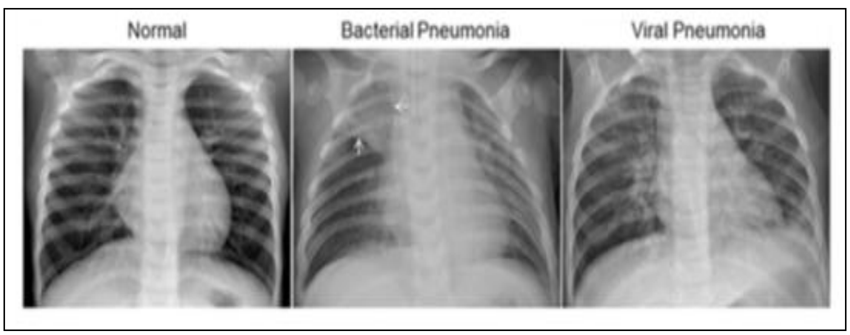

FIG. 6: THE NORMAL, BACTERIAL, AND VIRAL PNEUMONIA X-RAY IMAGES

From the pictures, I can tell you there are differences in the rib cage shape of the patient with pneumonia compared to a normal chest. Somehow the x-ray returns a more precise image of an average person and a foggy image is infected. Also, the normal chest is symmetric between the right and left parts. Know the case: After analyzing the x-ray, the physician examines for white patches in the chest (provided by the web) that indicate an infection.

This testing also determines whether a person has pneumonia-related issues, like blisters or pulmonary edema (fluid surrounding the lungs). Infection is a severe illness. It might be microorganisms' pneumonia, virus pneumonia, mycobacterium pneumonia, or fungus pneumonia. This dataset includes pneumonia instances from the first two classifications. Using Cyclic Generative Adversarial Networks for Data Generation. The training accuracy of 94% for generated data.

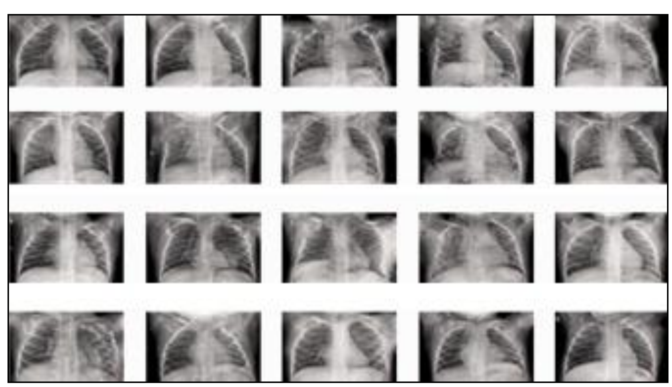

FIG. 7: DETECTION OF COVID-19 PATIENTS USING FEATURES

FIG. 8: BACTERIAL PNEUMONIA

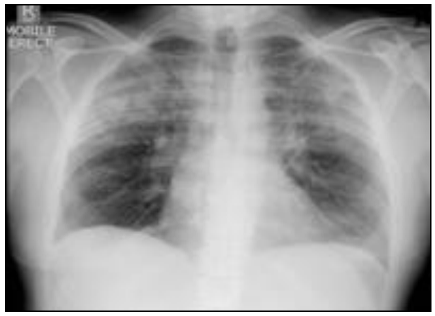

FIG. 9: VIRAL PNEUMONIA

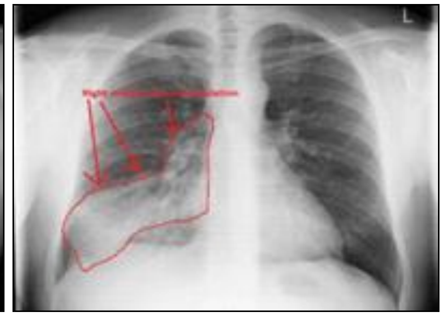

FIG. 10: ASPIRATION PNEUMONIA

In execution used, Tensor Flow Data Augmenter is to generate similar instances of an image on a virtual cache.

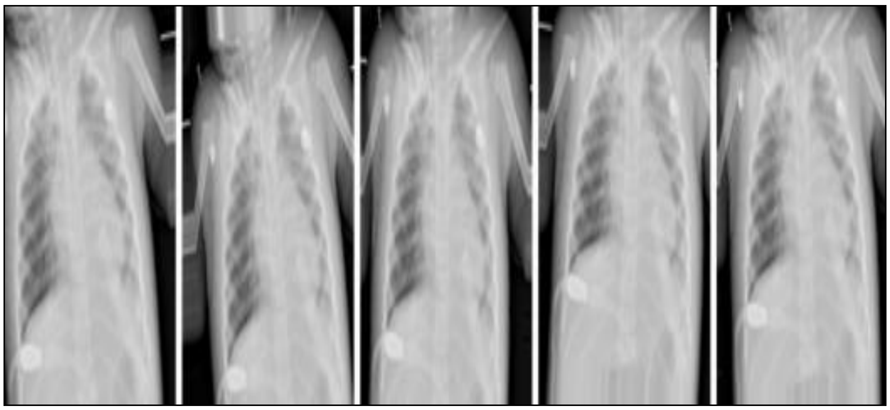

FIG. 11: THE INFECTED COVID-19 X-RAY IMAGES

To resize the image so that all images have the same form: width of 150 and height of 150, Image Data Generator augmentations might cause "bleeding" and essential crop features. The chest area is contained in the image. While in some images, the chest area fits so perfectly that even tiny slight parameters may crop them. A Neural convolutional network is used to classify the X-rays into three categories, *i.e.*, Normal, Viral, and Bacterial.

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 150, 150, 3)]	0
conv2d_5 (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d_5 (MaxPooling2	(None, 74, 74, 32)	0
conv2d_6 (Conv2D)	(None, 72, 72, 32)	9248
max_pooling2d_6 (MaxPooling2	(None, 36, 36, 32)	0
conv2d_7 (Conv2D)	(None, 34, 34, 32)	9248
max_pooling2d_7 (MaxPooling2	(None, 17, 17, 32)	0
conv2d_8 (Conv2D)	(None, 15, 15, 32)	9248
max_pooling2d_8 (MaxPooling2	(None, 7, 7, 32)	0
flatten_2 (Flatten)	(None, 1568)	0
dense_4 (Dense)	(None, 128)	200832
dense_5 (Dense)	(None, 1)	129

Total params: 229,601
Trainable params: 229,601
Non-trainable params: 0

FIG. 12: MODEL SUMMARY OF CNN MODEL

We did a comparative study using optimizers like Adam, RMSprop and Bayesian. We attain

Training Accuracy: 98%

Validation Accuracy: 92%

Working of Filters:

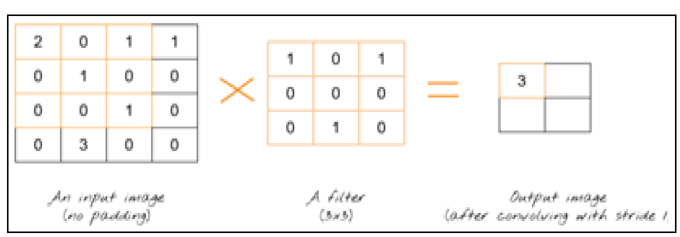

FIG. 13: FILTERING INPUT IMAGES

Working of MaxPooling Layer:

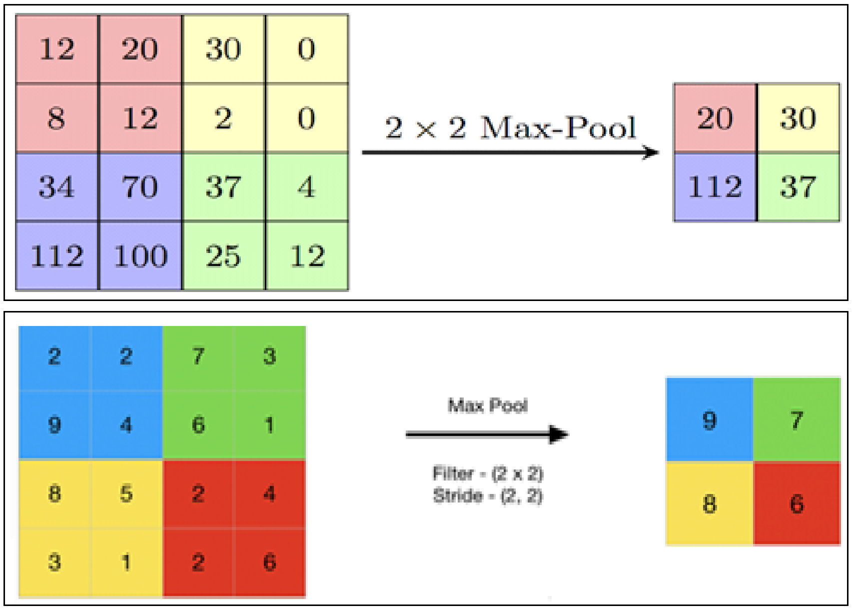

FIG. 14: 2X2 MAX-POLLING OF CNN

Total Params: 5,318,817

Trainable Params: 5,318,817

Non-trainable Params: 0

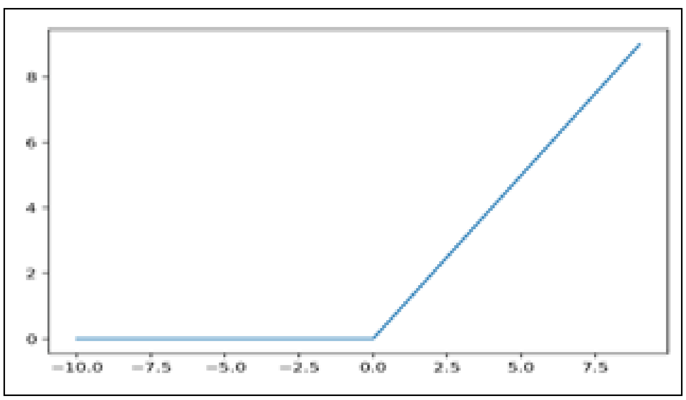

FIG. 15: RELU FUNCTION OF CXR IMAGE DIAGNOSIS OF COVID 19

Adam Optimizer:

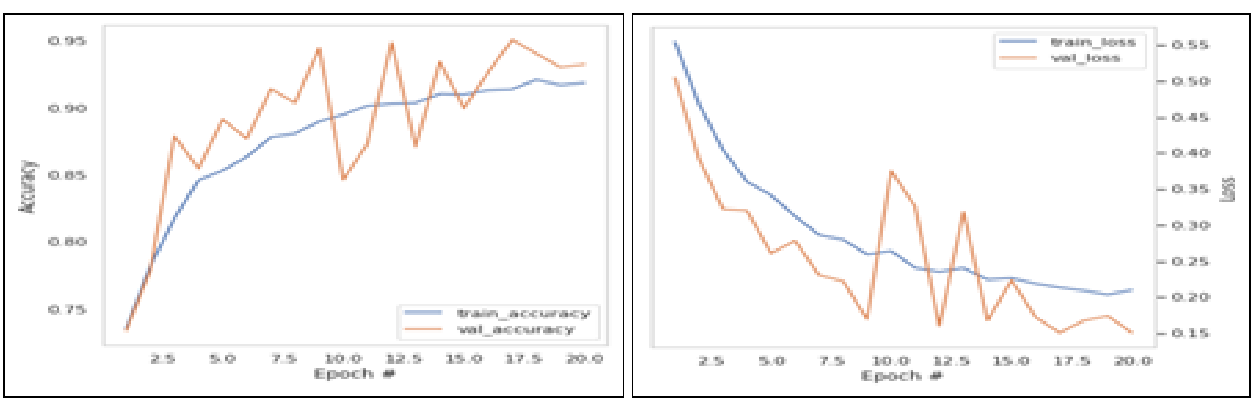

FIG. 16: TRAINING AND VALIDATION CURVE OF GAN MODEL WITH ADAM OPTIMIZER

Confusion Matrix with Heat Map:

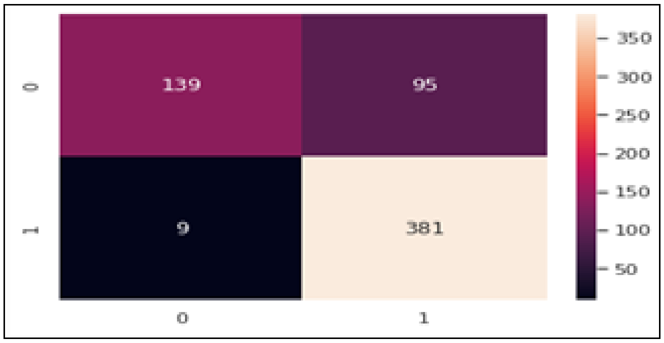

FIG. 17: HEAT MAP REPRESENTING THE CONFUSION MATRIX OF THE GAN MODEL UTILIZING ADAM OPTIMIZER

Adam (learning rate=0.001) batch=100, epoch=20. The training score seems better than a previous partitioning that contains only 16 samples of validation partition. The metrics converge in less noise. Training accuracy is good but seems overfitting since the test accuracy is around ~0.7. Since we know more than 60% of the test set is Pneumonia class, that value is not much different from predicting all images as pneumonia. The confusion matrix indicates poor precision because the model predicts the image as pneumonia.

RMS Prop Optimizer Results:

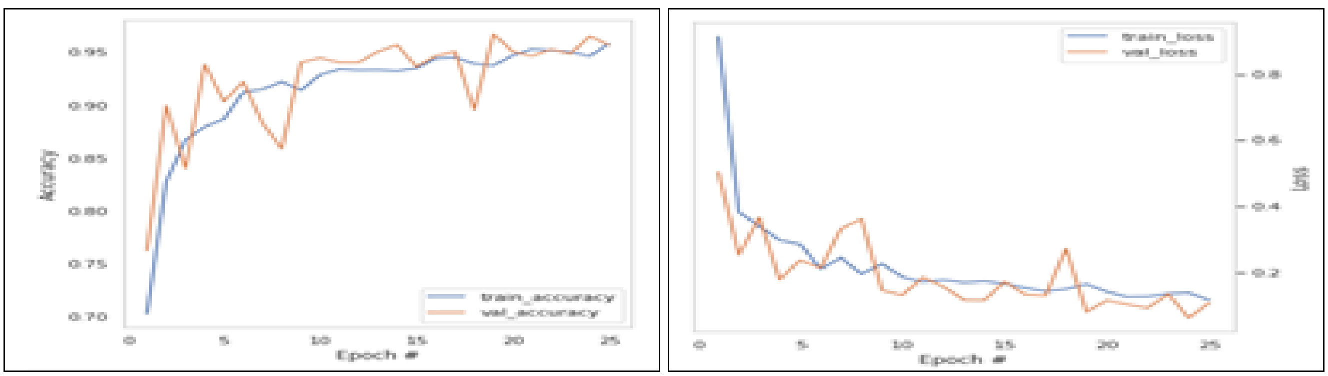

FIG. 18: TRAINING AND VALIDATION CURVE OF GAN WITH RMSPROP OPTIMIZER

Confusion Matrix with Heat Map:

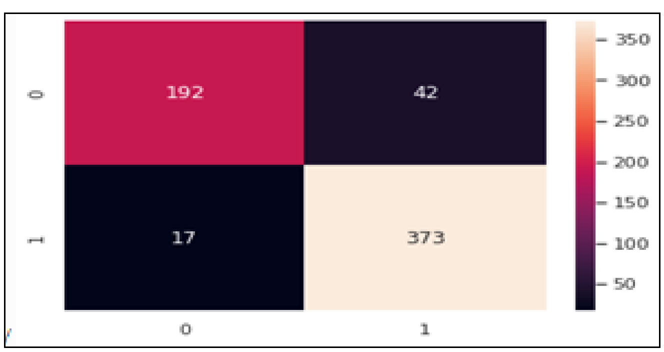

FIG. 19: HEAT MAP REPRESENTING THE CONFUSION MATRIX OF THE GAN MODEL UTILIZING RMSPROP OPTIMIZER

RMSProp (learning rate=0.0001), batch=100, epoch=20 The training way better in small learning rate and converged. The training is way better in small learning rate and converged. Should try more epochs. The test result by looking confusion matrix is also good enough to result in a low recall, Even better when the model can correctly predict 3 out of 4 images from other resources.

RMSProp (learning rate=0.00008), batch=100, epoch=25 Try more epoch with bit lower learning rate. The result is even better, but the model correctly predicts 2 out of 4 images from other resources. End here.

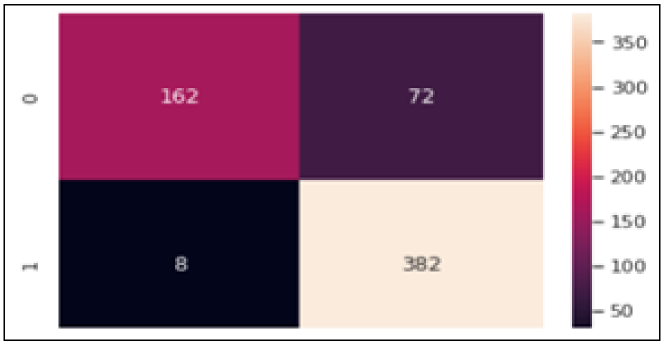

FIG. 20: HEAT MAP REPRESENTING THE CONFUSION MATRIX OF GAN MODEL EMPLOYING RMSPROP OPTIMIZATION FOR MORE EPOCHS

BO (Bayesian Optimization) for Hyperparameter Tuning, the Bayes theorem, is at the heart of BO. The Bayes theorem states that: $P(H|E) \propto P(H) \times P(E|H)$. The hypothesis is denoted by H in this case. E is the evidence. The prior probability is denoted by P(H).

The probability is denoted by P(E|H). The posterior probability is denoted by P(H|E). The aim function is employed that we are attempting to evaluate via BO. BO optimizes these functions without specifying its gradient by obtaining data samples from the hyperparameter space.

The function's evaluation at these sample points attempted to determine the optimal solution. The substitute function is this estimate of the objective function. It serves as the precedence for our objective function. When the optimal control algorithm is difficult to solve, hyperparameter tweaking is suitable for BO.

val_f1: 0.9607681035995483

Best val_f1 So Far: 0.9700961112976074

Total elapsed time: 00h 22m 36s.

TABLE 1: MODELS OF TWO CYCLES

	Model 1	Model 2
0	1	0
1	1	0
2	1	1
3	1	1
4	1	0

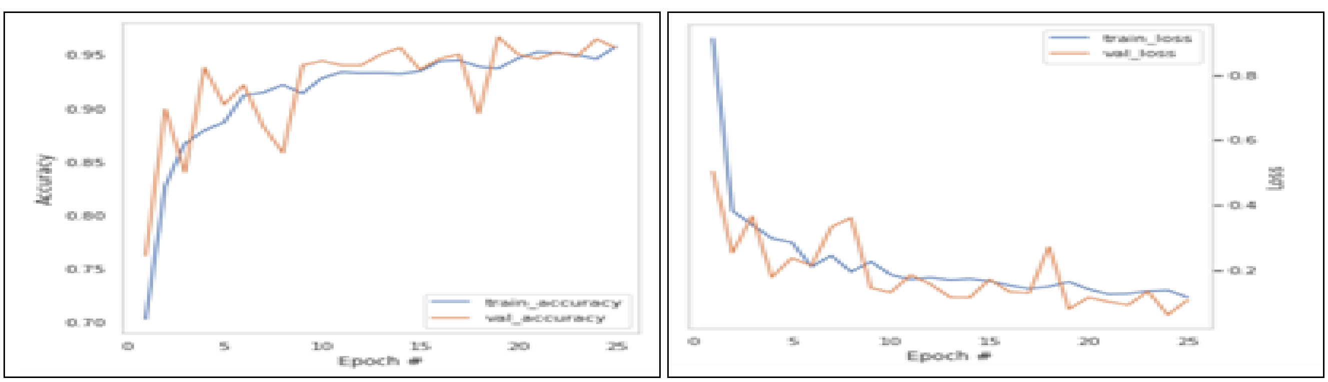

FIG. 21: THE MODEL TRAINING ACCURACY AND LOSS FUNCTION

Model Validation: We validated our prediction model using the ADAM and RMSprop optimizers utilizing Coronavirus Chest X-ray images.

It is also influential that Cyclic Generative Adversarial Networks (CGANs), Convolutional Neural Networks (CNNs) and Random approaches were utilized in the learning phase to boost the capabilities of the algorithms.

Additionally, we included global mean pooling and needed two subsequent classifiers.

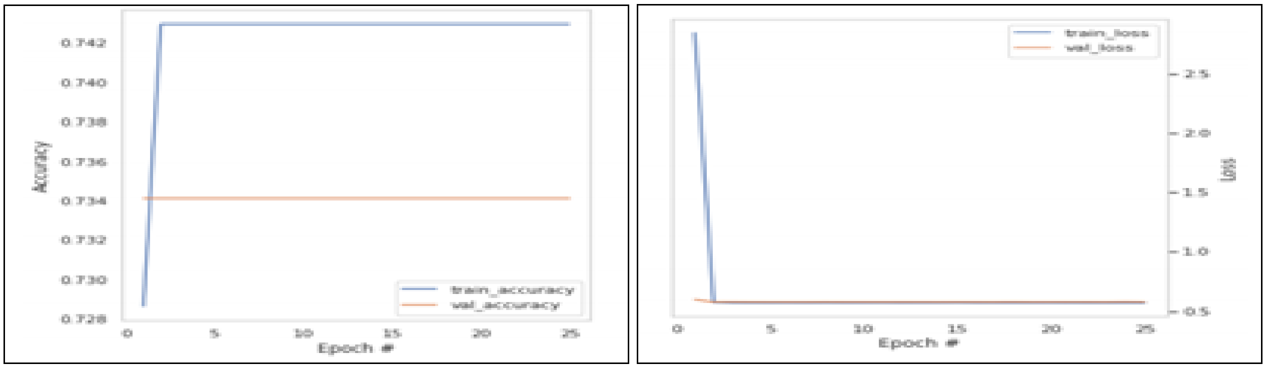

FIG. 22: THE MODEL TRAINING ACCURACY AND LOSS FUNCTION AFTER MORE CYCLES

Performance Analysis: Previously, these images were trained on Convolutional Neural Networks for predictive classification, with a training accuracy of 93% and validation accuracy of 90%. Our architecture, which includes Generative Adversarial networks and Data Augmentation, has a more efficient model with a training accuracy of 95% and a validation accuracy of 92%. The experimental outcomes can infer that proposed CNN, GAN *via* ADAM, RMSPROP and BOs attained an accuracy of 96.87%. Compared to the VGG16 utilizing the ADAM and RMSPROP optimization algorithms, BO is a deterministically acceptable approach for optimization techniques.

DISCUSSION: Designing and synthesizing computer-aided analysis techniques for consistently and effectively identifying COVID-19 using CXR images are critical for better epidemic therapy. To address this requirement, we provide with this article a multi-feature DL model for classifying CXR pictures into three types: virus pneumonia and ordinary robust patients. The research was motivated by the use of better interpretation of CXR images in order to increase the detection rate. Toward that purpose, we proposed a CXR picture-enhancing approach depending on the local process. AI may play a variety of functions in utilizing new mammography analysis by utilizing DL techniques, which include the possibility of testing, quarantining and enhancing the efficiency with which diagnostics are rendered. It can also give the radiologist a quick "second opinion" to back up the final interpretation. It can potentially be utilized to make the final diagnosis in regions where radiologists are in low supply. Imaging investigations using COVID-19 are linked with disease severity and death. AI might aid in tracking the progression of the disease and perhaps identifying those most at risk. There is a significant promise if a simple, rapid screening test like a CXR can effectively affect confinement and avoid the transmission of deadly diseases like Coronavirus early in their occurrence. The investigational results indicate that the recommended model, which employs ADAM, RMSprop, and a Bayesian optimizer, achieves high precision. Bayesian optimization within proposed techniques accurately predicts the diagnosis of covid-19 cases.

CONCLUSION: The predicted solutions and phases offered in the AI approaches assessment were appropriate for handling COVID-19 instances. The critical concerns with Coronavirus investigated were GANs, geotechnical problems, high-risk persons, perception, and radiography. These steps allow AI professionals to evaluate massive datasets and assist clinicians in training computers, setting computations, or improving the analyzed data for faster and more accurate disease management. Professionals in AI and clinicians might collaborate. In whatsoever case, it should be well recognized. AI accelerates the development of anti-Coronavirus methods. Genuine studies should occur since a thorough understanding of the merits and drawbacks of AI-based methods for COVID-19 has yet to be established. A fresh perspective is required to prepare for situations of this complexity. Defeating COVID-19 in its final demise fundamentally depends on establishing an arsenal of phases, methods, views, and tools that work together to achieve the desired goals and recognize protecting many lives.

Future Scope: This analysis and prognosis can be combined with natural languages to make a diagnostic chatbot where users can interact via language and get a prognosis for their X-ray images. This analysis and prognosis can be combined with natural languages to make a diagnostic chatbot where users can interact *via* language and get a prognosis for their X-rays' images. Covid-19 Open Dataset in Kaggle can be used to study SARs in depth using high-level NLP techniques like a transformer and large pre-trained NLP models like BERT and GPT-3. This project can leverage an open-source project of making a prognostic chatbot for AI medical consultants to classify different diseases depending on their symptoms. This research can further analyze the risk metric of patients with diabetes and hypertension and the future effects they might face if they got infected with SARs-19.

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