COVID-19 Disease Detection based on X-Ray Image Classification using CNN with GEV Activation Function

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***Abstract*—The globe was rocked by unprecedented levels of disruption, which had devastating effects on daily life, global health, and global economy. Since the COVID-19 epidemic started, methods for delivering accurate diagnoses for multi-category classification have been proposed in this work (COVID vs. normal vs. pneumonia). XceptionNet and Dense Net, two transfer learning pre-trained model networks, are employed in our CNN model. The low-level properties of the two DCNN structures were combined and used to a classifier for the final prediction. To get better results with unbalanced data, we used the GEV activation function (generalized extreme value) to augment the training dataset using data augmentation for validation accuracy, which allowed us to increase the training dataset while still maintaining validation accuracy with the output classifier. The model has been put through its paces in two distinct scenarios. In the first instance, the model was tested using Image Augmentation for train data and the GEV (generalized extreme value) function for output class, and it got a 94% accuracy second instance Model evaluations were conducted without data augmentation and yielded an accuracy rating of 95% for the output class.**

Keywords*—*COVID-19; CNN; GEV function; image augmentation

I. Introduction

In December 2019 less than four months after coming in Wuhan for the first time, the coronavirus has deteriorated into a public health calamity. As of March 30, 2021, there were 127.34 million reported diseases and roughly 2.78 million deaths on a global scale [1]. The illness COVID-19 is brought on by a virus source that irritates the lungs and makes patients develop pneumonia. These pneumonia cases are treated and medicated very differently from those caused by other viruses or bacteria. In addition to the diagnosis, specific preventative measures are implemented if a person exhibits COVID-19 signs. To prevent the infection from spreading, the COVID-19 patient is isolated for a predetermined number of days. Therefore, it is crucial to accurately and promptly identify COVID-19-related pneumonia in order to stop the virus's transmission. In the medical field, machine learning algorithms for automated diagnosis have recently gained traction as a tool for physicians [2], [3]. Deep learning algorithms have been used to correctly classify skin cancer [4], [5], Breast cancer diagnosis [6], [7]. Psychiatric disorder classification, detection of pneumonitis using chest x-rays, and image segmentation, COVID-19 is most commonly diagnosed RT-PCR is the method used here. The early detection and treatment of this condition necessitates the use of chest CT and X-ray imaging. It's still possible to find symptoms on CT scans, even with test results that come back negative[8], because the RT-sensitivity of PCRs has dropped to 70% from 60% before [9], [10]. A good approach for diagnosing COVID-19 pneumonia when paired with CT has been demonstrated [11]. CT scans are often clear for the first two days or so after symptoms start to appear. When COVID-19 pneumonia survivors underwent CT lung examinations 10 days following the onset of symptoms, the most substantial pulmonary pathology was found [12], [13]. This is a black and white picture of the body's internal organs. The X-ray is a medical diagnostic tool that has been around for a long time and is still commonly used today. An X-ray image of the thoracic cavity can detect chest infections and other lung illnesses including pneumonia, making X-ray imaging a viable alternative diagnostic method for COVID-19, in light of the present healthcare crises throughout the world. In order to create a COVID-19 case identification system based on machine learning, we specified the following goals.

- Helping radiologists and other medical professionals identify minute, slow changes in X-rays that could otherwise go undetected.
- Because radiologists are so expensive, many people in developing nations do not have access to them. They might use this technology to identify their X-ray images as pneumonia, COVID-19, or normal; to build a model to scan complex data like CT and MRI scans for COVID-19 cases.

II. Related Works

Classification and recognition jobs have been proven to be an effective machine learning method. Different deep-learning techniques have been used by researchers to detect COVID-19 in clinical pictures such chest CT scans and X-rays Alakwaa, Wafaa, Nassef, and Amr Badr [14]. For the detection of COVD-19, several of these radiological imaging techniques have recently gained popularity, The segmented CT images were initially fed straight into 3D CNNs for classification, but this proved to be insufficient. Instead, nodule candidates in the Kaggle CT scans were first identified using a modified U-Net trained on LUNA16 data (CT scans with tagged nodules). The U-Net nodule detection method had a high rate of false positives, so regions of segmented CT scans of the lungs were used to feed 3D convolutional neural networks (CNNs) to determine whether the CT scan was positive or negative for lung cancer. These regions were where the U-Net output had identified the most likely nodule candidates. The test set accuracy produced by the 3D CNNs was 86.6%.

Hemdan Ezz, Marwa A. and Mohamed Esmail [15] using 25 confirmed positive COVID-19 instances on 50 chest X-rays serve as the study's validation data. Seven distinct deep convolutional neural network designs, including the updated (VGG19) and the second version of Google MobileNet, are included in the COVIDX-Net, experiments and evaluate the COVIDX-Net, 80–20% of X-ray pictures were used for the model's training and testing stages, respectively. With f1-scores of 0.89 and 0.91 for normal and COVID-19.[16] COVID-Net was developed by Alexander Wong, Linda, Wang and Zhong Lin ,COVID-19 identification is based on a deep model that achieved 93.2 percent accuracy rate in categorizing (COVID-19, normal and pneumonia). Tartaglione, Enzo, et al .[17] For COVID-19, we advocate a combination of Deep Learning and Transfer Learning, which has been the most thoroughly studied field of research these papers examine the extent to which COVID-19 identification may be improved by modifying popular deep models. Abdul Hafeez and Muhammad Farooq [18] are two such men. COVID-ResNet, Radiograph Detection, and more there are 5941 chest images in the COVIDx dataset, and the ResNet was trained with X-ray images of varying sizes and learning rates, resulting in an accuracy of 96.23 percent using COVID-ResNet. Tzani and Ioannis D .[19] used chest X-rays with different hyper parameter settings to test 5 different models for COVID-19 detection, all 1427 X-rays showed 224 people who had Covid-19 sickness, 700 people who had confirmed common pneumonia, and 504 people who were healthy. VGG-19, InceptionNet, MobileNetV2, XceptionNet, and Inception ResNetV2 are five conventional CNN designs that have been evaluated for the job of categorizing X-rays using various model parameters like the number of untrainable layers and the top layer neural network classifier settings achieve 96.78 %, 98.66 %, and 96.46 %, respectively, are the greatest levels of accuracy. Sultan Mahmud and Kh. Mustafizur Rahman [20] used Convolutional Neural Networks (CNNs) in a deep learning model that is proposed to automatically identify COVID-19 disease using CXR (Chest X-ray) pictures. Model was trained using 10293 X-ray pictures, 875 of which were from COVID-19 instances. The collection includes three separate types of tuples: pneumonia, COVID-19, and normal cases. The empirical results demonstrate that, while using a CNN with fewer layers than those works, the suggested model achieved 97% specificity, 96.3% accuracy, 96% precision, 96% sensitivity, and 96% F1-score, which are better than the works currently available. Junaid Latief and Asif Iqba [21] Exception’s CoroNet deep neural network was used to identify and diagnose COVID-19 in chest x-ray images. ImageNet and a chest X-ray dataset generated by merging COVID-19 and other publically accessible X-ray pictures were used to train this. Accuracy was attained in the model with 98% recall and 93% accuracy in three of the COVID instances after conducting several tests (COVID vs. pneumonia vs. normal). Rajib Kumar and Sagar Deep [22] used CNN models to identify COVID from chest X-ray images, the ensembles network is comprised of three CNN networks that have been trained. There was a 91.99 percent success rate for the NASNet, MobileNet, and DenseNet. Hasan K. Naji, Hayder K, Fatlawi,

Ammar J [23] implements classifiers using both ensemble classification algorithms (Adaptive Boosting and Adaptive Random Forest). The study of the data revealed a striking correlation between the patient's age, the presence of a chronic illness, and the rate of recovery. The experimental results show that adaptive boosting classifiers perform exceptionally well, reaching 99% accuracy, while adaptive random forest classifiers scored just 91% accuracy, Mahmoud B. Rokaya, [24]. The work emphasizes the value of bioscience in identifying recovered patients from mortalities. The decision trees (DT) could distinguish between recovered patients and mortalities with 94% accuracy even with little data. A shallow dense network attained a 75% accuracy rate. However, the net reached 99% accuracy when a 10-fold approach was used with the same data. They gathered the data for this study from King Faisal Hospital. Two parameters had the highest power to distinguish between recovered patients and mortalities, according to PCA analysis. When trained using only calcium and hemoglobin, the shallow net provides an accuracy of 92%.

Convolutional Neural Networks (CNNs) are used in a deep learning model suggested by Sohaib Asif, Ming Zhao, Fengxiao Tang, and Yusen Zhu [25] to automatically identify COVID-19 disease using CXR (Chest X-ray) images. They use a model to assess the performance of various pre-trained deep learning models (InceptionV3, Xception, MobileNetV2, NasNet and DenseNet201). Second, a lightweight shallow convolutional neural network (CNN) architecture with a low false-negative rate is developed for identifying X-ray pictures of a patient. The data set used in this study includes 2,541 chest X-rays from two separate public databases that have been confirmed as COVID-19 positive and healthy cases. The suggested model's performance is compared to those of pre-trained deep learning models. According to the results, the proposed shallow CNN has a maximum accuracy of 99.68% and more importantly sensitivity, specificity and AUC of 99.66%, 99.70% and 99.98%.

III. MATERIAL AND METHODS

According to the guidelines in this section, chest X-rays should be classified as normal, pneumonia, or COVID-19. The issue with medical imaging is the lack of huge data sets. Because it isn't recommended to start from scratch and build a DCNN, the medical images can be categorized by using the features learned through a process called transfer learning [26]. The ensemble architecture suggested here will make sure that all of the descriptors needed for picture classification are there, so that the process can go smoothly. To get features from photos, a layer called "Filter" is used. These features are combined and then applied to a FC classification. We used features from two trained models as a starting point for the proposed model, with Global Average Pooling added to them. This layer is to cut down on feature length, which means that there will be fewer neurons in the last classifier input layer. This is good because it reduces the number of parameters, which makes it less likely that the network will become over fit [27]. In this section, we will list the methods used in this model.

A. Convolutional Neural Networks

A convolutional layer, which is made up of groups of kernels or filters, is the most important part of a CNN. During training, the layer parameters are learned. Filters are often smaller in size than the original image, and each filter constructs an activation map by combining with the image. The filter is moved over the image height and width, and at each spatial position we calculate the dot product between each filter element and the input. Fig. 1 depicts the convolution process. When a filter is applied to an image, the first layer of the activation map (shown in blue in Fig. 1) is formed via convolution with the image blue component. This method is repeated for each image element to create the activation map. Stacking the activation maps of each filter is used to enable convolutional layers to build their output volume along the depth dimension. The output of a neuron helps equalize each component of the activation map.

As the previous data led to the conclusion, the size of input image is equal to the size of the corresponding filter because each neuron is connected to a small local area of the input image. There are also factors that are shared by all neurons in an activation map. Because the convolutional layer has such a strong local connection, the network is forced to train filters that respond strongly to a specific portion of the input. The first convolutional layer looks for low-level characteristics like lines. The next convolutional layers look for high-level features like shapes and individual objects, as shown in Fig. 1.

B. Data Augmentation

Accumulating fresh training data from previously collected data is known as "data augmentation". It is possible to improve photographs using simple image processing methods such as padding, cropping, rotation, and flipping. In order to train neural networks, these edited photographs are added to the original collection of photos, increasing the data set size. Data augmentation is used to artificially expand the training data set [28].

Imaging and labels are regularly altered in medical images to achieve this effect. Contrary to popular belief, data augmentation is a common practise in the training industry. It is simple to generate and decrease overfitting in CNNs using data augmentation and regression. COVID Image [29] is an excellent example of an image augmentation technique that uses only a little amount of training data to create modified copies of training data sets that belong to the same class as the original images.

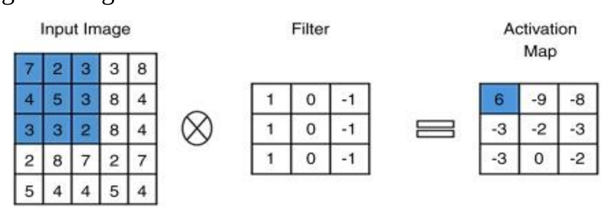

Fig. 1. Convolution Layer Sample.

The training data set is often utilized for data augmentation rather than validation or testing of the data sets. However, this is distinct from other data settings, such as pixel and image scaling. Consistency must be maintained across all datasets with which the model interacts. CNN models for deep learning have lately proved the necessity of data augmentation, since data augmentation enhances outcomes when training CNN on sparse data, but only when the augmentation procedures utilized are appropriate for each dataset [30].

There are a number of simple data augmentation strategies that are being tested. Table I shows the parameters utilized in the picture augmentation process.

C. Transfer Learning Features Extraction and Concatenation

Each layer of the CNN learns ever-more-complex filters. The initial layers demonstrate how to employ fundamental feature detection filters, such as corners and edges, to look for things. They learn how to use filters to look for parts of things, like eyes and noses. This is how the last layers work. They develop the ability to recognize complete things in a variety of shapes and orientations. For the time being, I'll briefly describe what transfer learning is and how it works. How can you train an image classifier in a few hours? Training image classification models might take many days or even weeks, depending on the size of the networks and datasets used.

As a result, why do not we use the work of dedicated data scientists working on in image classification projects at businesses like Google and Microsoft as a starting point for the image classification initiatives? Transfer learning is based on the concept of taking pre-trained models, i.e. known-weights models, and applying them to a new machine learning issue. You cannot simply replicate the model and expect it to operate, you must retrain the network using the new data. However, because the weights from earlier layers are more generic, they can be frozen for training.

Consider pre-initialized networks to be intelligently constructed networks rather than a randomly generated network. Because we are effectively tailoring the network, lower learning rates are often employed in transfer learning than in regular network training. Transfer learning may not be beneficial if high learning rates are applied and the network's early layers are not frozen. In many transfer learning cases, just the final layer or a few layers are taught. There are many free neural networks available online that can be used for transfer learning if the problem is fairly general and the user doesn't have enough data to train the network — this is common.

TABLE I. IMAGE AUGMENTATION PARAMETER USED

Parameter	Value
samplewise_center	True
width_shift	0.23
height_shift	0.22
shear	0.15
zoom	0.15
horizontal_flip	Ture
brightness	[0.4,1.5]

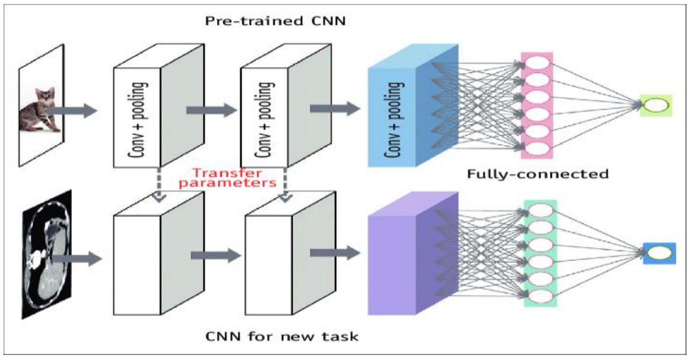

Fig. 2. Transfer Learning Model.

We may sum up this principle by saying that lower-level characteristics can be adapted to different environments by adjusting their weighting in later and fully connected layers, as we can see in Fig. 2, an example of a transfer learning model, as shown in Fig. 2.

The two-transfer model DCNN structures used in our model are described briefly below.

1) DenseNet169: In 2018, Huang et al. proposed densely linked convolutional networks, which interconnect each layer of a network in a feed-forward manner. A convolutional neural network with much more depth and accuracy was made feasible as a result of this groundbreaking achievement. Each layer of a dense network is linked directly to the next in a feed-forward method (inside every dense block). To create each subsequent layer, the feature mappings from prior layers are transferred to the new inputs.

2) xception Net: Deep detachable convolutions are used in the architecture of this CNN. A team of Google researchers came up with it. As a stepping stone between a regular convolution and a deep-separable convolution, Google has described the component units of convolutional neural networks. The input flow is the initial stop for data, followed by eight trips via the middle flow and a final stop at the outgoing flow. In addition, batch normalisation was used on all convolution and separable convolution layers in the final product.

D. GEV Activation Function

The majority of the data in a dataset is organized into a few number of classes, whereas several classes appear only sporadically. There is a considerable tail to the data in this example. Students who took classes with a larger number of students had a greater impact on their learnt traits. In this scenario, it's easier to simulate the more frequent classes than the rarer ones [31]. In both, binary and multiclass contexts, this problem exists.

When dealing with data that is very asymmetrical, with many instances in one class and few in the other, new techniques are needed. GEV distribution from extreme value theory yields a better activation function than sigmoid activation function when one class dominates the other. Binary and multiclass classification can be improved using GEV activation functions rather than sigmoid or softmax activation functions. COVID-19 and other diseases with limited training examples may benefit from this new paradigm. When one side of the training dataset is much better than the other, or when the dataset is very imbalanced. CNN may then be used to extract the pictures' characteristics. The characteristics are then reduced to a single value by a liner combination in the fully linked layer. GEV (Generalized Extreme Value) is the activation function used to transform this single value into a probability [32]. GEV activation is provided by the function.

$$GEV(x|\mu,\sigma,\varepsilon) = \begin{cases} exp\left\{-\exp\left(-\frac{x-\mu}{\sigma}\right)\right., if\ \varepsilon = 0, \\ exp\left\{-\left\{1+\varepsilon\left(\frac{x-\mu}{\sigma}\right)\quad\right\}^{-\frac{1}{\varepsilon}}\right. if\ \varepsilon \neq 0, \end{cases} \quad (1)$$

Where μ, σ, and ξ are in the deep learning framework, parameters must be learned. According to the extreme value theorem the properly normalized maximum of a sample of independent and identically distributed random variables, can only converge to the GEV distribution. To give a probability, the GEV activation rescales the values between zero and one.

The parameters, on the other hand, enable the curve to better model the long-tail distribution that occurs with extreme data [33].

E. Evaluation of Performance

The most crucial metric for assessing how well our deep learning classifiers perform is accuracy. It's the sum of true positive and negative values divided by the total value

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

Precision is a measure of how many predictions in a certain class are really in that class.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

Recall is a metric that measures how many correct class predictions might be produced given all of the data that was found to be correct.

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

The F1 score is measurement accuracy metric. The F1 score is equal to twice the ratio of the accuracy and recall measurements multiplied by the total of the accuracy and recall measures.

$$F1\ score = 2 * \frac{Precision*Recall}{Recall+precesion} \quad (5)$$

F. Data Collection

The images were captured from a number of publically available resources.

- https://www.kaggle.com/prashant268/chest-xray-covid19-pneumonia
- https://github.com/agchung
- https://github.com/ieee8023/covid-chestxray-dataset

Three sub-volumes comprises each of the two volumes ("training and testing") in which the data is organized and labelled into (COVID19, PNEUMONIA and NORMAL). Which contains 6,432 X-ray pictures make up the dataset divided as follows 1583 image as normal and 576 labelled COVID-19 and 4273 as pneumonia, which 20% of the data are test images. As seen in Fig. 3 and Fig. 4, we can see the dataset is highly unbalanced, we used GEV function to solve this problem. We plot some samples of data in Fig. 5.

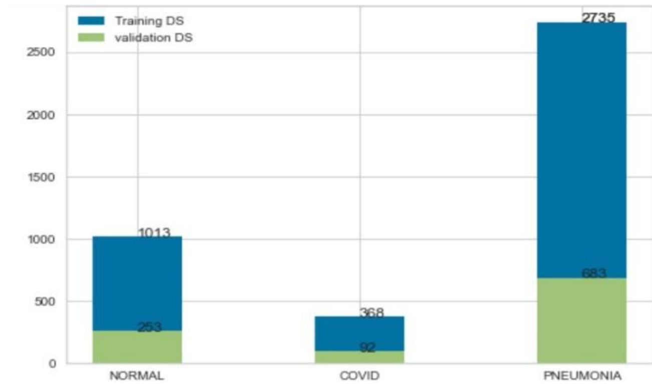

Fig. 3. Training and Validation Dataset.

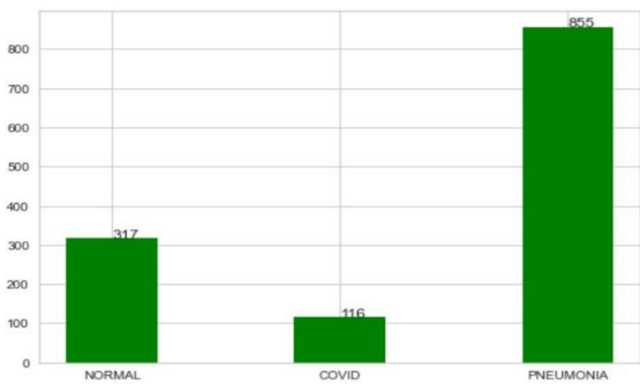

Fig. 4. Test Dataset.

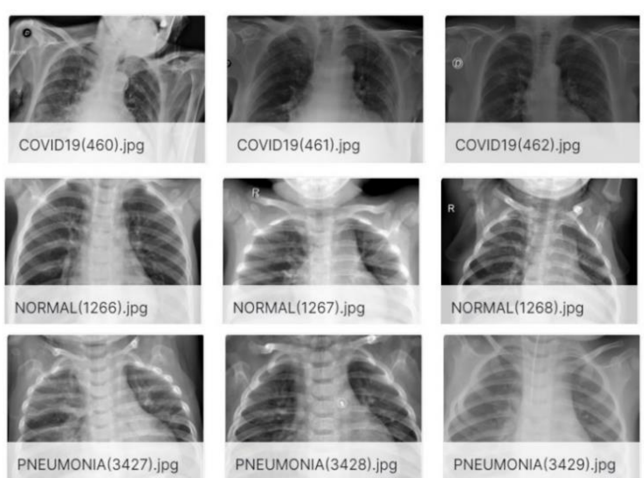

Fig. 5. Samples of Data.

IV. Results and Discussion

COVID-19 detection is the primary goal of this investigation. We used a dataset that was organized into (COVID19, PNEUMONIA, and NORMAL) instances and used our model to classify the COVID-19 by employing features derived from two separate transfer learning models using GEV activation function to accomplish our study goal. In our models, we have a three-step process. Every step of the process will be described in depth, including pre-processing, categorization, and validation. Fig. 6 depicts the suggested framework. During the classification phase, we feed the proposed model the "feature maps" generated by two previously trained models (DensNet 169 and xception Net). Filters or feature detectors are applied to the input image, and the outcomes of those operations are calculated to produce these feature maps. Based on the model's design, a variety of feature maps was generated. Table II displays the feature maps generated by the DensNet 169 model, which were [7, 7, 1664].

Using the ImageNet dataset, the input of the 224x224x3 form is sampled down to 7x7x1664 at the conclusion of the model. Table III indicates the xception Net feature maps generated, which is [7, 7, 2048] (see Table III). 224x224x3 input is down sampled to 7x7x2048 at the model's conclusion. ImageNet-trained model structure was used to create this feature. Table IV's concatenation output feature that was generated from two preview Models [7, 7, 3712], is the input to our proposed model. In the form of a feature map created by merging two previously trained models, this layer significantly speeds up deep network training and boosts neural network robustness by normalizing data between neural network layers instead of normalizing raw data. Instead of analyzing the full dataset, a flattening layer reduces the result of normalization to a single-dimensional feature vector, which aids learning by speeding up training and increasing the pace at which information is absorbed. The flattening layer combines all the pixel data from convolutional layers into a single vector.

Once the model has received the vector, it uses it as an input layer. To feed data to each neuron in our model, we utilise the flatten function, which reduces multi-dimensional input tensors to just one dimension. Flattening layer output is shown in Table IV as [3712]. When the vector data has been flattened, it is transmitted to the CNN's layers, which are referred to as "completely linked" or "dense layers," where it is processed in one of two ways. Because of these interconnections between neurons at every level, the brain may function as a single unit. It is the initial responsibility of dense layers to categories the picture using the flattened output results of convolution and pooling layers as input.

As a result, the categorization determination is ultimately driven by the completely linked layer. We used three fully connected (FC) layers, which represent the global averaged attributes of the two models utilizing three neural layers, were used to solve the classification problem. There are 128 nodes, 32 nodes, and then 3 nodes in each layer of the brain. Every FC layer has a PRELU Activation Function applied. Neurons can be activated or deactivated using an activation function. It will be determined whether or not the input from the neuron to the network is crucial, using simple mathematical approaches.

TABLE II. DENSNET 169 ARCHITECTURE

Layer	Output Shape	Parameter
Input Layer	224,224,3	0
DenseNet169	7,7,1664	12642880
Normalization	7,7,1664	6656
Global Average	1664	0
Flatten	1664	0
Dropout	1664	0
Dense	128	213120
PReLU	128	128
Dropout_1	128	0
Dense_1	32	4128
PReLU_1	32	32
Dropout_2	32	0
Dense_2	3	99

TABLE III. XCEPTION MODEL ARCHITECTURE

Layer	Output Shape	Parameter
Input Layer	224,224,3	0
XceptionNet	7,7,2048	20861480
Normalization	7,7,2048	8192
Global Average	2048	0
Flatten	2048	0
Dropout	2048	0
Dense	128	262272
PReLU	128	128
Dropout_1	128	0
Dense_1	32	4128
PReLU_1	32	32
Dropout_2	32	0
Dense_2	3	99

TABLE IV. PROPOSED MODEL ARCHITECTURE

Layer	Output Shape	Parameter
Input Layer	224,224,3	0
DensNet169	7,7,1664	12642880
XceptionNet	7,7,2048	20861480
Concatenate	7,7,3712	0
Normalization	7,7,3712	14848
Global Average	3712	0
Flatten	3712	0
Dropout	3712	0
Dense	128	475264
PReLU	128	128
Dropout_1	128	0
Dense_1	32	4128
PReLU_1	32	32
Dropout_2	32	0
Dense_2	3	99
GEV	3	7

It is common for CNNs to include a "dropout layer," a mask that eliminates particular neurons from the next layer while keeping all others intact. It is possible to apply a dropout layer to an input vector in two ways: either to eliminate part of the vector's attributes, or to delete neurons inside a hidden layer. The value [0.5] of Dropout was utilized in the first FC layer in order to avoid CNNs being unduly dependent on the training data. This implies that 50% of the neurons in the input were randomly deactivated. This model relies heavily on the learning rate parameter. The rate at which we learn determines how frequently we need to adjust the settings we're working with. The model will take a long time to converge if the learning rate is too low, because the parameters will only change by modest amounts. If the learning rate is excessively high, the parameters may hop over the low spaces of the loss function, and the network may never achieve a convergent state. The inverse is also true. Learning Rate (0.0003 to 0.00005) was the range of the steps we utilized on this model schedule. Once the model has ceased improving, this callback method will attempt to change the model by decreasing the learning rate. Up to 13 epochs of training data were utilized with the validation data (validation loss').

Using a GEV function to forecast the output class improved performance in the imbalance class, when there are a lot of samples from one class and a few from the other, but only a few instances from the other. GEV distribution from extreme value theory yields a better activation function than sigmoid activation function when one class dominates the other. Binary and multiclass classification can be improved using GEV activation functions rather than sigmoid or softmax activation functions, as shown in Fig. 6.

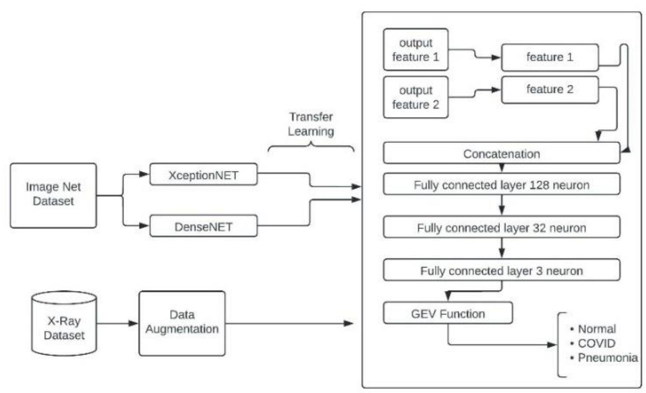

Fig. 6. Proposed Framework.

A. Results and Evaluation Model

The effectiveness of the proposed model is also compared to that of Dense Net and xception Net as single classifiers. As illustrated in Table V, to compare model output, we repeat the model without the image augmentation parameter, as shown in Table VI.

When compared to two independent models, Xception-NET and DenseNet, without augmentation, the estimated model accuracy is 95.5%, and with augmentation, it is 94% as we can see in Fig. 11. As shown in Fig. 7 and 8, DenseNet achieves an accuracy of 93.2 percent with picture augmentation and 94 percent without image augmentation, whereas Xception NET achieves an accuracy of 84 percent with image augmentation and 94 percent without image augmentation. 13 is the ideal number of epochs, as we can see in Fig. 12 based on intersection of the training line with validation line so we stopped the training model at epoch 13.

We can measure the metrics of the outcomes of our categorization investigation using the confusion matrix. The confusion matrix for the proposed CNN framework's test cases is shown in Fig. 13 with image Augmentation and Fig. 14 without, In addition, Fig. 9, 10 graphic representation of the CNN classifier performance evaluation shows loss both with and without image augmentation during the validation and training stages. Additionally, at epoch number 12, the validation and training losses attained by the suggested system are 0.1587 without image augmentation and 0.1777 with augmentation.

TABLE V. RESULT WITH IMAGE AUGMENTATION TECHNIQUE

Model Name	Precision	Recall	F1-score	Accuracy
Densnet	0.90	0.94	0.92	0.93
Xception	0.80	0.85	0.81	0.84
Proposed model	0.93	0.93	0.93	0.94

TABLE VI. RESULT WITHOUT IMAGE AUGMENTATION

Model Name	Precision	Recall	F1-score	Accuracy
Densnet	0.94	0.93	0.93	0.94
Xception	0.94	0.93	0.94	0.94
Proposed model	0.95	0.94	0.95	0.95

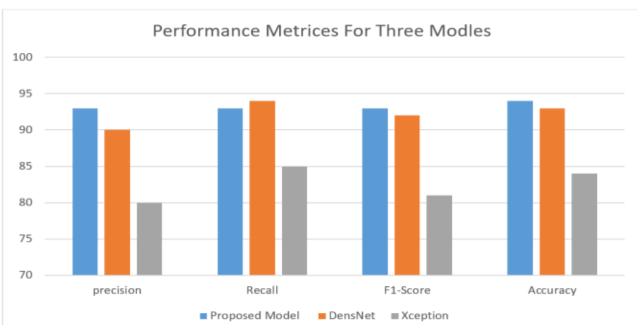

Fig. 7. Comparison of Three Model using Image Augmentation.

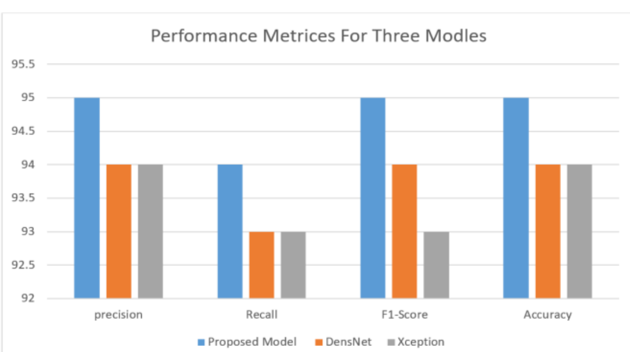

Fig. 8. Three Models are Compared without Image Augmentation.

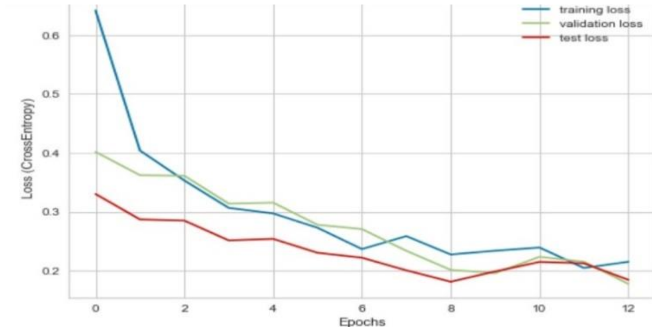

Fig. 9. Loss Value Plot with Image Augmentation.

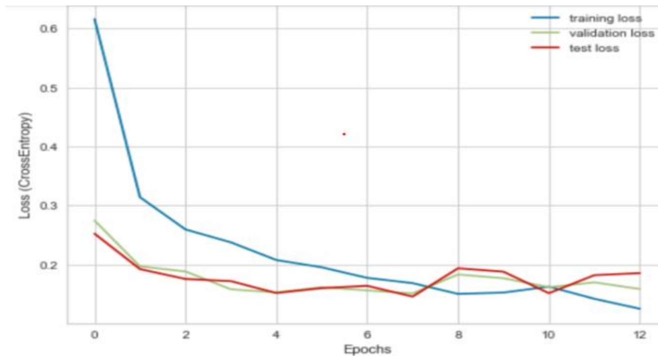

Fig. 10. Loss Value Plot without Augmentation.

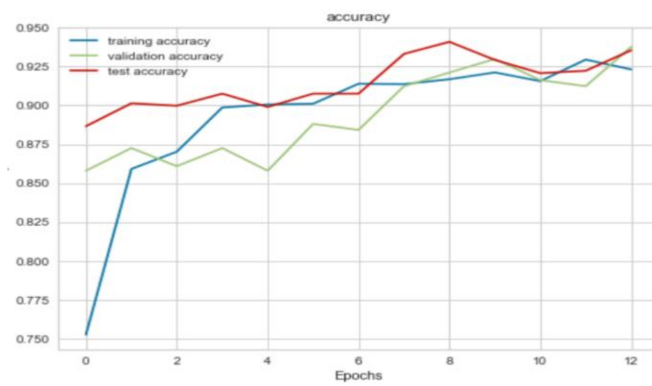

Fig. 11. Accuracy Graph of the Suggested Model's using Image Augmentation.

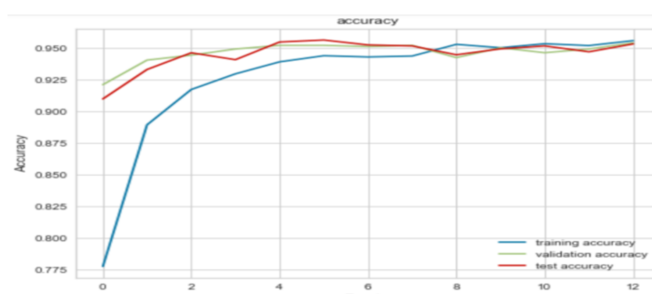

Fig. 12. Accuracy Graph of the Suggested Model's without Image Augmentation.

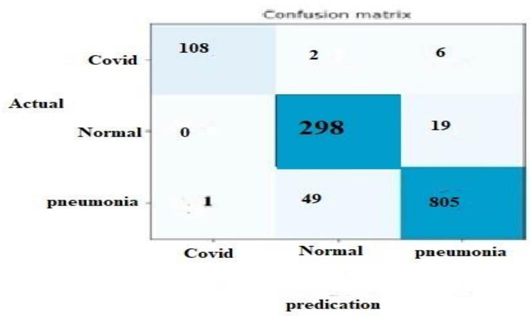

Fig. 13. Confusion Matrix of Suggested Model's with Image Augmentation.

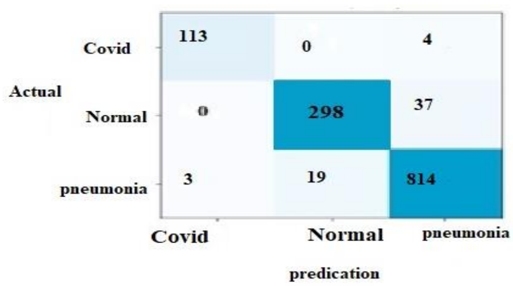

Fig. 14. Confusion Matrix of Suggested Model's without Image Augmentation.

V. Conclusion

Using the GEV activation function, For the purpose of identifying and classifying COVID-19 occurrences from X-ray images, we suggested a deep learning model using two DCNN structures. 95 percent of the time, our model is able to handle jobs that include numerous classes. To process the COVID dataset without data augmentation, our model achieved 95% accuracy in just 13 learning cycles. The GEV Function surpasses a single classifier in terms of generalization performance when features are combined from the two DCNN structures without picture augmentation. Radiologists can benefit from the suggested strategy by learning more about COVID-19's important components. Accuracy is expected to increase better with more and more training data. The following are some of the most important discoveries from this research: For effective and more accurate image categorization, CNN models require a sufficient number of images.

When employing an existing dataset with a GEV activation function, picture augmentation parameters have little impact on the performance of a CNN model.

In a statistically significant way, the suggested CNN model improves the performance of other single CNN models. The medical sector may greatly benefit from CNN-based diagnosis using X-ray imaging when dealing with large-scale testing situations like COVID-19.

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