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Analysis of AI-Based Health Solutions for Disease Detection and Treatment

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Abstract

In this research, we show how to evaluate deep transfer learning's effectiveness in creating a classifier that can use CT scan pictures to detect COVID-19-positive patients. In the study, COVID-19 cases were successfully identified with the help of deep learning (DL). As the COVID-19 viral pandemic develops worldwide, countries are adopting preventative steps. There has to be a highly sensitive and effective way for detecting COVID-19 to stop its spread. This study used COVID-19 chest X-ray pictures to demonstrate a hybrid image regrouping approach with ResNet and Densenet. The principal chest X-ray pictures were segmented and separated into tiny chunks of the lung region, and those sections were then randomly rebuilt into a regular image. The deep residual encoder block was also used to extract features from the regrouped images. In order to prevent overfitting and boost the model's generalization capabilities, data augmentation is applied to the training dataset. We looked at a series of pre-trained transfer learning models, including DenseNet and ResNet for Convolutional Neural Networks, whose increased performance we achieved by preprocessing the data with Contrast Stretching, Histogram Equalization, and Log Transformation.

INTRODUCTION

The amount and use of data in the modern world have both increased dramatically. The field of automated current diagnostics has greatly improved as a result of the use of vast amounts of data. Medical image analysis is critical for accurately diagnosing and treating diseases. Ultrasonography, positron emission tomography, computed tomography, magnetic resonance imaging, and positron emission tomography are only few of the imaging techniques utilized in medicine. All of these methods require very specialized tools. For instance, CT scanners generate CT scans by rotating an X-ray tube to collect data from multiple perspectives, and then using a computer to interpret and display that data. It's hardly shocking that abnormalities show up in CT scans given the multitude of CT scanner manufacturers (including Siemens, Fujifilm, and GE Healthcare). Furthermore, this is exacerbated by various scanning techniques, which exacerbates the problem. Figure 1.1 depicts the variation caused by multiple vendors. If a radiologist is not already trained for this change, he may need some time to adjust.

The (COVID-19)[1] Illness has spread over the globe, affecting virtually every element of human life. COVID-19 is identified utilising a variety of laboratory techniques, including (RT-PCR)[2] and isothermal amplification of nucleic acids COVID-19 is presently the most widely utilised method of detection. Because of sample contamination, damage, or virus alterations in the COVID-19 genome, there is a high rate of false alarms[3].

The disease-causing virus 19 COVID (SARS-CoV-2)[4] has had a significant impact on people and healthcare worldwide. To detect COVID-19-infected patients and provide early quarantine and therapy, advanced screening technology is required. RT-PCR is the most commonly used coronavirus screening technology, and it can detect SARS-CoV2 in upper respiratory tract mucus samples[5]. Although COVID-19 screening is highly specialized, its sensitivity varies according to the sampling method and the time frame from the onset of illness, and only a small number of studies have indicated COVID-19 sensitivity to be poor[6]. Testing results may also be delayed because RT-PCR is a laborious but necessary procedure..

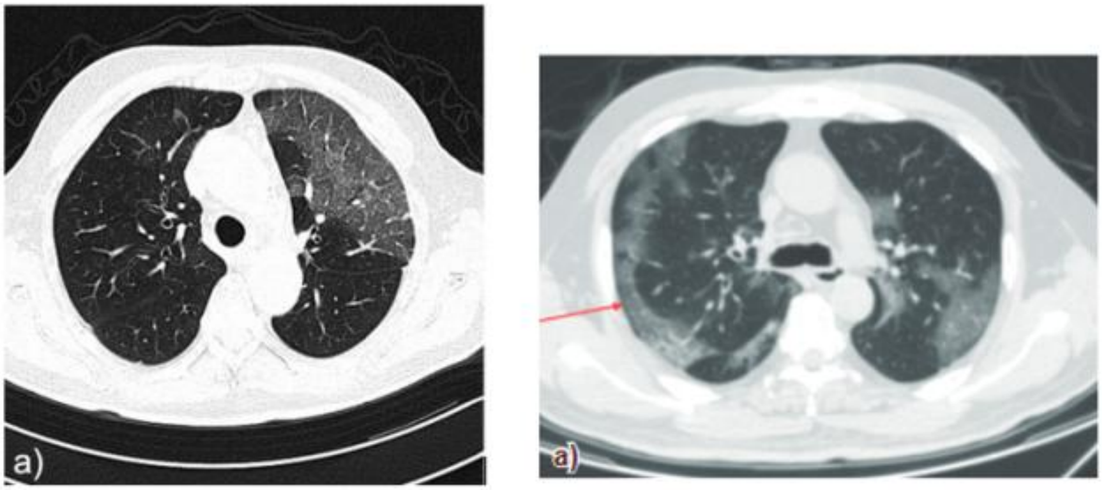

Figure 1 Variance of CT scans caused by different vendors.

Because of their great sensitivity, chest scans have been explored as a substitute screening tool for COVID-19 infection, and they may be especially successful when paired with RT-PCR testing[7]. During the early stages of the COVID-19 outbreak, CT imaging was routinely used. The use of recurrent CT scans for COVID-19 detection is limited due to cost and resource constraints[8].

The use of articles every week has recently significantly increased the use of machine learning techniques for classification jobs. Nowhere is this more true than in the realm of automatically classifying medical images. The classification of CT scans for the diagnosis of respiratory illnesses is one use of deep neural networks (DNNs) [3] in machine learning. Valid training data is required for accurate diagnosis. As a result, the earlier mentioned issue of data variance becomes more problematic. This is especially important in situations where an individual's fate may be determined by a neural network's decision. Because the classification process cannot tolerate any misclassification, the use of homogeneous training data is required.

Researchers created deep learning algorithms to automate the process of examining CT scan images and determining whether or not an individual is COVID positive. The findings of this study are encouraging, but there are two cautions. Since patients understandably prefer to keep their medical information private, there are no openly available CT-scan datasets of lungs. Consequently, this has a major bearing on research into and development of new AI algorithms for higher precision. When training models, DL approaches require large datasets in order to address the clinical necessity for outcomes. Given the current state of affairs, it looks unlikely that medical workers will be able to collect and interpret crucial CT scan data while delivering patient care. Second, because these programmes aren't transferable, the results of one hospital's trained model may not be applicable to another[9].

COVID-19, a novel coronavirus disease discovered at the end of 2019, has had a dramatic impact on the entire planet. As of April 8th, 2021, over 150 million people had been afflicted by the rapidly spreading virus, resulting in over 3 million deaths. It is still a hindrance to us now. Deep learning experts have worked long and hard to diagnose COVID-19 from images of chest CT scans and X-rays in the hopes of improving identification of the rare virus. Doctors all over the world are using real-time reverse transcription polymerase chain reaction (RT-PCR) to diagnose COVID-19 [4]. Because nucleic acids are rarely available in sufficient quantity or quality, this approach has limitations [5]. One possible side effect is the generation of false-negative results [6]. The requirement for human effort and specialized knowledge is also a hurdle. As a result, a procedure that can either automate, complement, or replace the RT-PCR test would be incredibly valuable. Using a variety of publicly available datasets, many alternative deep learning architectures have been successfully used to the precise diagnosis of COVID-19. We chose the COVID-19 classification as an example task to test our strategy to reducing cross-dataset variability (figure 1.2).

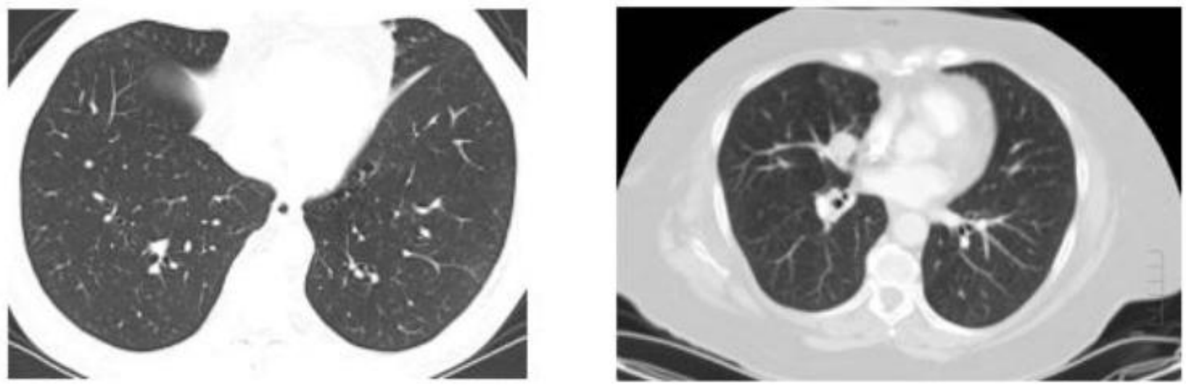

Figure 2 the difference in CT scans from public COVID-19 datasets

However, detecting coronavirus fast with high classification accuracy with minimal data remains problematic. When developing a detection algorithm, the amount of labelled data for training and the superiority of the data are two critical elements to consider. The number of chest CT images obtained for the studies from a publicly accessible dataset is restricted. Given the small amount of data, TL (Transfer Learning) is an appropriate classification method. TL—the process of transferring learned features from one task to another—is critical for maximizing efficacy with a confined dataset. The findings of TL are promising, demonstrating the efficacy of DL networks in binary classification. We did a number of experiments to see how accurate the information was[10].

Different approaches in minimizing cross-dataset variance

Many tried-and-true methods exist for handling cross-dataset variance in images. Transfer learning is one method [9]. Using transfer-learning, a model trained in one domain can be enhanced for use in another. Using this strategy, the model expands on what was learned in the first domain, simplifying the move to the second. [10] One such method to lessen the effects of data set-to-data set variation is the one described above. The goal is to supervisedly train a model across several domains, with a narrow attention to diagnostically important features.

Another approach would be to generate images with generative neural networks (such as Auto-encoder) and then train a diagnostic classifier with the generated artificial data. The following are some data mapping options:[11]

PROPOSED METHODOLOGY

Contrast Stretching (CS)

Researchers' CNN-based model was used to identify COVID-19. X-ray, CT, and MRI images have been used to test the 27-layer proposed model. In the experiments, they used 30% of the data for testing against the other dataset and 70% of the data for training. The suggested model's weighted average accuracies on X-ray, CT, and MRI are 94%, 85%, and 864%, respectively. Numerous tests show the model's value in contrast to cutting-edge efforts[74].

An image enhancement technique involves stretching variable colour values to increase the values of the processed image's current grey levels. This simultaneously adjusts each image's pixel value, making it easier to see the arrangement in both the light and dark portions of the image. Picture contrast is defined as the difference between the maximum and minimum pixel intensity. In a manner similar to histogram equalisation, this controls the uniform scale function of picture pixel values.

$$s = T(r) = \frac{1}{1+(m/r)^E} \tag{1}$$

Where r stands for the input image's intensities, s for the output image's comparable intensity values, and E for the function's slope

Histogram Equalization (HE)

An picture histogram addresses the dark stages. An image's clarity, low difference, and degree of colour separation can all be determined using a histogram. Histogram The histogram is used to equalise the image. It is used to enhance a photograph's aesthetic appeal. To do this, separate the components of a photo. The histogram is connected to measuring pixel values for the darker levels of the image's power, which ranges from 0 to 255[75].

HE is used to locate the power values and render them uniform pixel appropriation in order to obtain an improved image. In order to boost the pixel dynamic range for the image, the HE technique is applied. Simple equation for histogram equalisation –

$$E(l) = \max(0, round\left(\left(\frac{L}{N*M}\right) * t(l)\right) - 1) \qquad (2)$$

Where,

E(l)- equalized function

max- maximum dynamic range

L- no. of grey levels

N*M- the size of the image

T(l)- accumulated frequencies

Log Transformation

Log transformation is a technique for data transformation that substitutes a log for each variable x. (x). The logarithm foundation used in the study is often determined by the statistical modelling objectives. The letter ln stands for the nature log. The validity of statistical analysis results is increased when data that does not fit the bell curve is log converted to make it as "normal" as is practical. In other words, the distortion of our original data is reduced or eliminated by the log transformation. The original data must have a log-normal distribution or be somewhat near to one. This is the most important prerequisite. The log transformation won't work otherwise[76]. Here is the formula for the log transformation..-

$$s = c \log(r + 1) \tag{3}$$

The pixel values of the input and output images are s and r, respectively, while c is a constant. Since the input image's pixel intensity is o and log (o) equals infinity, each pixel's value is increased by 1 as a result. In order to make the minimum number at least one, the minimum number is raised by one.

Transfer Learning (TL)

A pre-trained neural network is trained using TL to adapt to various datasets or situations[77]. When there is not enough training data, fine-tuning from a pre-trained system may help with deep network adoption. For this project, especially for the COVID-19 class, we only have a small number of images to work with. TL is thus necessary.

Convolutional neural networks can be trained using the well-researched technique of transferring learning. In this way, the network is pre-trained using the massive database ImageNet. By importing such weights prior to installing the network in the existing design, this stage results in the development of the layer weights, which mitigates the vanishing gradient problem. This is a crucial advantage of TL since it increases goal convergence. The capability of this type of learning to extract pertinent visual elements, such as forms and edges, is another advantage. As a result, the computational time is reduced by restricting computations to the final layers of the training phase.

The network has been able to endure ResNet is a potent deep learning technology that surpasses a variety of other dense networks in terms of accuracy and computing complexity. Because of this, we were able to separate the coronavirus from other viral pneumonia infections using TL.

ResNet

The residual neural network was introduced with a novel architecture that differs from conventional CNN architectures, as seen in Figure 14. Gated units allow connections to be skipped in this system. One of its main duties is batch normalisation. The ResNet-20 is therefore able to train NN with up to 152 layers. The various layers in conventional CNNs can result in a high degree of complexity, but not with ResNet. This CNN is a top performer with a minimal complexity and a dataset error rate of just 3.57 percent[78]. Figure 1 shows the basic architecture of ResNet

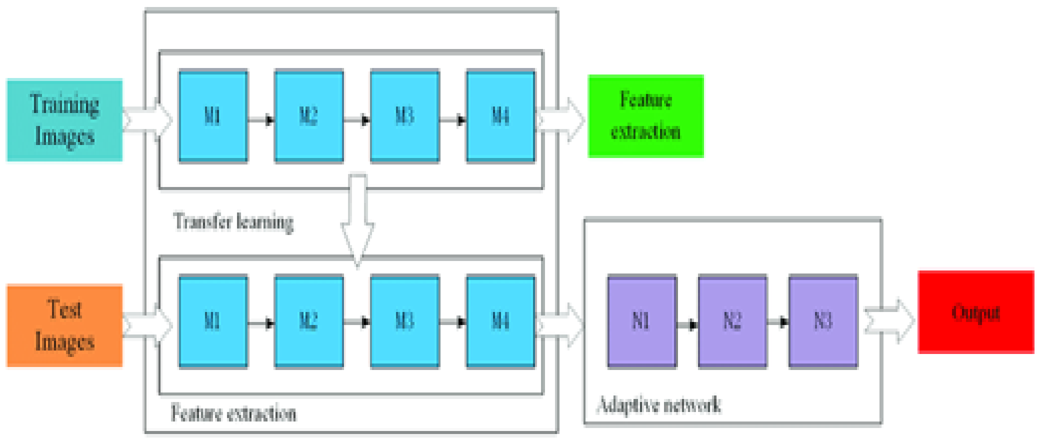

Figure 3 Figure showing the basic architecture of ResNet.

DenseNet

DenseNet is one of the well-known neural networks for detecting visual objects. Although there are a few significant differences, its architecture is comparable to ResNet's. The most crucial attributes can be extracted more easily thanks to this architecture's ability to maximise information flow throughout the network's layers. By coordinating feature map sizes across the network, the authors developed a densely connected neural network (DenseNet). They were able to link all of the layers directly to their succeeding ones as a result. DenseNet enhanced data flow across layers by utilising a number of different network designs. In contrast to many other networks, like ResNet, DenseNets combine the incoming feature maps with the layer's output feature maps rather than doing so[3]. Figure 2 shows the basic architecture of DenseNet.

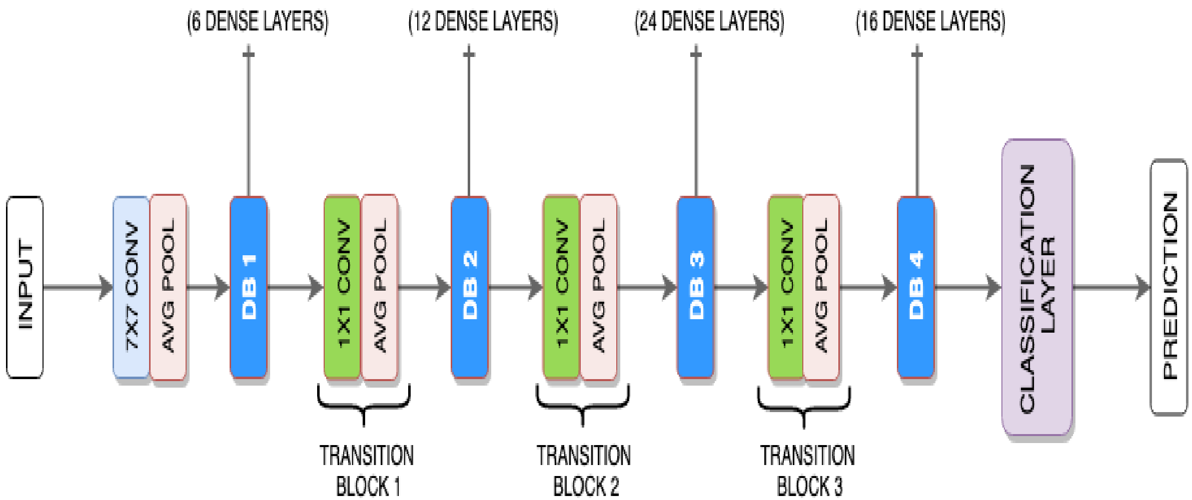

Figure 4 Figure showing DenseNet basic architecture.

EXPERIMENTAL ANALYSIS

Dataset Collection

With a total of 2482 CT scans, the trial produced SARS-CoV-2 CT-scan data. The hospitals in Sao Paulo, Brazil, provided the information. The images in this dataset are unspecified image sizes that were digitally scanned versions of printed CT scans. We employed the COVID 19 x-ray image dataset, which was divided into COVID and NON-COVID classes, with 1252 images belonging to the former and 1229 to the latter.

Data pre-processing

Pre-processing methods can help with lowering unwanted noise, identifying important portions of the image, and even the DL training step. The height and width of a picture must be resized to match the current aspect ratio. The size of all input images is minimised by the pre-processing approach of image filtering. We start by using three distinct preprocessing methods. - Equalization of the histogram

Stretching Contrasting

Transforming logs

The raw photographs are pre-processed differently by each application. The pre-processed pictures were then trained using ResNet and DenseNet models. Figure 3 displays the histogram and the original image. Figures 4, 5, 6, and 7 show the pre-processed sample image and the image's histogram after log transformation, contrast stretching, and histogram equalisation, respectively. Figures 4 and 5 also show the pre-processed sample image and the image's histogram.

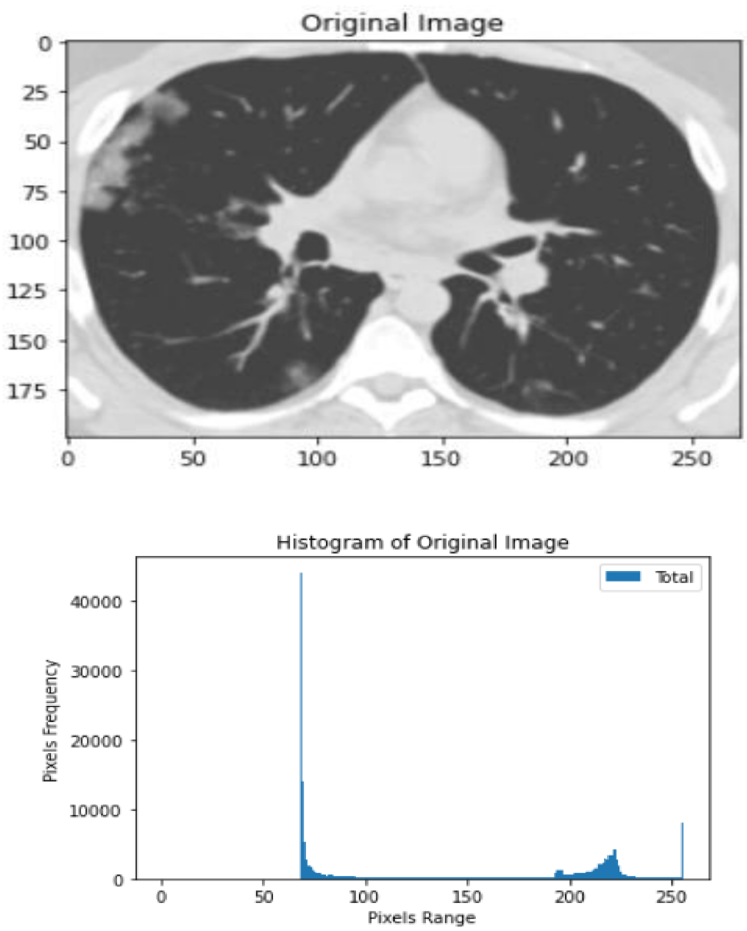

Figure 5 The figure shows the original image and the histogram of the original image.

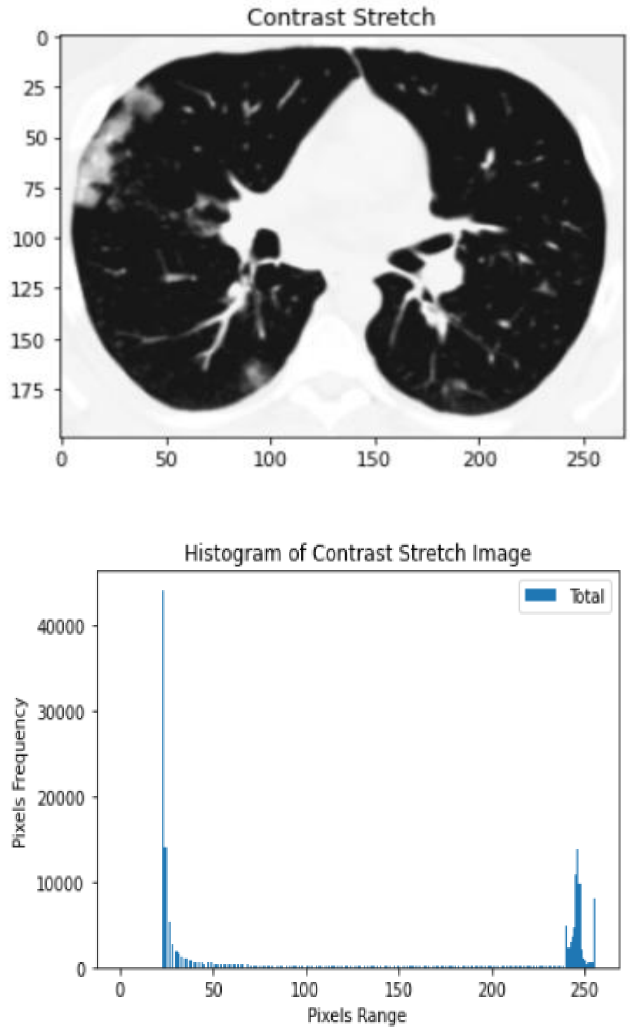

Figure 6 The figure shows the CS image and the histogram of the CS image.

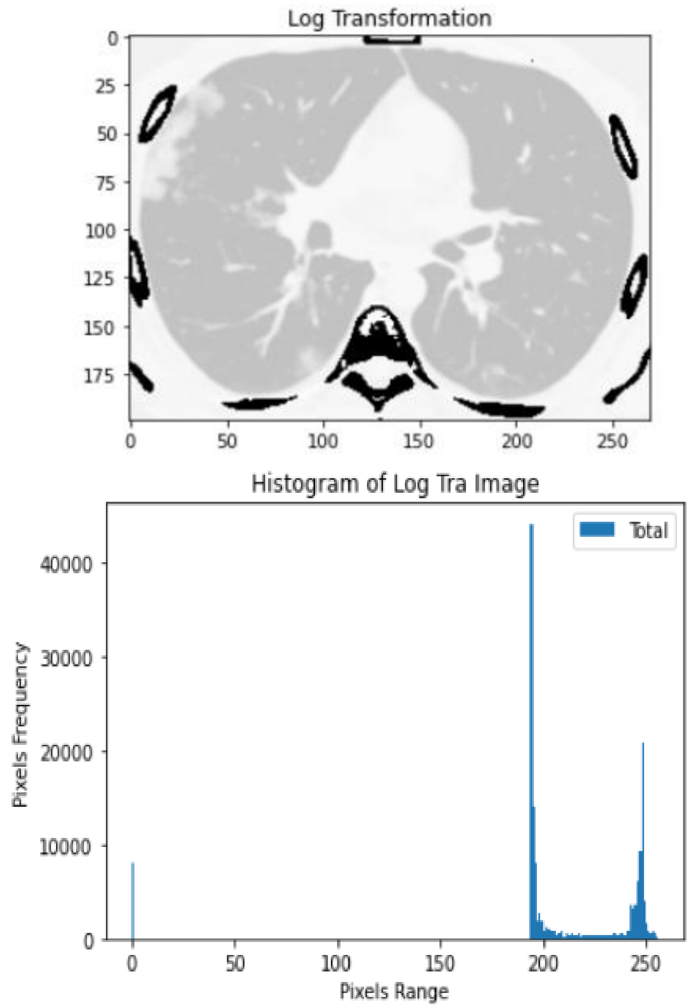

Figure 7 The figure shows the LT image and the histogram of LT image.

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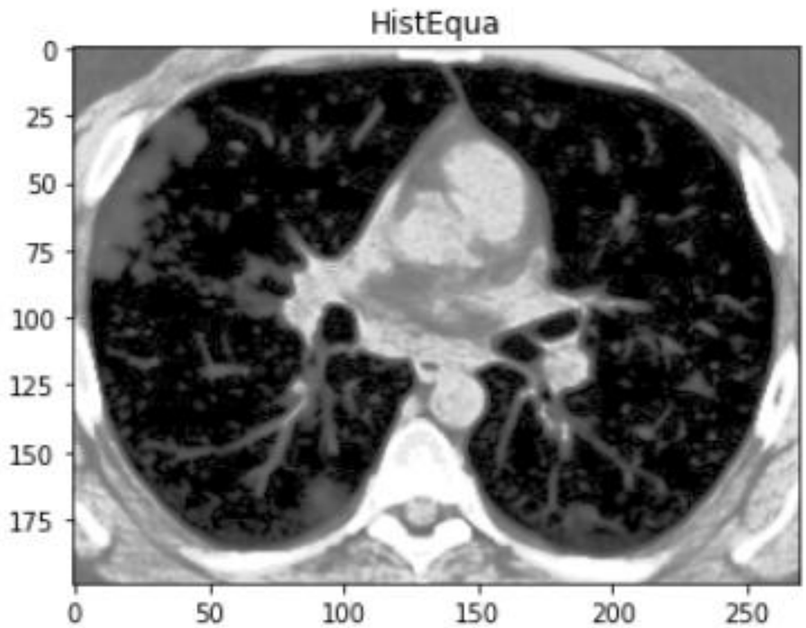


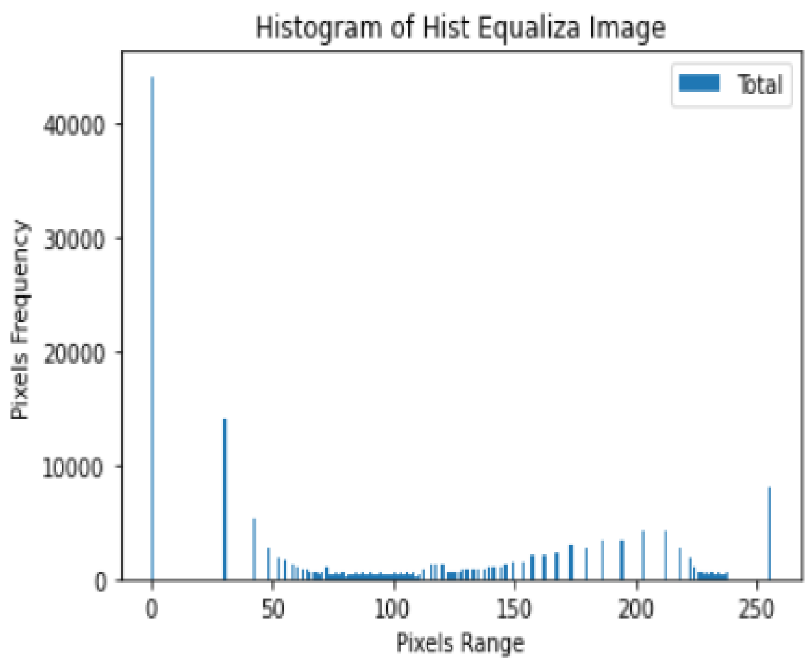


Figure 8 The figure shows the HE image and the histogram of the HE image.After pre-processing with various methods, get the final dataset ready for training with ResNet and DenseNet models. We create a data frame for every class and generate random pathways

for each shot. For the analysis of each class, the frequency histogram of each class is presented in the image.

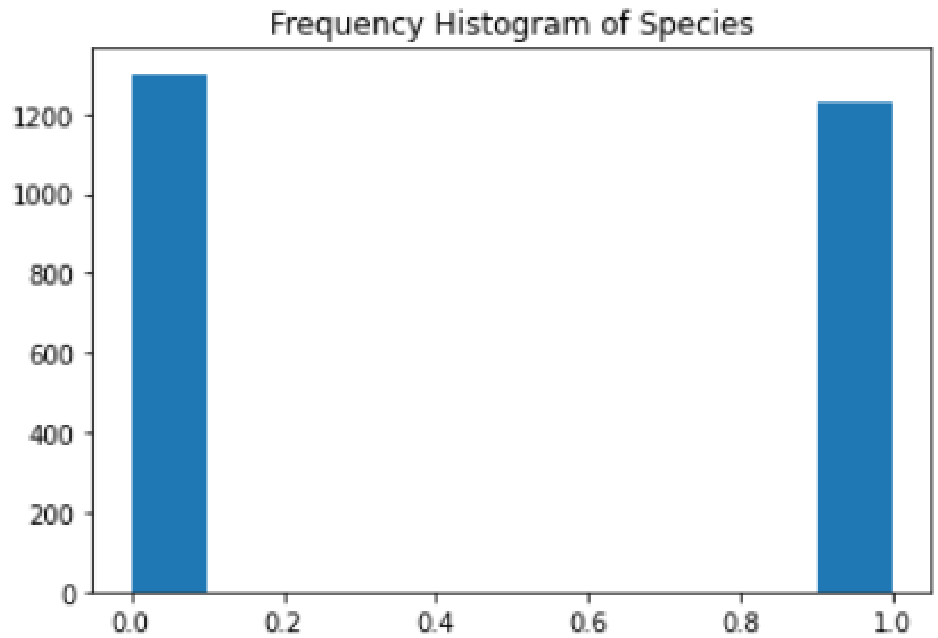


Figure 9 The figure shows a histogram of different species of classes.

Data Augmentation

It is a method for obtaining fresh data from an existing dataset. In this case, it creates jumbled copies of the existing photographs. The basic objective is to strengthen the neural network by including different diversities, creating a network that can differentiate between significant and irrelevant dataset parts. There are several options for improving images. Augmentation procedures are successfully used when data availability and quality let them. Many of the photographs had to be disregarded because they weren't appropriate for the training[79]. Image Data Generator, a novel method to create extra data from existing data, was used for batch picture loading and labelling with rotation range = 360, zoom range = 0.2, width shift range = 0.2, and height shift range = 0.2. 128*128 picture size, horizontal flip="True," and vertical flip="True."

Photos should be resized and reorganised to a height and width of 128*128 pixels for training and testing. To prepare data for training, normalise images using the pixel division method (./255), then transform them into categorical labels. Following the use of the augmentation technique, the entire set of images is trained and validated. While developing training classes, we used 80% of the dataset as a training set and 20% as a testing set.

Data that has been preprocessed using Log Transformation, Histogram Equalization, and Contrast Stretching is modelled using DenseNet169 and ResNet152. the ImageNet weight with conv2D and dropout layers, global average pooling, and an image size and shape of 128*128*3. After using the Softmax function as the output function and the Relu activation function as the input function, batch normalisation was used. Table 1 contains a list of the model parameters. Table 1 lists the parameters of the models that were used.

Model	DenseNet169, ResNet152
Weights	ImageNet
Shape	128*128*3
Layers	Conv2D, Dropout
Pooling	Global Average Pooling
Normalization	Batch normalization
Activation	Relu
Output Function	Softmax
Optimizer	ADAM
Learning rate	0.002
Loss	Categorical cross-entropy
Matrics	Accuracy,RMSE, SSIM and EKI

Performance Metrics

The degree to which a measured value is close to its true value is referred to as accuracy. The degree of closeness between all of the measured values is known as precision. In other words, accuracy is the proportion of correct categories in all classifications[39]. When a model's accuracy is greater than 90%, we also take into account the F1-score, a statistic that gives a clearer indication of examples that have been misclassified. This calculation makes use of the harmonic mean of recall and precision[40].

When a model's accuracy is greater than 90%, we also take into account the F1-score, a statistic that gives a clearer indication of examples that have been misclassified. This calculation makes use of the harmonic mean of recall and precision.-

$$MSE= \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})2 \tag{4}$$

$$RMSE = \sqrt{MSE}= \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})2 \tag{5}$$

$$PSNR = 10log_{10}(\frac{R^2}{MSE}) \tag{6}$$

R is the maximum fluctuation in the input image data type.

$$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma} \tag{7}$$

$$Num = (X+Y) \tag{8}$$

$$Den = (x^2)*(y^2) \tag{9}$$

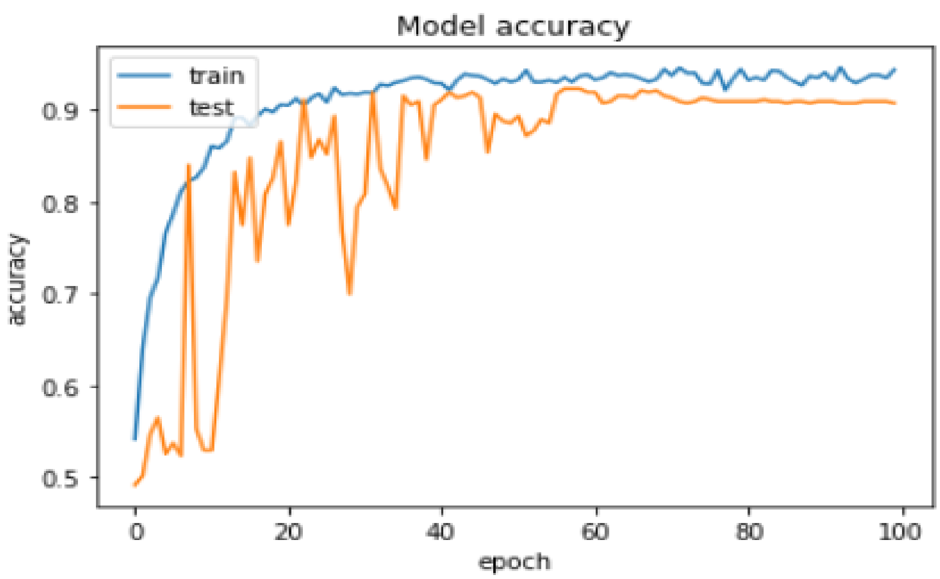
$$EKI(x,y) = \frac{Num}{\sqrt{Den}} \tag{10}$$

After training with the ResNet152 and DenseNet169 models, Table 2 displays the results of numerous strategies. As indicated in table 2, the training accuracy for the Densenet 169 model is 93.72, while the training accuracy for the ResNet 152 model is 89.80, with testing accuracy of 90.91. The edge maintaining index, rmse, psnr, ssim, and trained models for DenseNet169 and ResNet152 are shown in Table 3 with respect to epochs.

Table 2- Evaluation of results for Log Transformation.

Model	Train Accuracy	Test Accuracy	Loss	Precision	Recall	F1 Score
ResNet152	89.80	90.91	24.50	89	94	91
DenseNet169	93.72	92.69	15.61	94	91	93

The DenseNet169 model's testing accuracy for the Log Transformation technique is 92.69 percent, with 94 percent precision and 91 percent recall. The ResNet model for Log Transformation technique has a maximum testing accuracy of 90.91 percent, with precision of 89 percent and recall of 94 percent, according to the results.



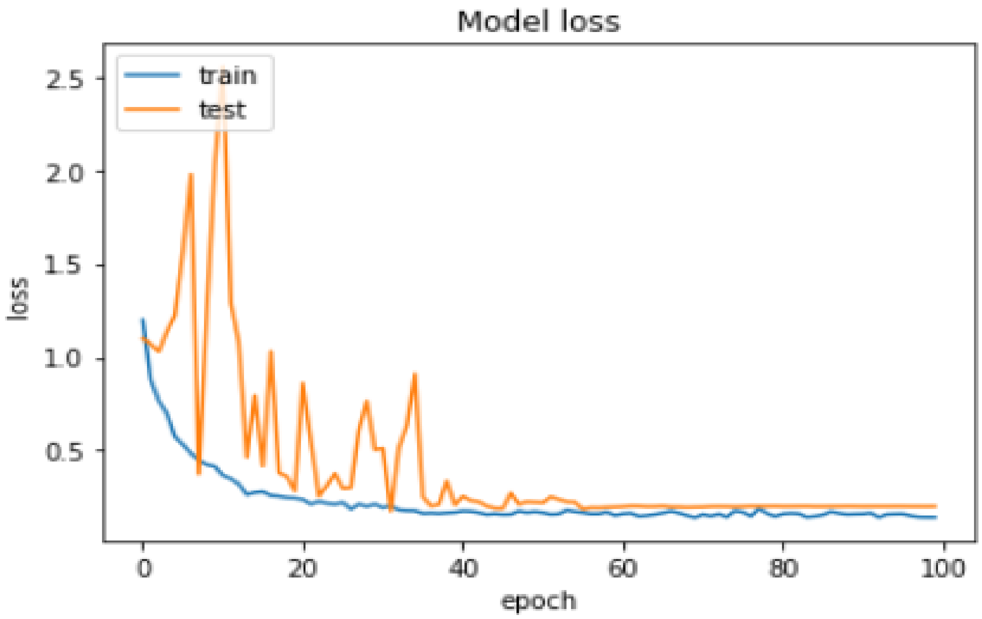


Figure 10 shows the model accuracy and the model loss graph of outcomes.

Our experimental results show that the networks we offer are accurate since they can perform extremely well in COVID detection tasks using the training accuracies. Figure displays the model accuracy graph of results.

Conclusion

COVID-19 is ongoing. More DL-based categorization and prediction models and public datasets have been generated. This research describes DL approaches for detecting COVID-19 in human lungs. These patterns classify COVID-19 and normal patients. The study employed CT scans to diagnose COVID-19. These photographs were used to train and test innovative categorization models based on DenseNet and ResNet. Computer vision relies on object classification and detection. It's an active area of pattern recognition and machine learning. For service providers and clients, forming and probing items is time-consuming. Sorting and labelling takes time. Training a large dataset takes time and resources. Picture recognition for ML can be done without any human input. This work examines picture categorization utilising a backend. Our learning algorithm uses a few thousand Fashion photographs as test and training datasets. Even when comparable pictures are scrambled, cropped, or rotated to make a totally original image for the input, the photographs are accurately identified, proving the algorithm's usefulness. The TL method has improved training and evaluating classification approaches. DenseNet169 and Resnet152 hybrid transfer learning.

Future Scope

This work lays the framework for future automatic picture classification. ML models can help sellers list products on marketplaces. Image-to-text machine learning algorithms automatically tag uploaded product photos. This can help eliminate product labelling problems, which can hurt demand because search results aren't accurate. CNN models must be combined with NLP techniques like Word2vec to predict text from visual input. Image classification can also detect fake goods. Examining a brand's logo's design, colours, and location can help discover counterfeit goods. Thanks to increases in processing power and machine learning, we may utilise a GAN to develop new fashion accessories and lessen our reliance on human ingenuity. Training a GAN model is challenging, but they could soon have commercial use in fashion.

References

[1] C. 19, “Coronavirus disease (COVID-19),” World Health Organization, 2020. .

[2] RT PCR, “Reverse transcription polymerase chain reaction,” WIKIPEDIA, 2022. .

[3] Y. Qiblawey et al., “Detection and severity classification of COVID-19 in CT images using deep learning,” Diagnostics, vol. 11, no. 5, 2021, doi: 10.3390/diagnostics11050893.

[4] SARA-COV-2, “No Title,” National Cancer Institute, 2022. .

[5] W. et al. Wang, “Detection of SARS-CoV-2 in Different Types of Clinical Specimens,” Jama Netw., 2020.

[6] Y. Yang et al., “Evaluating the accuracy of different respiratory specimens in the laboratory diagnosis and monitoring the viral shedding of 2019-nCoV infections,” medRxiv, 2020, doi: 10.1152/2020.02.11.20021493.

[7] T. Ai et al., “Correlation of Chest CT and RT-PCR Testing for Coronavirus Disease 2019 (COVID-19) in China: A Report of 1524 Cases,” Radiology, vol. 296, no. 2, pp. E32–E40, 2020, doi: 10.1148/radiol.2020200642.

[8] H. Gunraj, L. Wang, and A. Wong, “COVIDNet-CT: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases From Chest CT Images,” Front. Med., vol. 7, no. December, pp. 1–11, 2020, doi: 10.3389/fmed.2020.608525.

[9] A. Halder and B. Datta, “COVID-19 detection from lung CT-scan images using transfer learning approach,” Mach. Learn. Sci. Technol., vol. 2, no. 4, 2021, doi: 10.1088/2632-2153/abf22c.

[10] R. Sarki, K. Ahmed, H. Wang, Y. Zhang, and K. Wang, “Automated detection of COVID-19 through convolutional neural network using chest x-ray images,” PLoS One, vol. 17, no. 1 January, pp. 1–26, 2022, doi: 10.1371/journal.pone.0262052.

[11] R. Devesh, J. Jha, R. Jayaswal, M. Gwalior, and M. Pradesh, “Retrieval of Monuments Images Through ACO Optimization Approach,” Int. Res. J. Eng. Technol., vol. 4, no. 7, pp. 279–285, 2017.

[12] M. M. Krishna, M. Neelima, M. Harshali, and M. V. G. Rao, “Image classification using Deep learning,” Int. J. Eng. Technol., vol. 7, no. August, pp. 614–617, 2018, doi: 10.14419/ijet.v7i2.7.10892.

[13] J. Jha and S. S. Bhaduaria, “A novel approach for retrieval of historical monuments images using visual contents and unsupervised machine learning,” Int. J. Adv. Trends Comput. Sci. Eng., vol. 9, no. 3, pp. 3563–3569, 2020, doi: 10.30534/ijatcse/2020/162932020.

[14] R. Jayaswal, J. Jha, and M. Dixit, “Mining of Images by K-Medoid Clustering Using Content Based Descriptors,” Int. J. Signal Process. Image Process. Pattern Recognit., vol. 10, no. 8, pp. 135–144, 2017, doi: 10.14257/ijsip.2017.10.8.12.

[15] M. J. Jha, “Review of Various Shape Measures for Image Content Based Retrieval,” vol. 3, no. 6, 2015.

[16] T. Kang, “Using Neural Networks for Image Classification,” 2015.

[17] T. Jain, “Basics of Image Classification Techniques in Machine Learning,” Opengenus, 2020. .

[18] N. Sharma, V. Jain, and A. Mishra, “An Analysis of Convolutional Neural Networks for Image Classification,” Procedia Comput. Sci., vol. 132, no. Iccids, pp. 377–384, 2018, doi: 10.1526/j.procs.2018.05.198.

[19] P. Wang, E. Fan, and P. Wang, "Comparative analysis of image classification algorithms based on traditional machine learning and deep learning," Pattern Recognit. Lett., vol. 141, pp. 61–67, 2021, doi: 10.1526/j.patrec.2020.07.042.

[20] A. Anand, "Unit 13 Image Classification," Tutor. Process. Classif. Remote. Sensed Images, no. May, pp. 41–58, 2018.

[21] V. Aggarwal and G. Kaur, "A review:deep learning technique for image classification," Accent. Trans. Image Process. Comput. Vis., vol. 4, no. 11, pp. 21–25, 2018, doi: 10.19152/tipcv.2018.411003.

[22] K. S. B, "Stąpor K. (2018) Evaluating and Comparing Classifiers: Review, Some Recommendations and Limitations. In: Kurzynski M., Wozniak M., Burduk R. (eds) Proceedings of the 10th International Conference on Computer Recognition Systems CORES 2017. CORES 2017. Adv," vol. 1, no. May 2017, 2018, doi: 10.1007/978-3-319-59162-9.

[23] V. Nigam, "Understanding Neural Networks. From neuron to RNN, CNN, and Deep Learning," Analytics Vidhya, 2018. .