

Prediction of multi - lung disease

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Abstract: A completely unique coronavirus effect event has emerged as a virus poignant public health globally. Screening of huge numbers of people is that the would like of the hour to curb the unfold of malady within the community. Real- time PCR may be a commonplace diagnostic tool getting used for pathological testing. however the increasing variety of false check results has opened the trail for exploration of other testing tools. Chest X-Rays of COVID-19 and respiratory disorder T.B. and respiratory illness Chronic patients have verified to be a vital various indicator in Diseases screening. But again, accuracy depends upon imaging experience. A diagnosing recommender system which {will that may} assist the doctor to look at the respiratory organ pictures of the patients will scale back the diagnostic burden of the doctor. Deep Learning techniques specifically Convolution Neural Networks (CNN) have tried prospering in medical imaging classification. Four totally different deep CNN architectures were investigated on pictures of chest X-Rays for diagnosing of malady. These models are pre-trained on the keras and tensor flow Image internet info thereby reducing the requirement for big coaching sets as they need pre-trained weights. it had been ascertained that CNN based mostly architectures have the potential for diagnosing of malady.

Keywords: Coronavirus; Convolution Neural Networks; Keras; TensorFlow; X-ray pictures.

1. Introduction

They have an impression on of illness on health is quickly increasing because of alterations to the atmosphere, international international world temperature change, lifestyle, and various factors. This has enlarged the prospect of condition. about 3.4 million people died in 2016 because of chronic impeding pulmonic malady (COPD), affected usually by pollution and smoking, whereas 400,000 people depart this world from respiratory disorder [1,2].

Since COVID19 has been in toll for quite whereas, we've modified our project pipeline thereto and wished to create impact to the community through the appliance in a way or the opposite wherever ready to} able to check if the person is COVID19 positive or not, a minimum of for a few half it simply need to check the patients in a lot of safer version, this prevents the patient to travel to hospital for a medical checkup wherever there square measure multiple patients inflicted by COVID19 instead they will take a scan and transfer into our platform. Currently, AI victimisation deep learning plays a very important role within the medical image space because of its glorious feature extraction ability. Deep learning models (DLs) accomplish tasks by mechanically analysing multi-modal medical pictures. laptop vision refers to victimisation DLs in process pictures or videos and the way a laptop would possibly gain data and understanding from this technique. Advanced computer-aided diagnosing schemes square measure principally supported progressive strategies, like totally convolutional neural networks (FCNNs) [6], VGGNet [7], ResNet [9], Inception [9], and Xception [10]. Some samples of the appliance of AI embrace cancer detection and classification [11], the diagnosing of diabetic retinopathy [12], multi-classification of multi-modality skin lesions [13], polyp detection throughout endoscopy [14], etc. Since COVID-19 has become widespread, several researchers have dedicated their efforts to the appliance of machine vision and deep learning within the diagnosing of the malady supported medical pictures and have achieved smart results. They projected a model that uses DarkNet as a classifier and obtained a classification accuracy of 98.08% for binary classification (COVID-19 vs. no findings) and 87.02% for multiple classifications (COVID-19 vs. no findings vs. pneumonia). [15] They projected a deep model supported the Xception design to discover COVID-19 cases from chest X-ray pictures, that achieved associate overall accuracy of 89.6% and a recall rate for COVID-19 cases of ninety three in classifying COVID- nineteen, healthy conditions, microorganism respiratory disorder and pneumonia. [16] They used 3 progressive deep learning models (ResNet50, InceptionV3 and Inception-ResNetV2) and obtained the simplest accuracy of ninety eight with a pre-trained ResNet50 model for 2-class classification. However, they didn't embrace respiratory disorder cases in their experiment. Moreover, there square measure many deep learning models that use CT pictures to discover COVID-19. as an example, ResNet-18 was used because the CNN to diagnose the malady from chest CT, that achieved a locality underneath the curve of 0.92 and had equal sensitivity to a senior radiotherapist.

So, to contribute to those ever-ending researches for saving humanity, we tend to square measure dedicating our application towards finding if the patient is corona positive or negative, although it isn't a lot of contribution like others however we tend to believe we tend to square measure creating a modification here, a distinction on the face of humanity, the hassle and plan is least however the cause is astounding. This report provides United Nations agency specification and plan on however the method works effectively in various knowledge of various patients who has been positive and relatively negative.

For the implementation, the govt. agency chest X-ray image dataset is collected from Kaggle repository [8] And it's very associate open provide platform. a up to date hybrid formula is introduced throughout this paper and this formula is successfully applied on the on high of mentioned dataset to classify internal organ illness. the foremost contribution of this analysis is that the event of this new hybrid deep learning formula applicable for predicting internal organ illness from X-ray photos

S. G. Gino Sophia [17] et.al proposed Zadeh dominated fuzzy rule composition algorithm to solve the localization drawback in a picture employing a dominant localization max–min algorithmic program that will increase accuracy and reduces the search time. So that this algorithm the dominant values by comparison the values with the neighbours within the meticulous route. This rule helps to localize the iris image with a exactitude of 98.6% and a look time of 8.4 ms.

2. Related Work

For past few months from the start of 2020, many researchers at the side of doctors are attempting arduous to induce simple nonetheless effective suggests that to seek out COVID inflicted patients as before long as doable, however the matter is being simple comes with the value of effectiveness, all the solutions tried by numerous companies has been led to disbelief by the general public a minimum of most of them, however many has been fortunate however no on scale, there's a special hardware that been employed in hospitals named Computer-aided detection (CAD) could be a common incidence in hospitals they additionally understood that computing (AI) will facilitate clinicians distinguish COVID-19 from alternative respiratory disorder on chest CT.

Moreover, it's tough to tell apart soft tissue with poor distinction on X-ray. to beat these limitations, CAD systems are enforced to help clinicians in mechanically sleuthing and quantifying suspected diseases of important organs on X-rays . Notably, deep learning will mechanically notice clinical abnormalities from chest X-rays at tier extraordinary active specialist. because of the shortage of obtainable knowledge, however, the majority previous study knowledge originated from open datasets on cyberspace, and so it's unknown however well their corresponding models would perform with real-world knowledge. To the most effective of our information, there square measure few studies concerning localizing the disease. during this project, we tend to developed AN economical and correct deep learning model-based computer-aided detection theme for mechanically localizing COVID-19 from CAP on chest X-rays. The novel CAD theme comprised 2 completely different deciliters: the primary DL is employed to mechanically acknowledge and collect X-rays happiness to COVID-19 patients (i.e., the X-rays differentiated from CAP patients), and also the second deciliter is employed for sleuthing localization of left respiratory organ, right respiratory organ or pneumonic in every X-ray skiagraph. the main points of this work, together with the structure of the CAD theme and performance analysis, square measure manifested within the following sections.

Currently, computing victimization deep learning plays a very important role within the medical image space because of its glorious feature extraction ability. Deep learning models (DLs) accomplish tasks by mechanically analysing multi-modal medical pictures. pc vision refers to victimization DLs in process pictures or videos and the way a pc may gain data and understanding from this technique. Advanced computer-aided diagnosing schemes square measure principally supported progressive ways, like absolutely convolutional neural networks (FCNNs) [6] , VGGNet [7] , ResNet [9] , origination [9] , and Xception [10] . Some samples of the applying of AI embrace cancer detection and classification [11] , the diagnosing of diabetic retinopathy [12] , multi-classification of multi-modality skin lesions [13] , polyp detection throughout endoscopy [14] , etc.

3. Algorithm

Deep convolution neural network :

The predominant types of neural networks used for four-dimensional signal process square measure deep convolutional neural networks (DCNNs). The term deep refers generically to networks having several dozen or a lot of convolution layers, and deep learning refers to methodologies for coaching these systems to mechanically learn their purposeful parameters exploitation information representative of a particular downside domain of interest. CNNs square measure presently being utilized in associate degree passing broad spectrum of application areas, all of that share the common objective of getting the flexibility to mechanically learn and responses to circumstances not encountered throughout the coaching section. Ultimately, the learned options is employed for

tasks like classifying the varieties of signals the CNN is foreseen to method. The aim of this is twofold: to introduce the fundamental design of CNNs and perhaps, via a machine.

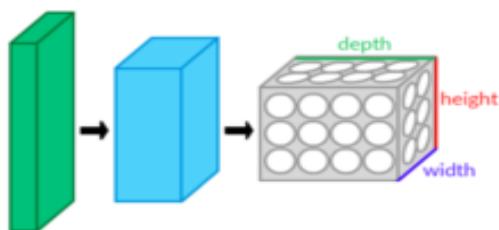


Fig 3.1

Deep convolutional neural networks (DCNN) became a hot field in medical image segmentation. The key variations between CNN and different deep convolutional neural networks (DCNN) square measure that the graded patch-based convolution operations square measure utilized in CNN, that not solely reduces machine price, however abstracts pictures on totally different feature levels. Since the patch-based learning is that the core operations for each CNN and multiatlas segmentation. As a result, important efforts square measure created to projected label fusion primarily based CNN/DNN networks to leverage the segmentation performance.

Cnn image classifier:

The classification of waste into reusable and non-reusable is completed exploitation the CNN classifier. This classifier uses the CNN formula for easier identification and separation of waste from the cluster and for easier separation into several sections. The dataset is that the collections of day to day life wastages like plastic, metal, food things etc. every of around 450-500 sample pictures area unit feed into the dataset for higher practicality of formula. every sample is created zoomed, differed wide and height, lightweight level over the article, and a few additional variations so the process of image will be created with smart level of accuracy.

The Convolutional layer works within the following manner – the layer receives some input volume, during this case a picture which can have a selected height, dimension and depth. There area unit filters gift that area unit primarily matrices that area unit initialized with random numbers initially. The Filters area unit tiny spatially, however have depth same as channels of the input image. For RGB the Filters can have depth three, for Greyscale, the Filters can have depth one then on. The Filter is convolved over input volume. It slides spatially through the image and computes scalar product throughout the image. The Filters find yourself manufacturing activation maps for the input image.

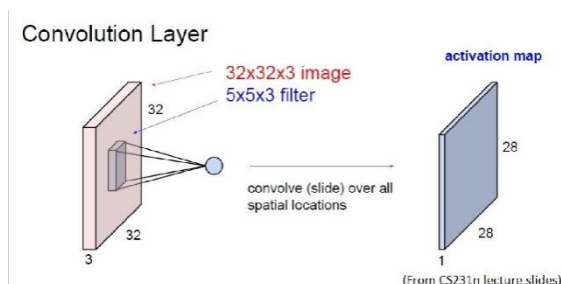


Fig 3.2.1

The scalar product is calculated within the following manner –

$$Wx + b$$

Where

W = Filter

x = the input image

b = bias

At the top of every convolutional layer, CNNs find yourself clearing of associate degree activation map of the filters. The activation perform is Relu (Rectified Linear Units.)

$$F(x) = \max(0, x)$$

This Activation perform finishes up by not saving values below zeroes, i.e. thresholds the minimum at zero. succeeding layer is that the soap pooling layer.

Max pooling - soap pooling is essentially simply down sampling of the activation maps. Usually, soap pooling layers of two*two filter and stride 2 area unit used, that find yourself reducing the input activation maps in [*fr1] abstraction maps. The precise location of a feature is a smaller amount necessary than its rough location relative to alternative options. The pooling layer serves to more and more cut back the abstraction size of the illustration, to scale back the quantity of parameters, memory footprint and quantity of computation within the network, and

hence to additionally management over fitting. It's common to insert a pooling layer between consecutive convolutional layers in CNN design. The pooling operation provides another kind of translation invariableness.

The pooling layer operates severally on each depth slice of the input and resizes it spatially. the foremost common kind could be a pooling layer with filters of size two*two applied with a stride of two down samples at each depth slice within the input by 2 on each dimension and height, was not saved seventy fifth of the activations:

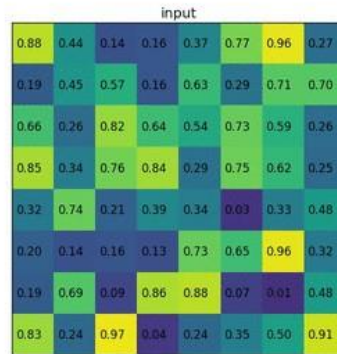


Fig 3.2.2

In this case, each pool operation is over four numbers. The depth dimension remains unchanged.

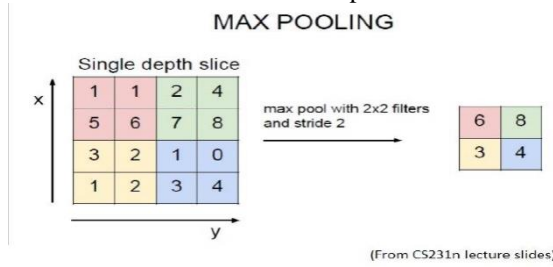


Fig 3.2.3

Another methodology of pooling is average pooling, within which the typical rather than the most of the sub matrix is preserved for succeeding layer.

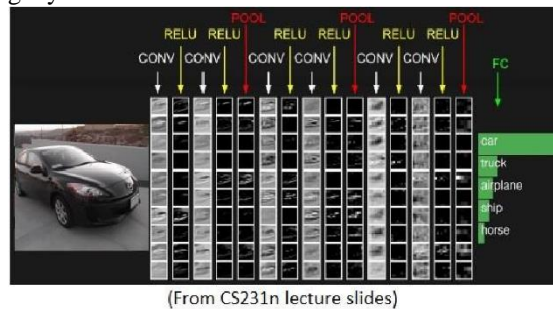


Fig 3.2.4

Classification

The algorithm works in an exceedingly two-phase cycle, the aerial and back propagation. throughout the aerial, the image is passed to every of the on top of layer and therefore the output is calculated. The expected output is compared to the particular output and therefore the error is calculated. once the error is calculated, the formula then adjusts the weights i.e. the abstraction values of every of the filters and therefore the biases up to the primary input layer. This adjustment of the weights or the abstraction values of the Filters is that the back-propagation part. This back-propagation part is employed in conjunction with optimisation techniques like gradient descent to lower the error the maximum amount as attainable.

The CNN employed in this project was enforced in Google’s TensorFlow, that provides a high level of abstraction over TensorFlow. All the photographs within the dataset were resized to 150x150 before feeding as input to the network. The network was created within the following manner –

- Layer zero – Input Image of size 150x150x3.
- Layer one – Convolution with thirty two filters of size 3x3 with stride a pair of
- Layer a pair of – easy lay Pooling with size 2x2 filter, stride 2
- Layer three - Convolution with thirty two filters of size 3x3 with stride a pair of

- Layer four - easy lay Pooling with size 2x2 filter, stride 2
- Layer five - Convolution with sixty four filters of size 3x3 with stride a pair of
- Layer six - easy lay Pooling with size 2x2 filter, stride 2
- Layer seven – absolutely connected layer with sixty four neurons
- Layer eight – absolutely connected layer with five neurons
- Result – paper-back book scores, 4 classes

The loss has been computed mistreatment binary cross-entropy and therefore the optimizer used is RMSprop. The CNN was trained for around three – three.5 hours on a GTX 1050 Ti. The train/validation split was 350-400/50-100 per category and fifty epochs were used. As increased samples square measure used for input, though they multiplied the dataset size, they were extremely related to. this might have resulted in over fitting of the info. the matter of over fitting was resolved by modulating the entropic capability of the network – the number of data hold on within the model. A model which will store a great deal of data has the potential to be additional correct however it additionally finishes up storing orthogonal options. In our case, we tend to used a really little CNN with few layers and few filters per layer aboard information augmentation and dropout of 0.5. Dropout additionally helps cut back over fitting, by preventing a layer from seeing doubly the precise same pattern. Thus, the model that stores less info finishes up storing simply the foremost important options found within the information and is probably going to additional relevant and generalizes higher.

Backpropagation algorithm :

Backpropagation (backprop, BP) is also a wide used algorithmic rule for coaching feedforward neural networks. Generalizations of backpropagation exists for alternative artificial neural networks (ANNs), and for functions typically. These categories of algorithms area unit all remarked generically as "backpropagation". In fitting a neural network, backpropagation computes the gradient of the loss perform with connection the weights of the network for one input–output example, and will therefore expeditiously, not like a naive direct computation of the gradient with connection every weight separately. This potency makes it possible to use gradient ways for coaching multilayer networks, change weights to scale back loss; gradient descent, or variants like random gradient descent, area unit unremarkably used. The backpropagation algorithmic rule works by computing the gradient of the loss perform with respect to every weight by the chain rule, computing the gradient one layer at a time, iterating backward from the last layer to avoid redundant calculations of intermediate terms inside the chain rule; usually this can be often associate example of dynamic programming.

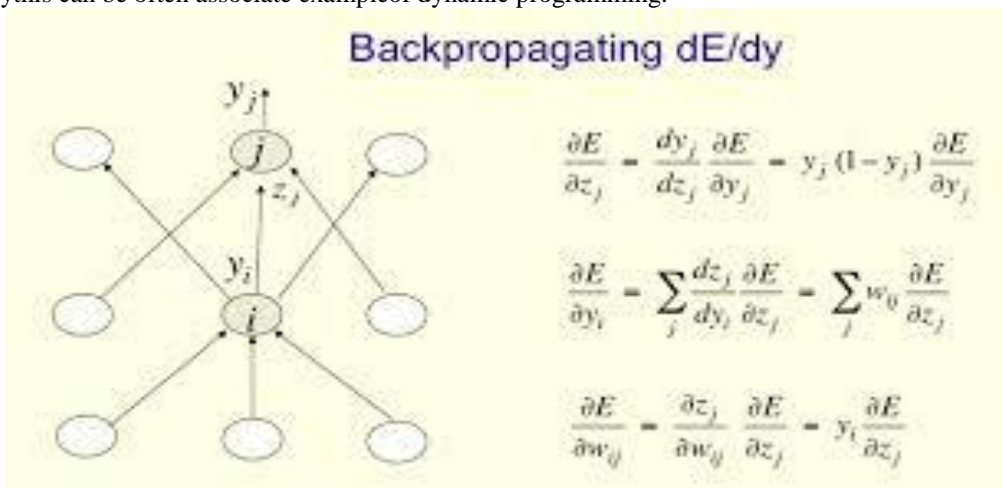


Fig 3.4

4. Proposed System

Though initial studies have incontestable promising results by mistreatment symptoms for the identification of COVID-19 and alternative respiratory organ diseases and detection of the infected regions, most existing strategies square measure supported unremarkably used supervised learning theme. this needs a substantial quantity of labor on manual labelling of the data; but, at such a pestilence scenario clinicians have terribly restricted time to perform the tedious manual drawing, which can fail the implementation of such supervised deep learning strategies. during this study, we have a tendency to propose a sapless supervised deep learning framework to find COVID-19 and alternative respiratory organ diseases infected regions totally mechanically mistreatment symptoms knowledge non-heritable from multiple centres and multiple symptoms.

There unit of measurement overtly accessible annotated chest X-ray databases with recorded patients. The dataset used during this study contains a whole of 3545 chest X-ray footage and is mentioned as COVID19-DB. to come back up with the COVID19-DB dataset, as associate example, chest X-ray radio- graphs, we have a

tendency to tend to combined and altered a pair of entirely totally different overtly accessible datasets: 1) chest X-ray radiographs of the disease cohort were collected from the RSNA disease Detection Challenge, and 2) the COVID-19 cohort with chest X-ray radiographs comprised. Four radiologists from Xiangya Hospital manually verified the COVID-19 from CAP on chest X-rays. This study was approved by the commission of the Xiangya Hospital of Central South University. consent was obtained from all participants.

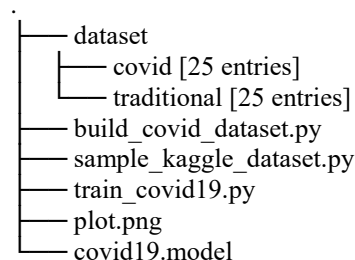
The size strategy is incredibly necessary in applying metric unit to large footage since the resolution is restricted by the GPU memory. In terms of our task, there unit of measurement few data accessible, which we have a tendency to use exhaustive data augmentation (such as random clipping, flipping, shifting, tilting and scaling) to extend the accessible dataset likewise as optimize the CAD theme generalization capability. To optimize and improve the projected CAD theme, we'll consistently expand the data of COVID19-DB. tons of specifically, we have a tendency to tend to collected 2004 radiographs of CAP, 1314 radiographs of healthy controls, and a pair of 04 radiographs of COVID- nineteen that were willy-nilly split into 2 freelance subsets for the Discrimination-DL, where the coaching job set used eightieth, and thus the validation set used 2 hundredth.

The coaching job and validation subsets were on utilised for model fitting and preventing model over-fitting among the training job section. There was no patient overlap between phases. Moreover, the objects of the Xiangya Hospital of Central South University were patients diagnosed with Covid-19 and CAP from January twenty 5, to May 1, 2020. The registered Covid-19 patients were confirmed as positive by RT-PCR on cavity swabs and throat swabs. Clinical manifestations, laboratory and X- rays of patients were collected.

All chest X-rays (CXRs) were ac- quired as computed or digital radiographs following usual native protocols. CXRs were learned among the posteroanterior (PA) or anteroposterior (AP) projection. X-ray footage were collected from twenty one Covid-19 patients, twenty CAP patients and twenty controls, that were primarily used as take a glance at data. The testing set was performed among the testing section to prove model generalization. for each of the COVID-19 patients among the COVID19-DB, the non- pneumonic region was divided into the left internal organ and right internal organ. By doing thus, we have a tendency to area unit able to acquire a sample of 2 hundred X-ray radiographs as a result of the coaching job set and twenty one X-rays from the Xiangya Hospital as a result of the testing for the Localization-DL. Among them, 157 and 183 were “positive” infected among the left pneumonic region and right pneumonic region, severally. we have a tendency to tend to willy-nilly assembled 200 X-rays of healthy controls as “negative” infections set in every pneumonic regions. Next, to localize the pneumonic region of COVID-19, we have a tendency to tend to conducted experiments to identify the infected region set among the left internal organ, right internal organ or bi-pulmonary region.

5. System Implementation

Extract the files and you'll be bestowed with the subsequent directory structure:
 Finding COVID-19 in X-ray pictures with Keras, TensorFlow, and Deep Learning
 \$ tree --dirsfirst --filelimit ten



3 directories, 5 files

Our coronavirus (COVID-19) chest X-ray information is within the dataset/ directory wherever our 2 categories of knowledgeseparated into covid/ and normal/.

Both of our dataset building scripts provided;

We will review

train_covid19.py script that trains our COVID-19 detector.

Training Our Detector With Tensorflow And Keras

With our train_covid19.py script enforced, we tend to currently able to train our automatic COVID-19 detector.

Finding COVID-19 in X-ray pictures with Keras, TensorFlow, and Deep Learning

\$ python train_covid19.py --dataset dataset

[INFO] loading pictures...

```

[INFO] compilation model...
[INFO] coaching head...
Epoch 1/25
5/5 [=====] - 20s 4s/step - loss: 0.7169 - accuracy: 0.6000 - val_loss:
0.6590 - val_accuracy: 0.5000
Epoch 2/25
5/5 [=====] - 0s 86ms/step - loss: 0.8088 - accuracy: 0.4250 - val_loss:
0.6112 - val_accuracy: 0.9000
Epoch 3/25
5/5 [=====] - 0s 99ms/step - loss: 0.6809 - accuracy: 0.5500 - val_loss:
0.6054 - val_accuracy: 0.5000
Epoch 4/25
5/5 [=====] - 1s 100ms/step - loss: 0.6723 - accuracy: 0.6000 - val_loss:
0.5771 - val_accuracy: 0.6000
...
Epoch 22/25
5/5 [=====] - 0s 99ms/step - loss: 0.3271 - accuracy: 0.9250 - val_loss:
0.2902 - val_accuracy: 0.9000
Epoch 23/25
5/5 [=====] - 0s 99ms/step - loss: 0.3634 - accuracy: 0.9250 - val_loss:
0.2690 - val_accuracy: 0.9000
Epoch 24/25
5/5 [=====] - 27s 5s/step - loss: 0.3175 - accuracy: 0.9250 - val_loss:
0.2395 - val_accuracy: 0.9000
Epoch 25/25
5/5 [=====] - 1s 101ms/step - loss: 0.3655 - accuracy: 0.8250 - val_loss:
0.2522 - val_accuracy: 0.9000
[INFO] evaluating network...
exactitude recall f1-score support
  covid 0.83   1.00   0.91  5
traditional 1.00   0.80   0.89  5
accuracy 0.90 10

macro avg 0.92   0.90   0.90 10
weighted avg 0.92   0.90   0.90 10
[[5 0]

[1 4]]
acc: 0.9000
sensitivity: 1.0000
specificity: 0.8000
[INFO] saving COVID-19 detector model...

```

6. Conclusion

As you will see from the results on high of, our automatic COVID-19 detector is obtaining ~90-92% accuracy on our sample dataset based solely on X-ray footage — no various data, in addition as geographical location, population density, etc. was accustomed train this model.

We are obtaining 100% sensitivity and eightieth specificity implying that:

- Of patients that do have COVID-19 (i.e., true positives), we've an inclination to might accurately establish them as “COVID-19 positive” 100% of the time victimization our model.
- Of patients that do not have COVID-19 (i.e., true negatives), we've an inclination to might accurately establish them as “COVID-19 negative” alone eightieth of the time victimization our model.

As our coaching job history plot shows, our network is not overfitting, despite having very restricted coaching job data:

This deep learning coaching job history plot showing accuracy and loss curves demonstrates that our model is not overfitting despite restricted COVID-19 X-ray coaching job info used in our Keras/TensorFlow model.

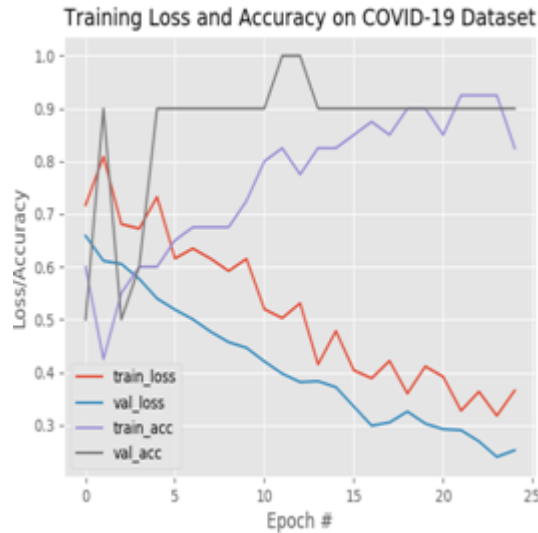


Fig.6.1

Being able to accurately notice COVID-19 with 100% accuracy is great; however, our true negative rate is also a touch concerning — we've an inclination to don't want to classify someone as "COVID-19 negative" once they unit of measurement "COVID-19 positive".

In fact, the ultimate factor we might wish to try to do is tell a patient they are COVID-19 negative, then have them go back and infect their family and friends; thereby causing the illness any.

We to boot want to be terribly careful with our false positive rate — we've an inclination to don't want to mistakenly classify someone as "COVID-19 positive", quarantine them with various COVID-19 positive patients, then infect somebody United Nations agency never actually had the virus.

Balancing sensitivity and specificity unit of measurement unbelievably tough once it involves medical applications, significantly infectious diseases which is able to be apace transmitted, like COVID-19.

When it involves medical computer vision and deep learning, we've an inclination to should bear in mind of {the fact|the very fact|the actual fact} that our foreshadowing models can have terribly real consequences — a enigmatic designation can worth lives.

7. Limitations And Improvements

One of the most important limitations of this technique is knowledge. We merely don't have enough (reliable) knowledge to coach a COVID-19 detector. Hospitals square measure already weak with the amount of COVID-19 cases, and given patients' rights and confidentiality, it becomes even tougher to assemble quality medical image datasets in a very timely fashion. I imagine within the next 12-18 months we'll have additional top quality COVID-19 image datasets; except for the nowadays, we will solely contend with what we've.

For the COVID-19 detector to be deployed within the field, it might have to be compelled to undergo rigorous testing by trained medical professionals, operating hand-in-hand with knowledgeable deep learning practitioners. the strategy coated here nowadays is never such a technique, and is supposed for academic functions solely. Furthermore, we'd like to be troubled with what the model is truly "learning". It would take a trained medical skilled and rigorous testing to validate the results starting of our COVID-19 detector.

And finally, future (and better) COVID-19 detectors are going to be multi-modal.

Right now, we tend to square measure mistreatment solely image knowledge (i.e., X-rays) — higher automatic COVID-19 detectors ought to leverage multiple knowledge sources not restricted to only pictures, together with patient vital organ, population density, geographical location, etc. Image knowledge by itself is usually not adequate for these varieties of applications.

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