

COVID-19 PNEUMONIA IDENTIFICATION

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ABSTRACT- The presence of symptoms of COVID-19 respiratory disorder is also just like alternative styles of viral infection. owing to this, it is tough to inform what's inflicting your condition while not being tested for COVID-19 or alternative metabolism infections. to work out however COVID-19 respiratory disorder differs from alternative styles of respiratory disorder. info from these studies will probably facilitate in diagnosing and in furthering our understanding of however SARS-CoV-2 affects the lungs we have a tendency to gift a Convolutional Neural Network in TensorFlow and Keras primarily based Covid-19 respiratory disorder classification. the projected system supported CNN exploitation respiratory disorder pictures to classifying the Covid-19, normal, respiratory disorder this technique exploitation CNN model. it's foreseen that the success of the obtained results can increase if the CNN technique is supported by adding further feature extraction strategies and classify with success covid-19&pneumonia. we've incontestable the effectualness and potential of exploitation deep CNN to photographs.

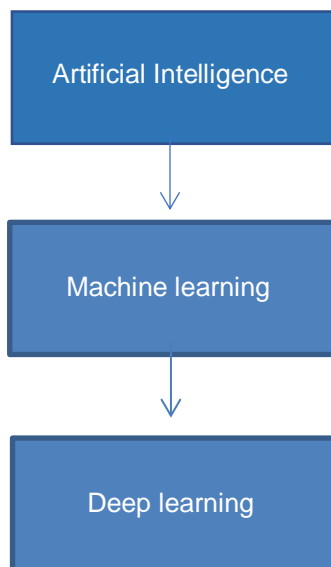
KEYWORDS- Covid-19 and Pneumonia, deep learning, TensorFlow, Keras, CNN.

INTRODUCTION-

The coronavirus malady 2019 (COVID-19) has become a worldwide pandemic since the start of 2020. The malady has been considered a Public Health Emergency of International Concern (PHEIC) by the globe Health Organization (WHO) and also the finish of January 2020. Up to Apr ten, 2020, there are quite one.5 million cases of COVID19 reportable globally, with quite ninety two thousands deaths. The most common symptoms of

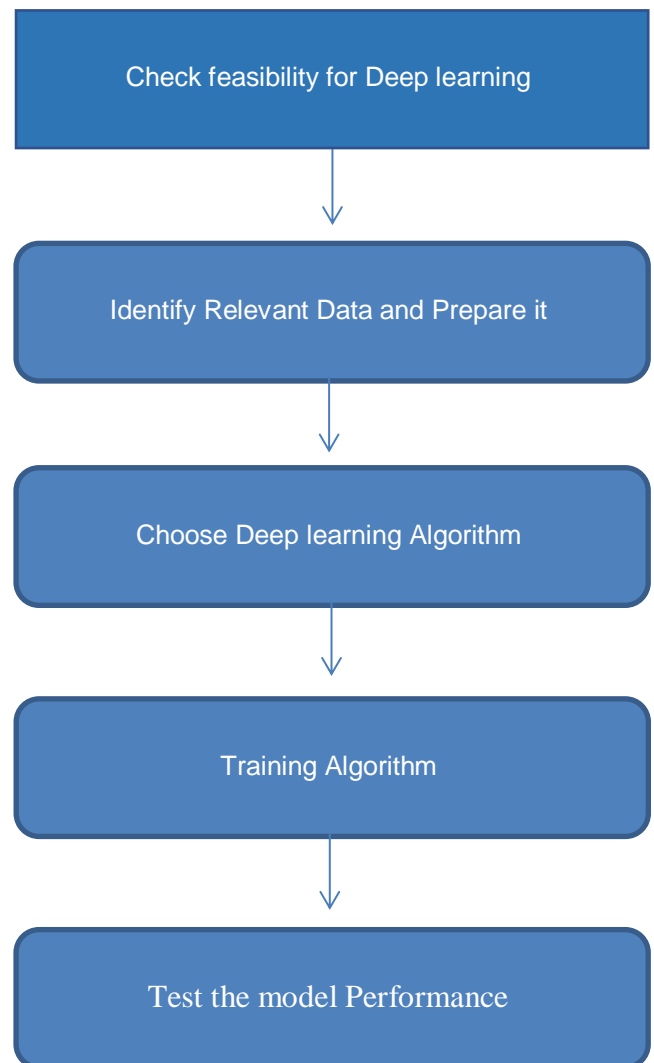
COVID-19 patients embrace fever, cough and shortness of breath, and also the patients generally suffer from respiratory disorder. Chest x ray imaging plays a important role for detection of manifestations within the respiratory organ related to COVID-19, wherever segmentation of the infection lesions from X-ray scans is very important for quantitative mensuration of the malady progression in correct diagnosing and follow-up assessment. As manual segmentation of the lesions from 3D volumes is effortful, long and suffers from inter- and intra-observer variabilities, automatic segmentation of the lesions is extremely fascinating in clinic follow. Despite its importance for diagnosing and treatment selections, automatic segmentation of COVID-19 respiratory disorder lesions from x-ray scans is difficult thanks to many reasons. First, the infection lesions have a range of advanced appearances like Ground-Glass Opacity (GGO), reticulation, consolidation et al.. Second, the sizes and positions of the respiratory disorder lesions vary mostly at completely different{completely different} stages of the infection and among different patients. additionally, the lesions have irregular shapes and ambiguous boundaries, and a few lesion patterns like GGO have a coffee distinction with encompassing regions. These challenges not solely create it troublesome to mechanically phase the lesions, however conjointly bring obstacles for getting correct manual annotations for coaching. In recent years, deep learning with Convolutional Neural Networks (CNNs) has achieved progressive performance for several medical image analysis tasks. For medical image segmentation, its success depends on correct annotation of an outsized set of coaching pictures enforced by consultants.

Deep learning- It is a branch of machine learning that is totally supported artificial neural networks, as neural network goes to mimic the human brain thus deep learning is additionally a sort of mimic of human brain. It's on plug today as a result of earlier we have a tendency to failed to have that a lot of process power and plenty of knowledge. a proper definition of deep learning is- neurons Deep learning may be a explicit quite machine learning that achieves world power and suppleness by learning to represent the globe as a nested hierarchy of ideas, with every thought outlined in relevancy easier ideas, and additional abstract representations computed in terms of less abstract ones. In brain roughly a hundred billion nerve cells all at once this can be an image of a personal nerve cell and every neuron is connected through thousands of their neighbours. The question here is however it recreates these neurons in an exceedingly laptop. So, it creates a man-made structure referred to as a man-made neural internet wherever we've got nodes or neurons. It has some neurons for input worth and a few for output worth and in between, there could also be variant neurons interconnected within the hidden layer.



it got to establish the particular downside so as to urge the correct resolution and it ought to be understood, the practicability of the Deep Learning ought to even be checked (whether it ought to match Deep Learning or not). It must establish the relevant information that ought

to correspond to the particular downside and will be ready consequently. opt for the Deep Learning formula fitly. formula ought to be used whereas coaching the dataset. Final testing ought to be done on the dataset.



Methodology-Preprocessing and coaching the model (CNN): The dataset is preprocessed like Image reshaping, resizing associate degree conversion to an array kind. Similar process is additionally done on the check image. A dataset consisting of regarding nineteen totally different plant species is obtained, out of that any image may be used as a check image for the computer code. The train dataset is employed to coach the model (CNN) so it will determine the check image and also the malady it's CNN has totally different layers that square measure Dense, Dropout, Activation, Flatten, Convolution2D, and MaxPooling2D. when the model is trained with success, the computer code will determine

the malady if the plant species is contained within the dataset. when in coaching and preprocessing, comparison of the check image and trained model takes place to predict the malady.

CNN Model steps-

Conv2D- It's the layer to flex the image into multiple pictures activation is that the activation perform.

MaxPooling2D- It's accustomed gamma hydroxybutyrate pool the worth from the given size matrix and same is employed for consequent two layers.

Flatten- It's accustomed flatten the scale of the image obtained when convolving it.

Dense- It's accustomed build this a completely connected model and is that the hidden layer.

Dropout- It's accustomed avoid over fitting on the dataset and dense is that the output layer contains just one nerve cell that attempt to that class image belongs.

Image knowledge Generator- It's that rescales the image, applies shear in some vary, zooms the image and will horizontal flipping with the image. This Image knowledge Generator includes all doable orientation of the image.

Training Process-Train_datagen.flow_from_directory is that the perform that's accustomed prepare knowledge from the train_dataset directory Target_size specifies the target size of the image. Test datagen flow from_directory is employed to organize take a look at knowledge for the model and every one is analogous as higher than. fit_generator is employed to suit the info into the model created higher than, different factors used area unit steps_per_epochs tells us concerning the quantity of times the model can execute for the coaching knowledge. Epochs: It tells us the quantity of times model are trained in forward and backward pass. Validation process: validation_data is employed to feed the validation/test knowledge into the model. Validation_steps denotes the quantity of validation/test samples.

Architecture of CNN-

A typical design of a convolutional neural network contains Associate in Nursing input layer, some convolutional layers, some fully-connected layers, Associate in Nursing an output layer. CNN is meant with some

modification on LeNet design. it's half dozen layers while not considering input and output. Input Layer: The input layer has pre-determined, fastened dimensions, therefore the image should be pre-processed before it will be fed into the layer. Normalized grey scale pictures of size forty eight X forty eight pixels from given dataset square measure used for coaching, validation and testing. For testing propose laptop computer digital camera pictures are used, during which face is detected and cropped victimization OpenCV Haar Cascade Classifier and normalized.

Convolution and Pooling (ConvPool) Layers-

Convolution and pooling is completed supported execution. every batch has N pictures and CNN filter weights square measure updated on those batches. every convolution layer takes image batch input of 4 dimension N x Color-Channel x dimension x height. Feature map or filter for convolution is additionally four dimensional (Number of feature maps in, range of feature maps out, filter dimension, filter height). In every convolution layer, four dimensional convolutions square measure calculated between image batch and have maps. when convolution solely parameter that changes is image dimension and height.

New image dimension = previous image dimension – filter dimension + one

New image height = previous image height – filter height + one

After every convolution layer down sampling / subsampling is done for spatial property reduction. This method is named Pooling. goop pooling and Average Pooling square measure 2 noted pooling ways. during this project goop pooling is completed when convolution. Pool size of (2x2) is twelve taken, that splits the image into grid of blocks every of size 2x2 and takes most of four pixels. when pooling solely height and dimension square measure affected. 2 convolution layer and pooling layer square measure utilized in the design. initially convolution layer size of input image batch is Nx1x48x48. Here, size of image batch is N, range of color channel is one and each image height and dimension square measure forty

eight component. Convolution with feature map of $1 \times 20 \times 5 \times 5$ results image batch is of size $N \times 20 \times 44 \times 44$. when convolution pooling is completed with pool size of 2×2 , which ends image batch of size $N \times 20 \times 22 \times 22$. this is often followed by second convolution layer with feature map of $20 \times 20 \times 5 \times 5$, that results image batch of size $N \times 20 \times 18 \times 18$. this is often followed by pooling layer with pool size 2×2 , which ends image batch of size $N \times 20 \times 9 \times 9$.

Fully Connected Layer: This layer is impressed by the method neurons transmit signals through the brain. It takes an outsized range of input options and transforms options through layers connected with trainable weights. 2 hidden layers of size five hundred and three hundred unit square measure utilized in fully-connected layer. The weights of those layers square measure trained by forward propagation of coaching knowledge then backward propagation of its errors. Back propagation starts from evaluating the distinction between prediction and true worth, and back calculates the burden adjustment required to each layer before. we are able to management the coaching speed and also the quality of the design by standardisation the hyper-parameters, like learning rate and network density. Hyper-parameters for this layer embody learning rate, momentum, regularization parameter, and decay. The output from the second pooling layer is of size $N \times 20 \times 9 \times 9$ and input of initial hidden layer of fully-connected layer is of size $N \times 500$. So, output of pooling layer is two-dimensional to $N \times 1620$ size and fed to initial hidden layer. Output from initial hidden layer is fed to second hidden layer. Second hidden layer is of size $N \times 300$ and its output is fed to output layer of size adequate range of facial features categories. **Output Layer:** Output from the second hidden layer is connected to output layer having seven distinct categories and output is obtained victimization the chances for every of the seven categories. The category with the best chance is that the expected class.

Literature Survey:

1.Title: Automatic Detection and Diagnosis of Severe Viral Pneumonia CT Images Based on LDASVM

Author: Gengfei Ling, Congcong Cao

The identification of pneumonia types mainly depends on the experience of doctors, but some CT images of pneumonia are very similar, even experienced doctors are prone to misdiagnosis. In order to solve the problems of inefficiency, coarse granularity and poor accuracy under the background of large data, LDA-SVM (Linear Discriminate Analysis-support vector machine) classification algorithm in machine learning field is introduced. LDA is used to extract features from images, and SVM classifier is used to classify the sub-datasets with strong fusion features. On this basis, fusion index and intermediary centrality index are selected to measure the fusion degree of patent sub-centralization technology and identify the key technologies in the fusion process, Because of the fusion of several algorithms, the algorithm needs many iteration training, and the computation time is too long. And simulation results show that our proposed method has significant improvement on identification accuracy rate. The algorithm needs many iteration training, and the computation time is too long. LDA is used to extract features from images, and SVM classifier is used to classify the sub-datasets with strong fusion features.

2.Title: Dual-Sampling Attention Network for Diagnosis of COVID-19 from Community Acquired Pneumonia

Author: Xi Ouyang , Jiayu Huo , Liming Xia , Fei Shan

The coronavirus disease (COVID-19) is rapidly spreading all over the world, and has infected more than 1,436,000 people in more than 200 countries and territories as of April 9, 2020. Detecting COVID-19 at early stage is essential to deliver proper healthcare to the patients and also to protect the uninfected population. To this end, They develop a dual-sampling attention network to automatically diagnose COVID-19 from the community acquired pneumonia (CAP) in chest computed tomography (CT). In particular, we propose a novel online attention module with a 3D convolutional network (CNN) to focus on the infection regions in lungs when making decisions of diagnoses. Note that there exists imbalanced distribution of the sizes of the infection regions between

COVID-19 and CAP, partially due to fast progress of COVID-19 after symptom onset. Therefore, we develop a dual-sampling strategy to mitigate the imbalanced learning s. In the training-validation stage, we collect 2186 CT scans from 1588 patients for a 5-fold cross-validation. In the testing stage, we employ another independent large-scale testing dataset including 2796 CT scans from 2057 patients. COVID-19, it is important to get the diagnosis result at soon as possible. Although RT-PCR is the current ground truth to diagnose COVID-19, it will take up to days to get the final results and the capacity of the tests is also limited in many places especially in the early outbreak [8]. In this study, we explore a machine learning method to perform automatic COVID-19 diagnosis from CAP in chest CT images. We evaluate our method by the largest multi-center CT data in the world, to the best of our knowledge.

3.Title: Field Trial of Aspiration Pneumonia Predicion based on Electronic Medical Records

Author: Masahiro Hayashitani, Eiji Yumoto, Toshinori Hosoi, Masahiro Kubo.

A prediction method of aspiration pneumonia in department of neurosurgery and demonstrate the method in a hospital in order to reduce workload about care for aspiration pneumonia. In a field trial, medical staff provide preventive cares based on the output of the method. They show that the trial reduces workload of the medical staff, and the number of patients with aspiration pneumonia was reduced. They proposed the prediction method of aspiration pneumonia in department of neurosurgery in order to reduce workload about care for aspiration pneumonia. The prediction method is based on electronic medical records including age, sex, and vital signs. They demonstrated the method in KIH. In the field trial, the medical staff provided preventive cares based on the output of method. They showed that the trial reduced care time of the medical staff by 10%, and the number of patients with aspiration pneumonia was reduced. A long-time trial will be conducted in order to confirm further effects.

4.Title: Trend Prediction of Influenza and the Associated Pneumonia in Taiwan Using Machine Learning

Author: Sing-Ling Jhuo, Mi-Tren Hsieh, Ting-Chien Weng, Mei-Juan Chen and Chieh-Ming Yang

Trend prediction of influenza and the associated pneumonia can provide the information for taking preventive actions for public health. This paper uses meteorological and pollution parameters, and acute upper respiratory infection (AURI) outpatient number as input to multilayer perceptron (MLP) to predict the patient number of influenza and the associated pneumonia in the following week. The meteorological parameters in use are temperature and relative humidity, air pollution parameters are Particulate Matter 2.5 (PM 2.5) and Carbon Monoxide (CO), and the patient prediction includes both outpatients and inpatients. Patients are classified by textiles into three categories: high, moderate, and low volumes. The regional data analyses with various age groups are also provided in this paper. The meteorological parameters (temperature and relative humidity), air pollution parameters (PM 2.5 and CO) of 30 consecutive days, and the number of AURI patient of previous week are utilized to forecast the trend of the patients of flu and viral pneumonia of subsequent week by MLP machine learning. This work can provide prevention actions for diffusion of influenza.

5. Title: Cloud-Based Smart Dog Music Therapy and Pneumonia Detection System for Reducing the Difficulty of Caring for Patients with Dementia

Author: Mei-Jung Lyu , Shyan-Ming Yuan

There is currently no cure for Alzheimer's disease, leaving patients to rely solely on good quality care services to prolong their life. Besides, it has been found that the onset of pneumonia can accelerate the progression of dementia and even lead to death. This has led to an increased caregiving burden and a level of emotional stress among caregivers that can be unbearable. The aim of this study was to build a Smart Dog music therapy and pneumonia detection system, which combines a robotic dog, cloud technology, a multi-agent system, an adaptive network-based fuzzy

inference system (ANFIS), a web application, and sensor technology to deliver care for patients with Alzheimer's disease and help mitigate the difficulties faced by caregivers. The use of the system to determine its usefulness in caregiving work and whether it improved their overall caregiving experience. A majority of the interviewed caregivers agreed that the system brought about improvements.

6. Title: Deep Regression via Multi-Channel Multi-Modal Learning for Pneumonia Screening

Author: Qiuli Wang, Dan Yang, Zhihuan Lij, Xiahong Zhang

Pneumonia screening is one of the most crucial steps in the pneumonia diagnosing system, which can improve the work efficiency of the radiologists and prevent delayed treatments. In this paper, we propose a deep regression framework for automatic pneumonia screening, which jointly learns the multi-channel images and multi-modal information (i.e., clinical chief complaints, age, and gender) to simulate the clinical pneumonia screening process. We demonstrate the advantages of the framework in three ways. First, visual features from multi-channel images (Lung Window Images, High Attenuation Images, Low Attenuation Images) can provide more visual features than single image channel, and improve the ability of screening pneumonia with severe diseases. Second, the proposed framework treats chest CT scans as short video frames and analyzes them by using Recurrent Convolutional Neural Network, which can automatically extract multiple image features from multi-channel image slices. Third, chief complaints and demographic information can provide valuable prior knowledge enhancing the features from images and further promote performance. The proposed framework has been extensively validated in 900 clinical cases. Compared to the baseline, the proposed framework improves the accuracy by 2.3% and significantly improves the sensitivity by 3.1%.

Existing System-This reports Segmentation of respiratory disease lesions from CT scans of COVID-19

patients is very important for correct diagnosing and follow-up. Deep learning includes a potential to modify this task however needs an oversized set of high-quality annotations that square measure troublesome to gather. Learning from screaming coaching labels that square measure easier to get includes a potential to alleviate this drawback. to the current finish, we tend to propose a completely unique noise-robust framework to be told from screaming labels for the segmentation task. Despite its importance for diagnosing and treatment selections, automatic segmentation of COVID-19 respiratory disease lesions from CT scans is difficult thanks to many reasons. First, the infection lesions have a range of advanced appearances like Ground-Glass Opacity (GGO), reticulation, consolidation et al. For the COVID-19 respiratory disease lesion segmentation task, the pixel-level annotations square measure typically screaming and clean annotations square measure very troublesome to gather thanks to many reasons. First, completely different annotators might have different annotation standards that result in inter-observer variability, and high intra-observer variability may exist. These variabilities square measure terribly possible to cause noise within the annotations, that demonstrates disagreement between 2 annotators. Second, to cut back the annotation efforts, some researchers use a human-in-the-loop strategy, wherever the commentator solely provides refinements to algorithm-generated labels for expansion. In such cases, the annotations are often mostly biased towards the results of the formula and therefore contain screaming pixel-level labels. additionally, collection less correct annotations from non-experts is another promising answer to beat the restricted convenience of specialists, however these annotations also are screaming at component level and will limit the performance of the deep learning model. this may be either thanks to challenges for correct annotation, like low distinction, ambiguous boundaries and complicated appearances of the target, or caused by inexpensive inaccurate annotations like annotations provided by non-experts, human within the loop methods and a few

algorithms generating pseudo labels. They One advantage of our noise sturdy Dice loss perform is that it doesn't depend upon a particular and might be combined with totally different coaching methods, like a typical coaching method and also the self-assembling framework in our methodology.

Drawback-

- It has not centered on AlexNet CNN in keras and TensorFlow as classifier.
- They aren't mistreatment OpenCV laptop vision technique.
- It has not centered on increasing the popularity rate and classification accuracy of severity image of chest X-ray.

Proposed System- We are proposing recognition framework supported the structured 2 dimensional convolutional neural networks (CNNs) style of AlexNet to classify the Covid-19&Pneumonia and improve the accuracy of advancement. — The projected methodology for this project is to coach a Deep Learning rule capable of classifying Covid-19&Pneumonia pictures and knowledge preprocessing and visualizing the image then feature extracting to create AlexNet CNN mistreatment Covid-19&Pneumonia image dataset we have a tendency to classify it like Covid-19,normal,pnemonia this technique mistreatment CNN model. — it's foretold that the success of the obtained results can increase if the CNN methodology is supported by adding further feature extraction ways and classify with success covid-19&pneumonia.We have incontestable the efficaciousness and potential of mistreatment deep CNN to photographs.

Advantages-

- The great deal of chest x-ray knowledge will be train on artificial neural network.
- It is best model for deep learning technique to simply classifying Covid-19&Pneumonia.

Modules-

1.Import the given image from dataset and coaching the module with manual CNN (module01).

2.To train the dataset by exploitation AlexNet (module02).

3.To train the dataset exploitation LeNet (module03).

4.Deploying the model in Django Framework and predicting output (module 04).

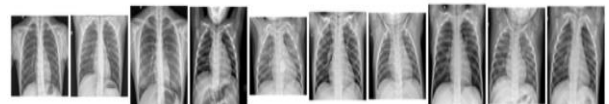
Module 01- Import the given image from dataset:

we've got to import our information set exploitation keras preprocessing image information generator operate additionally we have a tendency to produce size, rescale, range, zoom range, horizontal flip. Then we have a tendency to import our image dataset from folder through the information generator operate. Here we have a tendency to set train, test, and validation additionally we have a tendency to set target size, batch size and class-mode from this operate we've got to coach exploitation our own created network by adding layers of CNN.

NORMAL

Trained data for dir_name_train_NORMAL:

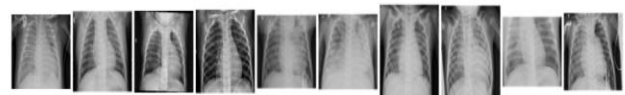
```
===== Images in: Data/train/NORMAL
images_count: 471
min_width: 993
max_width: 2534
min_height: 617
max_height: 2534
```



PNEUMONIA

Trained data for PNEUMONIA:

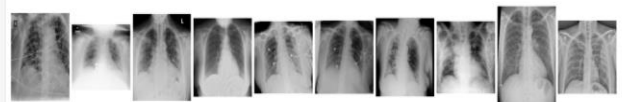
```
===== Images in: Data/train/PNEUMONIA
images_count: 517
min_width: 502
max_width: 1944
min_height: 307
max_height: 1944
```



COVID

Trained data for COVID19 type disease:

```
===== Images in: Data/train/COVID19
images_count: 460
min_width: 224
max_width: 4757
min_height: 224
max_height: 4757
```



Module 02- To train the dataset by using AlexNet :

To train our dataset victimisation classifier and work generator operate conjointly we have a tendency to build coaching steps per epoch's then total variety of epochs, validation knowledge and validation steps victimisation this knowledge we will train our dataset.

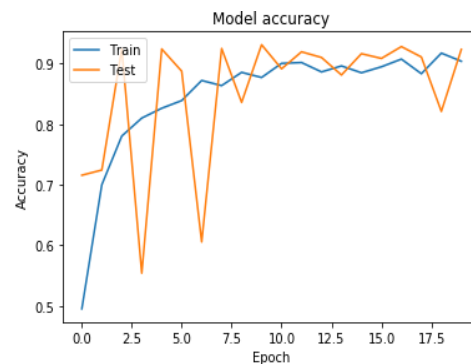
Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 75, 75, 32)	896
max_pooling2d (MaxPooling2D)	(None, 37, 37, 32)	0
conv2d_1 (Conv2D)	(None, 12, 12, 128)	36992
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 256)	1179904
dense_1 (Dense)	(None, 3)	771
Total params: 1,218,563		
Trainable params: 1,218,563		
Non-trainable params: 0		

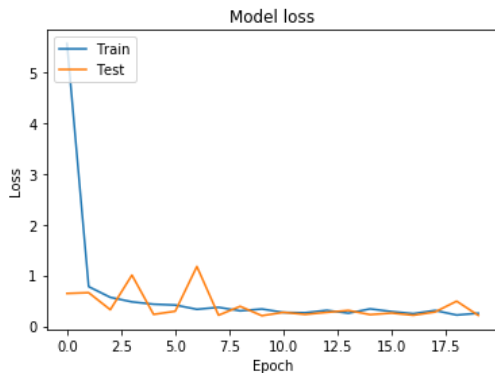
Module 03- To train the model using LeNet:

A Convolutional Neural Network (ConvNet/CNN) could be a Deep Learning algorithmic rule which may soak up associate input image, assign importance (learnable weights and biases) to varied aspects/objects within the image and be able to differentiate one from the opposite. The pre-processing needed in an exceedingly ConvNet is way lower as compared to alternative classification algorithms. whereas in primitive ways filters area unit hand-engineered, with enough coaching, ConvNets have the power to find out these filters/characteristics. The design of a ConvNet is analogous to it of the property pattern of Neurons within the Human Brain and was impressed by the organization of the visual area. Individual neurons reply to stimuli solely in an exceedingly restricted region of the field of regard called the Receptive Field. Their network consists of 4 layers with one,024 input units, 256 units within the initial hidden layer, eight units within the second hidden layer, and 2 output units. Input Layer: Input layer in CNN contain image information. Image information is portrayed by 3 dimensional matrixes. It has to reshape it into one column. Suppose you have got image of dimension twenty eight x twenty eight =784, it got to convert it into 784 x one before feeding into input.

Convo Layer: Convo layer is usually known as feature extractor layer as a result of options of the image area unit get extracted inside this layer. initial of all, native section of image is connected to Convo layer to perform convolution operation as we have a tendency to saw earlier and conniving the real number between receptive fields (it could be a local region of the input image that has constant size as that of filter) and therefore the filter. results of the operation is single whole number of the output volume. Then the filter over consecutive receptive field of constant input image by a Stride and do constant operation once more. it'll repeat constant method once more and once more till it goes through the full image. The output are going to be the input for consecutive layer.



Pooling Layer: Pooling layer is employed to scale back the spacial volume of input image when convolution. it's used between 2 convolution layers. If it applies FC when Convo layer while not applying pooling or scoop pooling, then it'll be computationally overpriced. So, the scoop pooling is simply thanks to cut back the spacial volume of input image. it's applied scoop pooling in single depth slice with Stride of two. It will observe the four x four dimension input is reducing to two x two dimensions. absolutely Connected Layer (FC): Fully connected layer involves weights, biases, and neurons. It connects neurons in one layer to neurons in another layer. it's accustomed classify pictures between totally different classes by coaching. Softmax / supply Layer Softmax or supply layer is that the last layer of CNN. It resides at the top of FC layer. supply is employed for binary classification and softmax is for multi-classification.



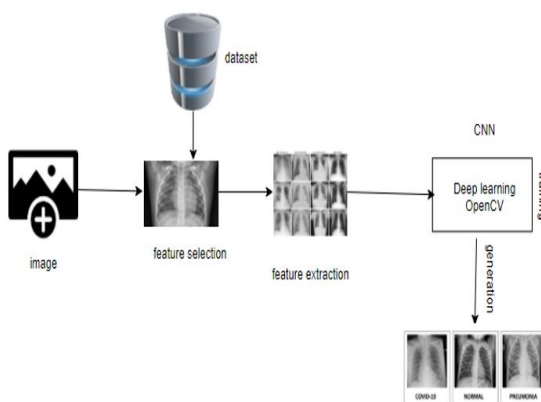
Output Layer:

Output layer contains the label that is within the style of one-hot encoded. currently you've got an honest understanding of CNN.

Module 04- Deploying the model in Django Framework and predicting output:

During this module the trained deep learning model is born-again into stratified data formatting file (.h5 file) that is then deployed in our django framework for providing higher program and predicting the output whether or not the given chest X-ray is covid-19 / respiratory disease / traditional.

Architecture-



Libraries Required-

numpy : To method the image matrices

os: To access the filing system to browse the image from the train and check directory from our machines.

random: To shuffle the info to beat the biasing.

matplotlib: To show the results of our prognostic outcome.

tensorflow: simply to use the tensor board to check the loss and adam curve our result knowledge or obtained log.

References-

- [1] N. Zhu, D. Zhang, W. Wang, X. Li, B. Yang, J. Song, X. Zhao, B. Huang, W. Shi, R. Lu, P. Niu, F. Zhan, X. Ma, D. Wang, W. Xu, G. Wu, G. F. Gao, and W. Tan, "A novel coronavirus from patients with pneumonia in China, 2019," *N. Engl. J. Med.*, vol. 382, pp. 727–733, 2020.
- [2] D. Benvenuto, M. Giovanetti, M. Salemi, M. Prosperi, C. De Flora, L. C. Junior Alcantara, S. Angeletti, and M. Ciccozzi, "The global spread of 2019-nCoV: A molecular evolutionary analysis," *Pathog. Glob. Health*, pp. 1–4, 2020.
- [3] F. Shi, J. Wang, J. Shi, Z. Wu, Q. Wang, Z. Tang, K. He, Y. Shi, and D. Shen, "Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation and Diagnosis for COVID-19," *IEEE Rev. Biomed. Eng.*, vol. 3333, no. c, pp. 1–13, 2020.
- [4] WHO, "Coronavirus disease 2019 (COVID-19) Situation Report - 81," 2020. [Online]. Available: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200410-sitrep-81-covid-19.pdf?sfvrsn=ca96eb84_2
- [5] M.-Y. Ng, E. Y. Lee, J. Yang, F. Yang, X. Li, H. Wang, M. M.-s. Lui, C. S.-Y. Lo, B. Leung, P.-L. Khong, C. K.-M. Hui, K.-y. Yuen, and M. D. Kuo, "Imaging profile of the COVID-19 infection: Radiologic findings and literature review," *Radiol. Cardiothorac. Imaging*, vol. 2, no. 1, p. e200034, 2020.
- [6] L. Huang, R. Han, T. Ai, P. Yu, H. Kang, Q. Tao, and L. Xia, "Serial quantitative chest CT assessment of COVID-19: Deep-learning approach," *Radiol. Cardiothorac. Imaging*, vol. 2, p. e200075, 2020.
- [7] J. Lei, J. Li, X. Li, and X. Qi, "CT imaging of the 2019 novel coronavirus (2019-nCoV) pneumonia," *Radiology*, p. 200236, 2020.
- [8] L. Li, L. Qin, Z. Xu, Y. Yin, X. Wang, B. Kong, J. Bai, Y. Lu, Z. Fang, Q. Song, K. Gao, D. Liu, G. Wang, Q. Xu, X. Fang, S. Zhang, J. Xia, and J. Xia, "Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT," *Radiology*, p. 200905, 2020.
- [9] F. Shan, Y. Gao, J. Wang, W. Shi, N. Shi, M. Han, Z. Xue, and Y. Shi, "Lung infection quantification of COVID-19 in CT images with deep learning," *arXiv*, p. 2003.04655, 2020.
- [10] Y. Cao, Z. Xu, J. Feng, C. Jin, X. Han, H. Wu, and H. Shi, "Longitudinal assessment of COVID-19 using a deep learning-based quantitative CT pipeline: Illustration of two cases," *Radiol. Cardiothorac. Imaging*, vol. 2, no. 2, p. e200082, 2020.
- [11] H. Wang, S. Zhao, Q. Dong, Y. Cui, Y. Chen, J. Han, L. Xie, and T. Liu, "Recognizing brain states using deep sparse recurrent neural network," *IEEE Trans. Med. Imaging*, vol. 38, no. 4, pp. 1058–1068, 2019.
- [12] D. Shen, G. Wu, and H.-I. Suk, "Deep learning in medical image analysis," *Annu. Rev. Biomed. Eng.*, vol. 19, no. 1, pp. 221–248, 2017.
- [13] D. Karimi, H. Dou, S. K. Warfield, and A. Gholipour, "Deep learning with noisy labels : exploring techniques and remedies in medical image analysis," *arXiv:1912.02911*, pp. 1–17, 2020.
- [14] A. Ghosh, H. Kumar, and P. S. Sastry, "Robust loss functions under label noise for deep neural networks," in *AAAI*, 2017, pp. 1919–1925.
- [15] H. Zhu, J. Shi, and J. Wu, "Pick-and-Learn : Automatic quality evaluation for noisy-labeled image segmentation," in *MICCAI*, 2019, pp. 576–584.
- [16] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *MICCAI*, 2015, pp. 234–241.
- [17] Z. Zhang and M. R. Sabuncu, "Generalized cross entropy loss for training deep neural networks with noisy labels," in *NeurIPS*, 2018, pp. 8778–8788.
- [18] F. Milletari, N. Navab, and S.-A. Ahmadi, "V-Net: Fully convolutional neural networks for volumetric medical image segmentation," in *IC3DV*, 2016, pp. 565–571.
- [19] Z. Mirikharaji, Y. Yan, and G. Hamarneh, "Learning to segment skin lesions from noisy annotations," in *MICCAI MIL3ID Work.*, 2019, pp. 207–215.

- [20] A. Tarvainen and H. Valpola, "Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results," in *NeurIPS*, 2017, pp. 1195–1204.
- [21] L. Yu, S. Wang, X. Li, C. W. Fu, and P. A. Heng, "Uncertainty-aware self-ensembling model for semi-supervised 3D left atrium segmentation," in *MICCAI*, 2019, pp. 605–613.
- [22] G. French, M. Mackiewicz, and M. Fisher, "Self-ensembling for visual domain adaptation," in *ICLR*, 2018, pp. 1–13.
- [23] C. S. Perone, P. Ballester, R. C. Barros, and J. Cohen-Adad, "Unsupervised domain adaptation for medical imaging segmentation with selfensembling," *Neuroimage*, vol. 194, no. January, pp. 1–11, 2019.
- [24] Z. Zhou, M. M. Rahman Siddiquee, N. Tajbakhsh, and J. Liang, "Unet++: A nested u-net architecture for medical image segmentation," *MICCAI Work. DLMIA*, vol. 11045 LNCS, pp. 3–11, 2018.
- [25] S. Jin, B. Wang, H. Xu, C. Luo, L. Wei, W. Zhao, X. Hou, W. Ma, Z. Xu, Z. Zheng, W. Sun, L. Lan, W. Zhang, X. Mu, C. Shi, Z. Wang, J. Lee, Z. Jin, M. Lin, H. Jin, L. Zhang, J. Guo, B. Zhao, Z. Ren, S. Wang, Z. You, J. Dong, X. Wang, J. Wang, and W. Xu, "AI-assisted CT imaging analysis for COVID-19 screening: Building and deploying a medical AI system in four weeks," *medRxiv*, 2020.
- [26] J. Chen, L. Wu, J. Zhang, L. Zhang, D. Gong, Y. Zhao, S. Hu, Y. Wang, X. Hu, B. Zheng, K. Zhang, H. Wu, Z. Dong, Y. Xu, Y. Zhu, X. Chen, L. Yu, and H. Yu, "Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study," *medRxiv*, 2020.
- [27] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *CVPR*, 2016, pp. 770–778.
- [28] D. T. Nguyen, C. K. Mummadi, T. P. N. Ngo, T. H. P. Nguyen, L. Beggel, and T. Brox, "SELF: Learning to filter noisy labels with self-ensembling," *CoRR abs/1910.01842*, pp. 1–15, 2019.
- [29] M. Ren, W. Zeng, B. Yang, and R. Urtasun, "Learning to reweight examples for robust deep learning," *ICML*, vol. 10, pp. 6900–6909, 2018.
- [30] C. Xue, Q. Dou, X. Shi, H. Chen, and P. A. Heng, "Robust learning at noisy labeled medical images: Applied to skin lesion classification," in *ISBI*, 2019, pp. 1280–1283.