Web Application for COVID-19 Detection using Super Resolution

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Abstract: Owing to the advancement in artificial intelligence computing, deep-learning neural networks have been used for transforming low resolution images into high-resolution images. This transformation is referred to as Super-resolution. Super-resolution has many applications worldwide like enhancing optical-microscope photographic images, satellite imagery, the study of the galaxy, etc. This technique can be used to fight against the growing number of COVID cases. COVID is presenting itself in the form of different strains, some of which are not detectable using RT-PCR (Reverse Transcription Polymerase Chain Reaction) or Rapid Antigen Test, however X-Rays or CT-Scans have higher chances of detecting them. These scans sometimes miss little details because of the blurriness/low-resolution of the image. This problem can be overcome by using the Fast Super-Resolution Convolutional Neural Network (FSRCNN). The purpose of this paper is to discuss a model that using FSRCNN and classification can detect Covid status in patients along with providing other vital information to the user. For the transformation of a low-resolution image into a high-resolution image, FSRCNN and for classifying whether the person is having coronavirus or not a Convolutional Neural Network (CNN) is used. Our models are trained and tested on 4 datasets, which are Set5, Set14, covid-chestxray-dataset, and chest-xray-pneumonia. Our results depict that after applying super-resolution on the X-Rays or the CT-Scans, the classification of COVID-19 attained a higher accuracy. These were the results after running the model for 20 epochs. Hence, with the help of the FSRCNN model, the classification of COVID-19 is much easier and accurate as compared to without the image super-resolution technique.

***Index Terms* - Image Super-Resolution, Keras, FSRCNN, COVID-19, CNN.**

I. INTRODUCTION

COVID-19 predictions are taking place through RT-PCR and Rapid Test, but due to lack of infrastructure and a slow response rate the number of tests in que increases. We propose the use of a web application to overcome this problem that uses X-Ray images of lungs to help in identification of COVID-19.

These X-Ray images due their low resolution can lead to some uncertainty in the model in terms of predicting the above. We use a fast super resolution convolutional neural network (FSRCNN) to improve the quality/resolution of a given X-Ray image while maintaining its feature and then classify it as covid or normal using a convolutional neural network (CNN). We use Flask web architecture due to its quick deployment feature and compatibility with python models.

II. LITERATURE SURVEY

One of the most important features of image super-resolution is textures and clear edges. The authors proposed an iterative interpolation approach that uses the non-sub-sampled contourlet transform (NSCT) to generate better high-resolution images while preserving textures and transparent edges [1]. Deep Learning image processing methods are gradually gaining popularity in a number of areas including medical imaging. In this paper, Koki Yamashita and Konstantin Markov discuss the same. Classification, segmentation, and denoising of images are some of the most demanded tasks. In this study, we aim at enhancing optic nerve head images obtained by Optical Coherence Tomography (OCT). However, instead of directly applying noise reduction techniques, we use multiple state-of-the-art image Super-Resolution (SR) methods. In SR, the low-resolution (LR) image is upsampled to match the size of the high-resolution (HR) image [2]. In this paper, Jingru Hou, Yujuan Si and Xiaoqian Yu use a novel and effective image super-resolution reconstruction technique via fast global and local residual learning model (FGRLR). The principle is to directly train a low-resolution small image on a neural network without enlarging it. This will effectively reduce the amount of calculation. In addition, the stacked local residual block (LRB) structure is used for non-linear mapping, which can effectively overcome the problem of image degradation. They also use skip connections to use low-resolution information for reconstructing high-resolution images [3]. In the next paper Researchers Jiangtao Nie, Yong Li, Lei Zhang and Yanning Zhang use a fusion based hyperspectral image (HSI) super-resolution method, which obtains a spatially high-resolution (HR) HSI by fusing a low-resolution (LR) HSI and a HR conventional image, which has been a prevalent method for HSI super-resolution. Experimental results shows the superiority of the proposed method for HSI super-resolution on three benchmark datasets [4]. Authors Yulun Zhang, Kunpeng Li, Kai Li, Lichen Wang, Bineng Zhong and Yun Fu propose a channel attention mechanism to adaptively rescale channel-wise features by considering interdependencies among channels. Extensive experiments show that our RCAN achieves better accuracy and visual improvements against state-of-the-art methods [5]. Further on we went through a survey paper by Xiaoming Niu written in 2018. Through analysing the algorithm of three aspects of super-resolution technology, this paper analyses its previous and latest research progress, and gives a outlook on the development of future super-resolution technology [6]. According to the image formation process, authors Guimin Lin, Qingxiang Wu, Qiu Lida, Xixian Huang and Xiyao Chen state a Deep Convolutional Network-based image Super-Resolution model DCNSR which is proposed and is trained using end-to-end. Experimental results demonstrate that the proposed model achieves a notable improvement in terms of both quantitative and qualitative measurements [7]. In the next paper authors Christian Ledig, Lucas Theis, Ferenc Husz´ar, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang and Wenzhe Shi focus on recovering the finer texture details when we super-resolve at large upscaling factors. An extensive mean-opinion-score (MOS) test shows hugely significant gains in perceptual quality using SRGAN. The MOS scores obtained with SRGAN are closer to those of the original high-resolution images than to those obtained with any state-of-the-art method [8]. The following paper authored by

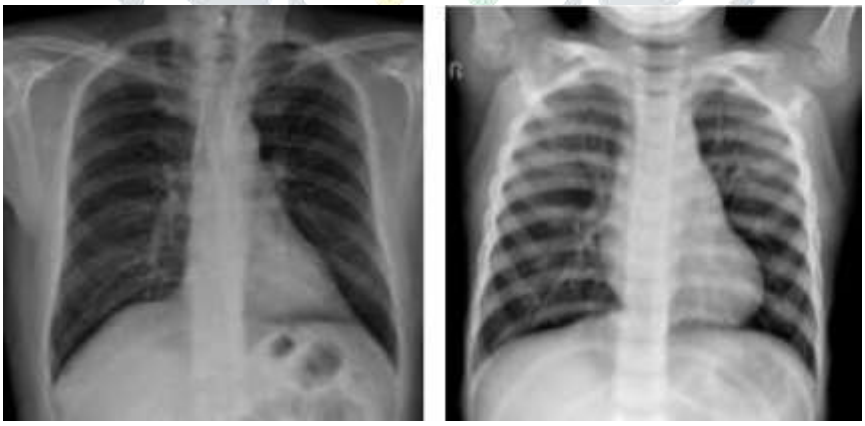
Linwei Yue, Huanfeng Shen, Jie Li, Qiangqiang Yuan, Hongyan Zhang and Liangpei Zhang discusses an exhaustive summary of the current applications using SR techniques. Lastly, the article discusses the current obstacles for future research.[9]. Authors Chao Dong, Chen Change Loy, Kaiming He and Xiaoou discuss new ways, that unlike traditional methods that handle each component separately, our method jointly optimizes all layers. Our deep CNN has a lightweight structure, yet demonstrates state-of-the-art restoration quality, and achieves fast speed for practical on-line usage. We explore different network structures and parameter settings to achieve trade-offs between performance and speed.[10].

III. RESEARCH METHODOLOGY

The purpose of this study was to build a web application that took advantage of existing and easily available infrastructure, i.e. X-ray machines and CT-Scans for quick and efficient detection of COVID-19, along with providing other necessary details to the user. For the efficient detection of COVID-19 we propose the usage of FSRCNN algorithm for increasing the resolution of the image followed by a classification algorithm for COVID-19 detection. The following key phases were considered while developing the COVID-19 detection model: Image pre-processing, Image degradation, Image super-resolution, and CNN. Secondary information that was selected to be displayed in the web app included recent statistics on COVID-19 with graphical representation, and general health information addressing the same.

The FSRCNN super resolution model is required to learn the mapping between low resolution images to high resolution images. To achieve this Set5 and Set14 datasets were used. These are common evaluation dataset for Super Resolution of images, containing various images from buildings to animal faces. Images were pre-processed and the dimensions were converted into 224 for length and width and had 3 channels. An image dataset of 1344 was used with a test train split of 75 is to 25 was used. This consisted covid-chestxray-dataset dataset is used which contains the X-Rays of lungs categorized into two classes namely COVID and NORMAL Hyper tuning of the parameter was done with binary cross-entropy and ADAM optimizer per epoch for 20 epochs.

Figure 3.1: Sample images of Set5 and Set14 datasets (high-resolution images)



(A) (B)

Figure 3.2: covid-chestxray-dataset and chest-xray-pneumonia dataset of both (A)COVID positive and (B)normal case

Information sources used to supplement secondary information, i.e., cases and health information were taken from two different sources. Covid statistics were taken from COVID-19 API which was independently built by Kyle Redelinghuys. The data is sourced from COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. The data present is automatically updated on a regular (hourly to daily) basis. General health information query related to COVID-19 is hard coded and taken from the World Health Organization website.

Flask is a micro-framework which was chosen to supplement the project, reason being its simplicity, ease of building prototypes and smaller codebase (leading in reduced application size), along with ease of integration with machine learning models.

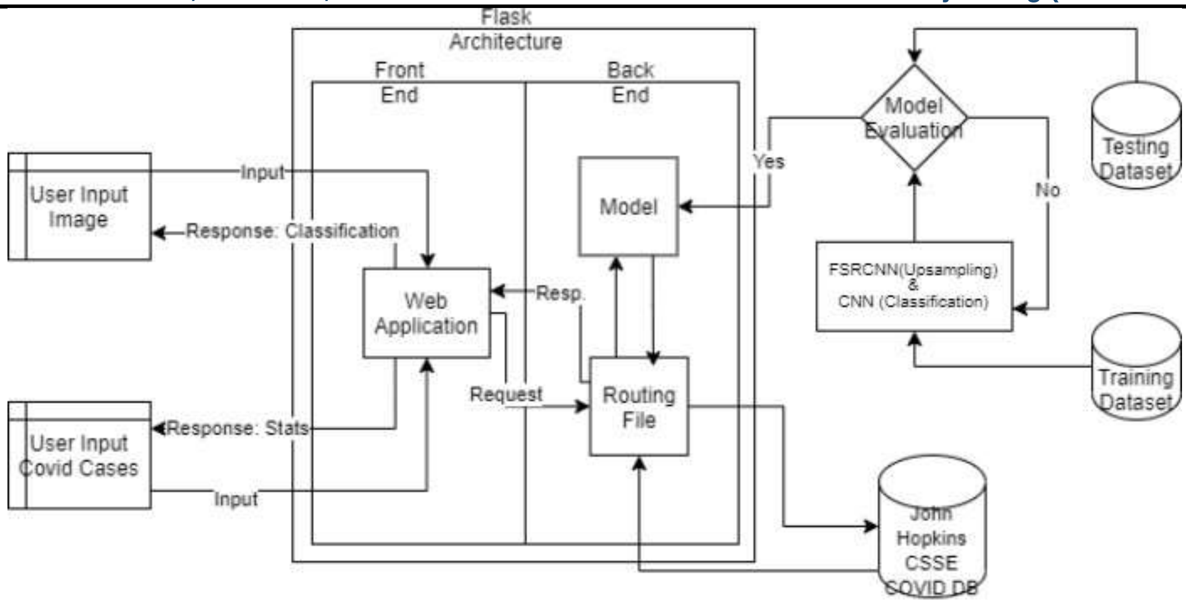


Figure 3.3: Application Architecture

IV. RESULTS

The accuracy that was attained after 20 epochs of training was 96.23%. This accuracy was higher than the accuracy of the model in which image super-resolution was not considered. Due to image super-resolution, our model achieved this accuracy. For hyper tuning, we hyper-tuned loss function, optimizer, epochs, and the learning rate. The corresponding values for the hyperparameters were: binary cross entropy as the loss function, ADAM as the optimizer, 20 is the number of epochs, and 0.002 as the learning rate.

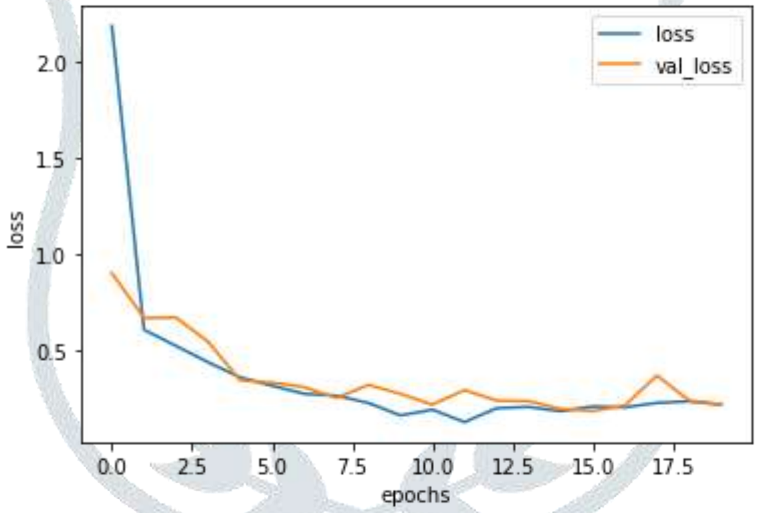


Figure 4.1: Accuracy for training and testing model

Figure 4.1 provides the representation of the increase in accuracy of the model throughout the 20 epochs. There were some mountains that were generated in the testing phase as the image dataset was not sufficient. Due to the lack of data, the model was fluctuating but it became stable after the 17th epoch. Here the accuracy we got was 96.23%.

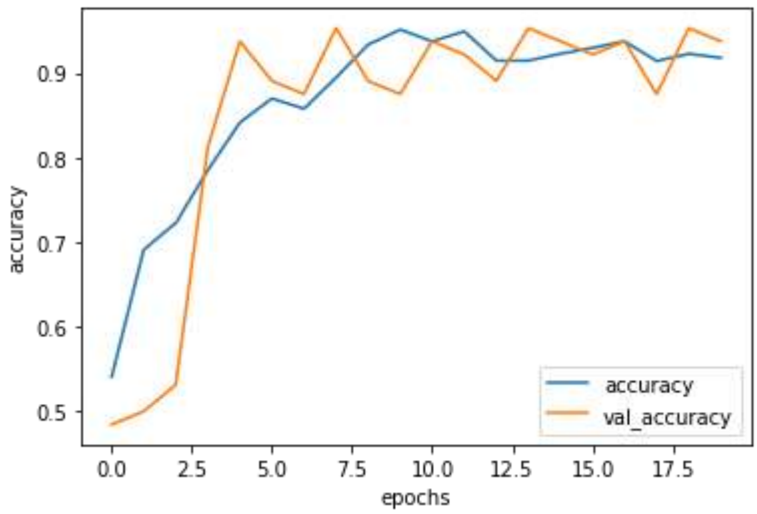


Figure 4.2: Loss for training and testing model

From figure 4.2, one can come to a realization that the loss is decreasing gradually till 15-17 epochs and after that, the graph is pretty much stagnant. This was the reason behind "why 20 epochs?". Here the loss we achieved was ~18%.

Therefore, from the results, we can say that due to the FSRCNN algorithm, the classification was better of whether or not a patient has COVID-19.

V. CONCLUSION

In this paper, an algorithm known as FSRCNN is used which converts a low-resolution image to a high-resolution image. This algorithm is applied before another algorithm known as CNN which is used to classify whether the patient has COVID-19 or not. The purpose of using an image super-resolution algorithm prior to classification was to get more accuracy. After applying super-resolution on the dataset, the results were boosted up by 3.5% and the total accuracy of the whole model that we got is 96.23%. The classification algorithm runs after FSRCNN and when the classification is complete, the web application fetches the results and displays them on the user's screen. This web application is a recourse to people as the world is prevailed by coronavirus. This application will require only a chest X-Ray or a chest CT-Scan and after the user inputs the data, the result will pop up accordingly. For the purpose of training and testing, we used four datasets namely Set5, Set14, covid-chestxray-dataset, and chest-xray-pneumonia. The accuracy mentioned above is reached after 20 epochs. The hyperparameters used were adam optimizer, learning rate of 0.002, and activation function as prelu and sigmoid.

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