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Ensemble Deep Convolution Neural Network for Sars-Cov-V2 Detection

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ABSTRACT- The continuing Covid-19 pandemic, caused by the SARS-CoV2 virus, has attracted the eye of researchers and many studies have focussed on controlling it. Covid-19 has affected the daily life, employment, and health of human beings along with socio-economic disruption. Deep Learning (DL) has shown great potential in various medical applications in the past decade and continues to assist in effective medical image analysis. Therefore, it is effectively being utilized to explore its potential in controlling the pandemic. Chest X-Ray (CXR) images were used in studies pertaining to DL for medical image analysis. With the burgeoning of Covid-19 cases by day, it becomes imperative to effectively screen patients whose CXR images show a tendency of Covid-19 infection. Several innovative Convolutional Neural Network (CNN) models have been proposed so far for classifying medical CXR images. Moreover, some studies used a transfer learning (TL) approach on state-of-art CNN models for the classification task. In this paper, we do a comparative study of these CNN models and TL approaches on state-of-art CNN models and have proposed an ensemble Deep Convolution Neural Network model (DCNN).

General Terms: Neural Network, Deep Learning (DL), Covid-19, Chest X-Ray (CXR), Medical Image Analysis.

Keywords: Convolutional Neural Network (CNN), Deep Convolutional Neural Network (DCNN), DenseNet121, VGG19, Support Vector Machine (SVM).

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1. INTRODUCTION

In March 2020, the World Health Organisation (WHO) declared COVID-19 as a pandemic and it is said to be one of the most detrimental pandemics in history. Initially, several names were used for the virus but WHO in January 2020 advocated the tentative name as a 2019-novel coronavirus (2019-nCov). Till 22 March 2020, the covid-19 epidemic had caused over 123 million infections and over 2.7 million deaths worldwide. The virus has varied symptoms ranging from some to critical illness and some of the common symptoms are cough, sore throat, loss of smell, difficulty in breathing, fever, dry cough, etc. The primary spread of this infection is through the air. A healthy person in close proximity to an infected person or in contact with a contaminated surface is highly probable to incur the infection. Therefore, it is always advised for an infected person to remain isolated during the infection period. Some infected patients don't develop any noticeable symptoms and don't get tested for the disease. These asymptomatic carriers tend to unknowingly spread the infection. Preventive measures can abate the risk of getting infected by Covid-19. It is advised to wear face masks and gloves in public places to avoid contact with contaminated surfaces and air particles.

Covid-19 patients suffer from lung infection and it can cause other lung issues such as ARDS (Acute Respiratory Distress Syndrome), pneumonia, and sepsis. It is essential for the world to fight covid-19 and screening potential covid-19 patients is one of the predominant tasks for taking a step against the covid-19 spread. Bio-Medical Image analysis is a popular research field and it has received a lot of attention in recent years. CXR images are widely available in various open databases for research and these databases have been used to classify CXR images to potential covid-19 cases using the DL technique. CXR images are preferred over CT images because CXR images are easily and cheaply available. DCNN technique has been widely used for classifying potential covid-19 positive CXR images by feature extraction and learning. The dataset is pre-processed and divided into training data, validation data, and testing data. Other hyperparameters such as optimizer, number of epochs, loss function, suitable batch size, are set for the model, and training data and validation data are used to learn the weights of the network. Furthermore, this trained model is used to classify the images in testing data.

2. SYSTEM MODEL

Rachna Jain et al. [1], in their paper, considered posteroanterior view scans of CXR for healthy and Covid-19 patients. The authors used three different DCNN models and compared these models using necessary evaluation metrics. The models considered were Xception Net (XN), Inception Net V3, ResNet.

It was concluded that the XN model gave the highest accuracy among the compared models. The dataset used was taken from the Kaggle repository and it constituted CXR scans of people affected with pneumonia, Covid-19, and healthy people. There were a total of 6432 CXR images, out of which 5467 images were considered for training and 965 images were considered for validation. The three models were trained using this dataset and used on the validation set for predictions. These models predicted whether the image in the validation set belonged to a normal, covid-19, or pneumonic person. Leaky RelU activation was used instead of ReLU to boost up the training system and avoid the issue of dead neurons. Categorical cross-entropy loss was used which optimizes the parameters used in the model. Moreover, Adam Optimizer (AO) was used with a learning rate of 0.001 for training. It was concluded that the XN model gave the highest testing data accuracy of 97% amongst the models the authors presented in their paper.

Mohd Zulfaezal Che Azemin et al. [2], in their study, used ResNet - 101, a CNN with 101 layers. The model's hyperparameters have been described briefly in *Table 1*. The dataset used for training and validation purposes was distilled from the CXR 14 dataset, which is a dataset of thoracic disorders amongst masses. The actual dataset had four labels namely: Fracture, Pneumothorax, Nodule - mass, Airspace Opacity. In this study, the authors made the intellectual decision of using only one label for training the model, airspace opacity which at the time was found to be linked to positive COVID - 19 cases. The authors based their study only on frontal CXR. The authors also introduced 5828 images labeled "no finding" to the dataset used in their study for the sake of simulating a population with a 2.57% spread rate. As the study was done at a time where there wasn't as much data available compared to a few months after the study was done, the study tends to have less desirable metrics compared to other models in our study. The performance metrics of the model are as follows: accuracy - 71.9 %, sensitivity - 77.3%, specificity - 71.8%.

Ioannis D. Apostolopoulos et al. [3], in their research, focused on evaluating the effectiveness of the models considered for the study. The models that were evaluated are complex and required large data sets for classification and feature extraction. However, the dataset used in the study is small so TL is used to train CNN models because of their capability to retain knowledge from one job and use it to perform another. The authors used two different CXR image datasets for their research. 224 covid-19 positive images, 700 confirmed common bacterial pneumonia images and 504 normal health patients' images were present in the first dataset. The second dataset was a slight modification of the first dataset. This dataset included 224 covid-19 positive cases images, 504 images of healthy patients, 400 bacterial, and 314 viral pneumonia patients. The study considered several state-of-art-CNN models and parameters tuned for TL purposes namely XN, Inception, MobileNet v2, Inception ResNet v2, and VGG19. These CNN models shared some common hyperparameters. All the convolutional network models used Rectified Linear Unit activation function (ReLU) and AO. The classification metrics observed in this study were confusion matrix, specificity and sensitivity. Furthermore, the authors calculated two different accuracies. The first accuracy, called the 3-class accuracy, was the total accuracy of the models in predicting the three classes. Nevertheless, 2-class accuracy was only related to Covid-19 patients. It was further observed that MobileNet v2 showed better results than VGG19 for specificity. Therefore, the authors concluded that MobileNet v2 was the best model for the specific classification task. The setup of the MobileNet v2 model was retained to perform the classification for the second dataset. Finally, the authors concluded that MobileNet v2 was the best model for the classification task amongst other models.

Arun Sharma et al. [4] used Artificial Intelligence-based techniques to classify CXR images for the screening of Covid-19 patients. A TL approach for the classification task to make the model efficient was implemented. The authors used CXR images for adults that were publicly available and performed 25 data augmentations on the dataset to increase its size for better analysis and 27 different datasets were created from it. Furthermore, the authors used all these datasets to train and validate 29 different models using the TL approach. One model from these 29 models was trained on the 1st dataset and 25 from the remaining models were trained on the 2nd to 26th datasets. The first convolutional layer (CL) used a filter size of 3 and 32 filters. The second CL used 64 filters, filter size 5, and the third CL used 128 filters and filter size 7. Finally, the last three models were trained with the last dataset with a different number of iterations and epochs than the previous 26 models. The three models with the highest accuracy were selected and presented as the best three models for the classification task.

Prabira Kumar Sethy et al. [5] used two different sets of datasets for their study. The first dataset contained positive COVID-19 X-ray images excluding MERS, SARS, and ARDS. However, the second dataset contained negative COVID-19 X-ray images. The authors considered these two datasets for DL feature extraction using several models separately. The models used in their study were DenseNet201, AlexNet, GoogleNet, VGG16, ResNet 101, ResNet18, ResNet 50, XN, InceptionV3, and InceptionResNetV2. After extracting the deep features from these models, the authors used the Support Vector Machine (SVM) to classify them. A wide range of classification metrics was used to test this study. These metrics on which the models were evaluated were Specificity, Accuracy, Matthews Correlation Coefficient (MCC), Sensitivity, False Positive Rate (FPR), Kappa and F1 score. It was finally concluded that the ResNet50 plus SVM model showed better results for classification than other considered models with an accuracy of 95.38 %.

Tulin Ozturk et al. [6] in their paper focused on building a DL model, DarkCovidNet, for the detection of Covid-19 cases using CXR images. The authors used their model for binary classification for images, the classes being Covid-19 and no findings. Moreover, they used their model for three-class classification, the classes being Covid-19, pneumonia and neither. The model uses an end-to-end architecture. The proposed model DarkCovidNet is inspired by the existing DarkNet model. DarkNet model is a classification model for real-time object detection and is a successful DL architecture.

The DarkCovidNet model has 17 CNN layers and each DarkNet layer has a CL, Batch Norm, and Leaky ReLU layers one after the other. The model used AO, cross-entropy loss function, the learning rate of 3e-3, and had a total of 1,164,434 parameters. This model was used for binary and multi-class classification using five-fold cross-validation. The authors split the dataset into 80% training and 20% validation data and trained the DarkCovidNet model for 100 epochs. Evaluation metrics used in this study were sensitivity, specificity, precision, F1-score, and accuracy. The model gave an average multi-class classification percentage accuracy of 87.02 % and the average binary classification percentage accuracy of 98.08%.

Shervin Minaee et al. [7] used a prominent concept of TL to fine-tune four popular DL models named ResNet18, ResNet50, DenseNet-121 and SqueezeNet, to predict Covid-19 positive cases from CXR images. These four models were evaluated and compared with each other to determine the model with the best performance. The authors also created a dataset COVID-Xray-5k from the Joseph Cohen dataset, COVID-Chestxray-dataset, and ChexPert dataset. This dataset was divided into 2,031 training samples and 3,040 testing samples and each image had a corresponding binary label that tells whether it is a Covid-19 positive case or not. The study used a TL approach because the labeled data for Covid-19 X-ray images was limited and it might not be possible to train a model from scratch. Each model went through 100 epochs for fine-tuning, learning rate of 0.0001, batch size of 20, used AO, and downsampling of images to 224*224. The authors found that the dataset was imbalanced which made sensitivity and specificity good evaluation metrics. Moreover, the authors also considered ROC and AUC for evaluation. Finally, it was concluded that for a sensitivity rate of 97.5%, these models achieved a high 90% average for the specificity metric. Furthermore, ResNet50 and SqueezeNet performed better than the other two models.

A Stacked Ensemble DL Model named CoVNet-19 was proposed by Priyansh Kedia et al. [8] The researchers collected 6,214 CXR scans from five different open-sourced datasets and divided the dataset into Training, Validation, and Test Set. Two pre-trained DCNN were used namely VGG-19 and DenseNet121 which minimized noise, bias, and variance problems. Therefore, both models were used for feature extraction from the X-Ray images. The hyperparameters used were 10 epochs, 0.001 learning rate, and AO. The trained model was a robust and highly efficient classification model. SVM classified the images and the model achieved 99.28% accuracy for the three-class classification and 99.71% for the binary classification. Moreover, the proposed model was evaluated using accuracy, F1 Score, precision, confusion matrix, recall, and MCC score.

Stefanos Karakanis et al. [9], in their paper, first implemented a Conditional Generative Adversarial Network (cGAN) to create artificial data, as at the time of their study very limited data was available. Employing cGAN to generate synthetic data, certainly has improved the overall performance metrics of their proposed models for COVID-19 classification. The discriminator for the implemented cGAN architecture constitutes a standard Convolution Neural Network. The authors used AO for Stochastic Gradient Descent. Followed by the generation of the synthetic CXR image data, the authors have presented two DL models for COVID-19 classification. For binary classification, Stefanos et al., have proposed a CNN, consisting of a uni-CL with filter size 32 and kernel 4 x 4. Further, they've used the ReLU Function and Max pooling layer for feature extraction with a dense layer sized 128. For the multiple classes architecture, they've used 5 CNN layers, each having a ReLU function. The first layer is similar to the binary classification model, but the second one consists of one stride for convolution with a filter size of 64 and 4 x 4 kernels. Following this was a max-pooling activation operation, and 3 more layers with 128, 128, and 256 filter sizes and equivalent kernel size. There are two more dense layers with 512 and 128 filter sizes respectively. The final layer uses the softmax function for multi-class output. The COVID-19 data has been extracted from a Github repository made available by researchers at Montreal University. Another dataset containing CXRs of normal and pneumonia cases available at Kaggle has also been used. The proposed model for binary classification on the modified datasets achieved a 100%, 98.3%, 98.7% sensitivity, specificity, and accuracy respectively. The multi-class model achieved 99.3%, 98.1%, 98.3% sensitivity, specificity and accuracy respectively. These although may seem very good performance metrics, a lot of further studies are required to check how good the proposed models actually are.

Asif Iqbal Khan et al. [10], have implemented a CNN model for the purpose of classifying COVID-19 infected patients from the rest, on CXR image data. The authors have proposed a model which can classify the CXR images into 3 classes of pneumonia, namely- Bacterial, Viral, COVID-19. The proposed model is called CoroNet and has been derived from the XN model architecture. The proposed model has 33,969,964 parameters of which 54,528 are non-trainable. Their study is based on 3 datasets, of which two were for training and the dataset used by Tulin Ozturk et al. in their paper, for testing purposes. Dataset 1 contained 290 COVID-19 infected CXR images and 2 contained 660 bacterial, 931 viral, and 1203 non-infected images, of which only 1300 were used for training purposes to keep the dataset balanced. The dataset used for testing purposes contains 157 COVID-19 images and around 1000 non-Covid-19 images. The proposed model was implemented on Keras and was trained on a dataset that was optimized using AO. CoroNet achieved an accuracy of 96.6%, precision of 93.17%, recall of 98.25%, and F1 score of 95.6% for the COVID-19 class. For further improved performance metrics the authors fine-tuned the model and reduced the 4-class architecture to 3 classes by clubbing the bacterial and viral pneumonia classes into one class which increased the overall accuracy of the model from 89.6% to 94.59%.

3. PROPOSED 1D-CNN MODELS

The end goal of our model is to differentiate between the CXR images of patients who have tested positive for Covid-19, a person who is physically fit and patients with Pneumonia. Our proposed model is based on DCNN framework for the accurate COVID-19 patients' detection with the use of trained DCNN on the collected datasets of CXRs. Our model is bi-stacked ensemble model.

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In the primary level of our proposed model, we have collated two pre-trained models VGG19 and DenseNet-121. These models were chosen because of their high-performance metrics for the purpose of classification of the CXR images. The image noise was accounted for using the combinational characteristics from the two Deep Convolutional Neural Networks.

At the secondary level of our model, a SVM model was used for the classification purposes and trained on the features extracted from our primary model.

3.1 DenseNet121
This has 121 layers and advantages such as supporting reusing of features and solving the problem of vanishing gradient. This model was sourced and trained on the Imagenet dataset. As known, every layer of this model uses activation-maps of the preceding layer as the input. This considerably decreased the parameters which were trainable compared to a CNN model with equal layers.

3.2 VGG19
It consists of nineteen layers, with sixteen CLs and three dense layers. This model was sourced alongwith with the previously mentioned DenseNet 121 model. The input to our secondary layer of SVM model for the classification purposes has been obtained as a feature vector from the second last layer of this model which is a Dense Layer with thirty-two nodes.

3.3 Dataset Description
We have used multiple repositories which were available publicly. We then created one unified library of the datasets and made a random split between training, validation and testing set. The repositories that were used are mentioned in the *table*.

Table 1. Datasets used in our proposed mode

Dataset	Reference	COVID-19	Normal	Pneumonia
1	[11]	230	1231	1400
2	[12]	15	965	1334
3	[13]	359	0	56
4	[14]	60	500	0
5	[15]	89	256	24
Total		753	2952	2814

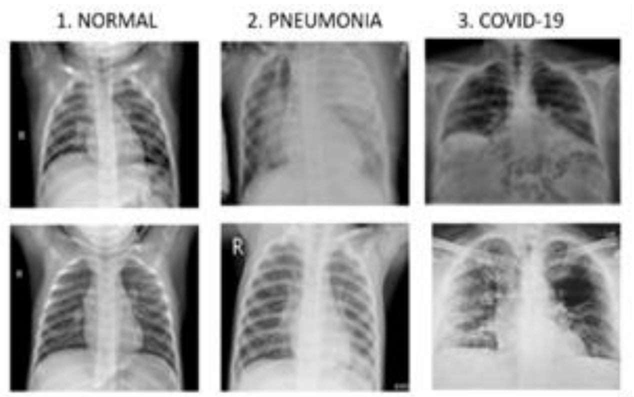

Figure 1: Random Images from our unified dataset

3.4 Model Hyperparameter
The reason behind using AO over others was the presence of finest properties from both the AdaGrad and RMSProp. It is significantly faster and highly reliable in reaching the Global minima with the pre-set hyperparameters. Binary Cross entropy and Categorical cross entropy were chosen as the loss function while training.

4. SIMULATION RESULT
After building our proposed model, we trained and tested it against the collected datasets. The results are further tabulated in detail in the subsequent sections.

4.1 Three Class Classification

Table 2. Datasets used in our proposed mode

Training	P	R	F1	Accuracy
COVID - 19	1.00	0.98	0.99	99.54%
Normal	0.99	0.97	0.97	
Pneumonia	0.97	0.96	0.96	
Validation	**P**	**R**	**F1**	**Accuracy**
COVID - 19	0.99	0.98	0.99	98.21%
Normal	1.00	0.97	0.97	
Pneumonia	0.97	0.98	0.95	
Testing	**P**	**R**	**F1**	**Accuracy**
COVID - 19	0.98	0.94	0.98	99.02%
Normal	0.99	0.98	0.97	
Pneumonia	0.97	0.99	0.99	

4.2 Two Class Classification

Table 3. Datasets used in our proposed mode

Training	P	R	F1	Accuracy
COVID - 19	1.00	1.00	1.00	99.94%
Pneumonia	0.99	0.99	1.00	
Validation	**P**	**R**	**F1**	**Accuracy**
COVID - 19	1.00	0.99	0.96	99.55%
Pneumonia	0.99	0.99	0.98	
Testing	**P**	**R**	**F1**	**Accuracy**
COVID - 19	1.00	0.99	0.98	99.83%
Pneumonia	0.97	1.00	1.00	

5. MODEL COMPARISON & DISCUSSION

The aforementioned papers notably proposed either comparative studies of various CNN architectures or self-developed optimized models based on existing DL algorithms. The central methodology of almost all of these studies was to augment or collect the datasets fine-tune and optimize the models that included determining the number of layers in the selected neural network, minimum batch size, maximum epochs, and learning rate. The accuracy, specificity, precision, F1-score, and recall values were then compared with the other existing models. The models worked upon classifying the CXR images, present in the datasets, chiefly into 3 classes, Covid-19 Positive, Pneumonia and normal. The major drawback of most of the studies was the small size of training and testing sets, owing to the fact that most of these were conducted within the first 3 quarters of the year 2020. Small datasets raise concerns about overfitted and biased models. One of the solutions put forth in [4] was to generate 25 different types of augmentations using CLodDSA. Another concern with regard to the datasets is that they include CXR images from different age groups. Even though this makes classification of the images easy but the learning algorithm might become biased since the lung size of an adult age group is much larger than the paediatric age group. The models need to be trained accordingly to include this criterion. Almost all the models were trained on the datasets having limited diseases for classification. A better and more inclusive model would want to include other diseases and syndromes like SARS, ARDS, MERS, etc.

Models proposed [7], [3] and [4] use the TL CNN approach, a technique used to transfer the knowledge of a model usually trained on a larger dataset into a comparatively smaller dataset. This technique saves time and effort and is a great way to train, validate and test the CNN model and achieve high accuracy even with a limited number of images in the training set. The TL approach is then applied along with few of the best performing CNN models like Inception, VGG19, XN, MobileNet v2, and Inception ResNet v2. In [3], even though VGG19 has greater accuracy, MobileNet V2 outperforms it owing to greater specificity and hence is claimed as the best model with an accuracy of 97.40% (2-class) and 92.85% (3-class). MobileNet V2 has less number of False Negatives as compared to VGG19, which is crucial in this classification task since close to none suspected positive cases should be ideally classified incorrectly. Similarly, the model proposed in [10] predicts a low number of False Negatives, consequently increasing the recall value. In [5], the authors conclude that for models using the SVM algorithm for classification, ResNet50 gives the highest accuracy and specificity and the lowest FPR amongst other models considered by the author.

For the wide adaptability of the various models and to ensure quick processing and management of the CXR image dataset to aid the medical facilities, the models should be lightweight and free from sample bias. The Covid-Net model developed in [9] is a promising simple lightweight model for binary and multi-class classifications which uses CNN and ReLU function for feature extraction. The model has achieved an impressive accuracy of 98.7% in two class classification and 98.3% in three class classification. The model does not require pre-trained weights that explains the reduced model size, parameters, and complexity but on the other hand, would require training the model every time we have a new set of image dataset. Another shortcoming is that the dataset used to train the model chiefly consists of synthetically generated images with the aid of conditional cGANs. This can be resolved by training and testing the model on more real-world data to finetune it further. Our model uses Stacked Ensemble DL Model which makes use of 2 DCNNs and an SVC model which undoubtedly increases the overall accuracy of the model to 99.83% which is the highest of all the other papers reviewed but in turn, makes the whole model bigger and complicated that restricts its rapid adaptability. The model also limits the feature extraction to 32 for 1 DCNN and does not finetune every CL. A model should aim to work on real-time object and anomaly detection rather than being very deep. The model developed in [6] provides a novel addition in the form of the heatmaps that highlight the portion of concern in the CXR images. These heatmaps are for the reference of the radiologists to decipher the severity of the disease through manual analysis.

Table 4. Comparison with other methods

Publication Time	Authors	Model	Accuracy
Aug 2020	Mohd Zulfaezal Che Azemin et al.	ResNet 101	71.90%
Apr 2022	Tulin Ozturk et al.	DarkCovidNet	98.08%
Feb 2021	Priyansh Kedia et al.	CovNet-19	99.71%
Dec 2020	Stefanos Karakanis et al.	Covid-Net	97.73%
May 2020	Asif Iqbal Khan et al.	CoroNet	96.60%
	Subrat Sarangi et al.	Proposed Model	99.83%

5. CONCLUSION & FUTURE SCOPE

The COVID-19 has posed a huge challenge in front of researchers, medical professionals, and scientists. The rapid and selfless response from some of the bright minds tried to share the burden of the already overwhelmed medical institutes. All the papers reviewed in our study provide models and combinations of algorithms to classify the CXR images the affected patients correctly. The problem of the limited size of the datasets available, overfitting, bias, inadequate parameters, and limited computational powers was skilfully handled by various models proposed.

The future scope of work includes training, validating, and testing our model on a large dataset made possible either through image augmentation or rapid testing for the virus. The model should also include various other pneumonia-based diseases to classify the images upon, in order to finetune the model. The model should be lightweight and shouldn't run on paid or bulky software so as to make sure that it can be used by a large number of medical agencies.

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Table 5. Comparison with best performing methods

Publication Time	Authors	Models Considered	Best Amongst Them	Accuracy of the Best Model
Oct 2020	Rachna Jain et al.	1. XN 2. Inception Net V3 3. RestNet	XN	97.97%
Mar 2020	Ioannis D. Apostolopoulos et al.	1. Inception 2. VGG19 3. MobileNet V2 4. Inception ResNet V2 5. XN	MobileNet V2	97.40%
Jul 2020	Arun Sharma et al.	1. 24 Epoch-based model 2. 49 Epoch-based model 3. 101 Epoch-based model	101 Epoch-based model using 60° rotated images	66.67%
Mar 2020	Prabira Kumar Sethy et al.	1. VGG16 2. DenseNet 201 3. GoogleNet 4. ResNet 50 5. ResNet 18 6. Inception ResNet V2 7. XN 8. ResNet 101 9. AlexNet 10. Inception V3	ResNet 50	95.38%
Apr 2020	Shervin Minaee et al.	1. ResNet 18 2. Squeezenet 3. ResNet 50 4. DenseNet 121	SqueezeNet	97.73%

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