COVID-19 Detection Using Chest X-Ray Images with a RegNet Structured Deep Learning Model

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Abstract. AI-based medical image processing has made significant progress, and it has a significant impact on biomedical research. Among the imaging variants, Chest x-rays imaging is cheap, simple, and can be used to detect influenza, tuberculosis, and various other illnesses. Researchers discovered that coronavirus spreads through the lungs, causing severe injuries during the COVID19 pandemic. As a result, chest x-rays can be used to detect COVID-19, making it a more robust detection method. In this paper, a RegNet hierarchical deep learning-based model has been proposed to detect COVID-19 positive and negative cases using CXI. The RegNet structure is designed to develop a model with a small number of epochs and parameters. The performance measurement found that the model takes five periods to reach a total accuracy of 98.08%. To test the model, we used two sets of data. The first dataset consists of 1200 COVID-19 positive CXRs and 1,341 COVID-19 negative CXRs, and the second dataset consists of 195 COVID-19 positive CXRs and 2,000 COVID-19 negative CXRs; all of these are publicly available. We obtained precision of 99.02% and 97.13% for these datasets, respectively. As a result of this finding, the proposed approach could be used for mass screening, and, as far as we are aware, the results achieved indicate that this model could be used as a screen guide.

Keywords: COVID-19· Chest X-Rays· Deep learning· RegNet· CNN · Image processing

1 Introduction

Coronavirus was first discovered in late 2019 in Wuhan, Hubei Province, China, and is now the most feared name in the world. According to the World Health Organization (WHO), in mid-April 2021, 138 million people were infected, and 2.97 million people have died. COVID-19 is distributed from person to person through respiratory transmission. In most cases, it is spread through direct contact with people who have COVID-19, such as through air or hand contact. The most common symptoms include fever, dry cough, exhaustion, sore throat, headache, nausea, muscle pain, and shortness of breath [1]. COVID-19 causes pneumonia in humans, which affects the lungs and results in severe injury. Real-time reverse transcription-polymerase chain reaction (RT-PCR) is the most widely used detection method for COVID-19 diagnosis. Since people infected with COVID-19 develop pneumonia, chest radiological screening, such as X-rays and computed tomography (CT) scans, can be used to diagnose the infection [3, 4]. After all, when the virus spreads to the lungs, it causes serious injuries. As a result, radiographic imaging of the chest may be used to diagnose disease [5].

In recent months, several researchers have successfully contributed to the early detection methodology of COVID-19 infection. This was possible as recent developments in artificial intelligence (AI) [7] and Machine Learning (ML) [6] and computational techniques. Through the study of computed tomography (CT) lung imaging, chest x-ray images, workplace employee safety, symptom identification using fluid systems, and hospital support for robots, several AI and ML-driven approaches to help COVID-19 were created [9–13]. It's difficult to create a classifier with a small number of details. Overcome this problem by considering unique class-specific features that need to be learned if the experience of common features can be imported or borrowed. RegNet Structured Deep Learning Model can be used to do this. Our contribution in this work is listed below:

- A ML model for classifying COVID-19-infected patients based on their chest x-ray images has been suggested.
- The model is trained and tested on an open dataset of COVID-19 infected chest x-ray images.
- A RegNet Structured deep learning model is proposed to learn features from the chest x-ray images.
- The proposed approach is higher than state-of-the-art learning algorithms available in the literature.

The remainder of the study is summarized as follows: The related works explaining COVID-19 detection using a Machine Learning Model are presented in Section II. COVID-19 Chest X-Ray is included in Section III. The proposed COVID-19 detection model is introduced in Section IV of the imaging datasets. Model evaluation is covered in Section V. The findings and discussion are described in Section VI. Finally, Section VII brings the work to an end.

2 Related Works

Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) causes Coronavirus Disease 2019 (COVID-19). Using a chest X-ray image, A.K. Jaiswal et al. [2] used deep learning to recognize pneumonia in the lungs. The researcher [8] used three different deep learning models to classify the pneumonia patient using

X-ray images: fine-tuned model, model without fine-tuning, and scratch-trained model. Another research obtained an average of 82.2% accuracy using the ResNet model and Multi-Layer Perception (MLP) as a classification tool. S.S. Yadav et al. [15] used X-Ray images of natural, bacterial, and viral pneumonia to classify pneumonia using classification algorithms such as SVM, InceptionV3, and VGG-16 models as a deep learning approach. To detect COVID-19 positive patients, we have used a chest X-Ray image data processing method. The study aims to develop a technique that uses image recognition and deep learning to detect the COVID-19 coronavirus. The suggested procedure is validated on a data collection of chest X-Ray photographs and Covid positive and negative chest images and provides tailored findings. In CXRs, K.C. Santosh et al. [16] used Faster R-CNN to locate foreign objects such as surgical tubing, instruments, and jewelry. The proposed DNN had a precision of 97%, a recall of 90%, and an F1 score of 93%. In another work, K.C. Santosh [17] addressed that AI-driven tools will facilitate to spot COVID-19 outbreaks and predict their nature of spread across the world. .Dipayan Das et al. [18] suggested an AI-driven screening method that uses a Truncated Inception Net Convolutional Neural Network (CNN) model to distinguish COVID-19 positive cases from chest x-ray images and found 99.96% accuracy. Himadri Mukherjee et al. [19] proposed a lightweight (9 layered) CNN-tailored deep neural network model to identify COVID-19 for both CT Scans and Chest X-rays images, and they achieved 96.28% accuracy. The authors [20] developed a shallow CNN-tailored architecture model with fewer parameters that can automatically identify COVID-19-positive cases with no false negatives using chest X-rays and achieved the highest precision of 99.69%. To diagnose COVID-19 cases using chest x-rays, Mesut Togaçar et al. [21] used the Fuzzy color approach, Stacking technique, Social mimic, and Deep learning approaches where the average accuracy rate was 99.27%. In their article, Ali Narin1 et al. [22] used five pre-trained convolutional neural network-based models (ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2) to diagnose coronavirus positive cases using chest X-ray images and achieved 96.1%, 99.5% and 99.7% accuracy for three separate datasets. Huang C et al. [23] published a paper on COVID-19's therapeutic and paraclinical dimensions in January 2020. They claimed that Ground-Glass Opacity (GGO) anomalies could be detected using chest CT scans (based on 41 positive cases). CT scans are commonly used to recognise irregular trends in COVID-19 confirmed cases [24–26]. Li and Xia [27] tested 51 CT scans (images) and found that COVID-19 could be identified in 96.1% of the cases. Zhou S et al. [28] tested 62 COVID-19 and Pneumonia mice, and their findings revealed a variety of trends that resemble lung parenchyma and interstitial diseases. Author of [29] and [30] addressed a convolutional neural network with transfer learning to detect for COVID-19 positive cases. Tulin Ozturk et al. [31] proposed a deep learning model called DarkCovidNet, which can detect COVID-19 cases with 98.08% accuracy using CXRs. Jing Xu et al.[32] proposed a self-regulated network for image classification. They used RNN and followed RegNet architecture. Emtiaz Hussain et al.[33] introduced a deep learning model called CoroDet to detect COVID-19 by using plain chest X-rays and

CT scan images with up to 99.1% accuracy. In a few recent works, authors' [34] proposed model is a multi-class classification model since it divides photos into four categories: bacterial pneumonia, viral pneumonia, natural, and COVID-19. In another work, authors[35] proposed a COVID-19 infection detection pipeline based on CXR images and achieved a classification accuracy of 99.65%. Deep learning methods are used to extract meaningful results from medical records. A Designing Network Design Spaces had introduced by Ilija Radosavovic et al. [37] they proposed a network called RegNet. The purpose of the network is to design a network with a low-compute, low-epoch regime using a single network block type on ImageNet. The authors [39] of this paper provided a concise overview of the use of DL, RL, and deep RL strategies in biological data mining. Finally, they explored future architecture viewpoints and open questions in this challenging research field. In another article, authors[40] proposed a hybrid deep learning model for diagnosing the virus from chest X-rays that combines a convolutional neural network (CNN) and a gated recurrent unit (GRU) (CXRs). The model was developed using 424 CXRs images divided into three groups(COIVD-19, Pneumonia, and Normal) and obtained promising results of 0.96, 0.96, and 0.95.

3 Dataset

In Artificial intelligence-based work, data is essential, and to achieve substantial efficiency, we need to analyze a large quantity of data. Data has been collected from several resources. We collected more than two thousand five hundred images from multiple sources for the COVID-19 dataset. COVID-19 was diagnosed in this study primarily using X-ray images collected from two separate sources. Tawsifur Rahman [34], [35] has developed a COVID-19 X-ray image dataset that is open access to everyone, and this dataset is available in Kaggle. This database

Table 1. Data collection publicly available

Collection	Positive cases	Negative cases
C1: COVID-19 Radiography Database	1200	1341
C2: COVID-XRay-5K DATASET	195	2000

is constantly updated with images shared by researchers from different regions. At present, there are 1200 COVID-19 positive X-ray images, 1341 normal X-Ray images. Sample CXRs given in figure 1.

Another source of COVID-19 X-ray image collection was COVID-XRay-5K DATASET [36] is an open-source dataset, which is made and maintained by Shervin Minaee and his team. At the time of the present study, it comprises 184 COVID-19 positive Chest X-ray and some other CXRs of diseases like viral Pneumonia, Normal, Fracture, Edema, etc. Our purpose is to use COVID-19 positive and negative CXRs images from this dataset.

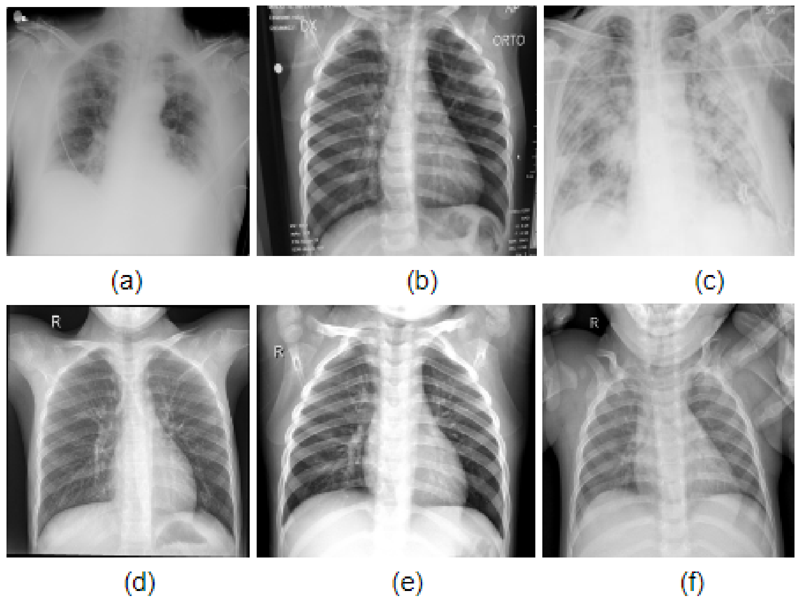

Fig. 1. Sample images of data set. (a-c) COVID-19 positive cases CXRs and (d-f) COVID-19 negative cases CXRs

These images had been collected from different published papers available online or from pdfs. Other qualities and sizes of images were noisy, skewed, and had different orientations. Moreover, the various grades and sizes of image handling was an extremely challenging task. We prepossessed each image before train our deep learning models. In this prepossessing, the data set was reconstructed using greyscale conversion. Then, we trained the two data sets using our deep learning models.

4 Proposed Model Architecture

Deep learning methods have been used for image processing in many fields, including medical image processing. Many researchers have used deep learning models for image recognition, segmentation, identification, and diagnosis of diabetes, brain tumors, and skin cancer using MRI, CT, and X-ray. We have followed the RegNet network to develop our deep learning model. We designed the model with CNN, consisting of three layers: a convolutional layer, pooling layer, and fully connected layer to perform these operations effectively. The feature extraction process takes place in both convolutional and pooling layers.

Our proposed model has nine convolution layers with three simple blocks of conv2d layer followed by ReLu. The block we used in our model, visually presented in figure 3 is based on the standard residual bottleneck block with

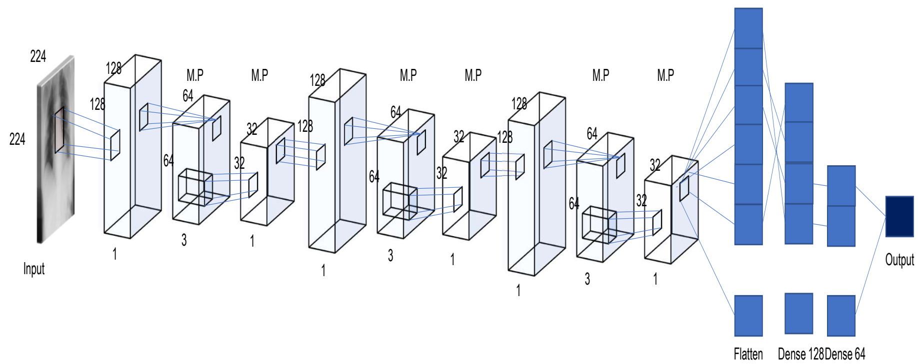

Fig. 2. The architecture of the RegNet structured proposed model.

group convolution. Each block consists of a 1×1 conv2d, a 3×3 group conv2d, and a last 1×1 conv2d and ReLU follow each conv2d layer. The second layer after the convolutional layer is the pooling layer. The pooling layer is usually applied to the created feature maps for reducing the number of feature maps and network parameters by applying corresponding mathematical computation. In this study, we used max-pooling with stride (s=1). The number of neurons was 128,64,32, respectively. To attain further knowledge about our model, see Figure 2, Figure 3 and Table 2. A fully connected layer is the last and most important layer of any deep learning model. This fully connected layer functions like a multi-layer perceptron, and Rectified Linear Unit (ReLU) activation function is most commonly used on a fully connected layer. In contrast, the Sigmoid activation function predicts output images in the last layer of a fully connected layer. We used 50% dropout on a fully connected layer.

We trained our model with five epochs, which is very few epochs compared to other trained deep learning models. Our model consists of input size 224x224, which ideal input size for RegNet structured network. In Table 2 we used 9 conv2d layer with filter size 128,64,32 and 1 flatten layer two dense layer for our model. The total number of learning parameters is 194,903,073 for 224x224 images.

5 Model Evaluation

The reason for using CNN to build our model is feature engineering is not required. CNN can extract features automatically from the image. CNN performs well, and it gives better accuracy compared to handcrafted features. It is covering local and global features. It also learns different features from images. CNN effectively uses adjacent pixel information to down-sample the image first by convolution and then uses a prediction layer at the end, and CNN is easy to implement. Our main target was to achieve higher accuracy with a few epochs and learning parameters, and we just used five epochs to get 99.02% accuracy.

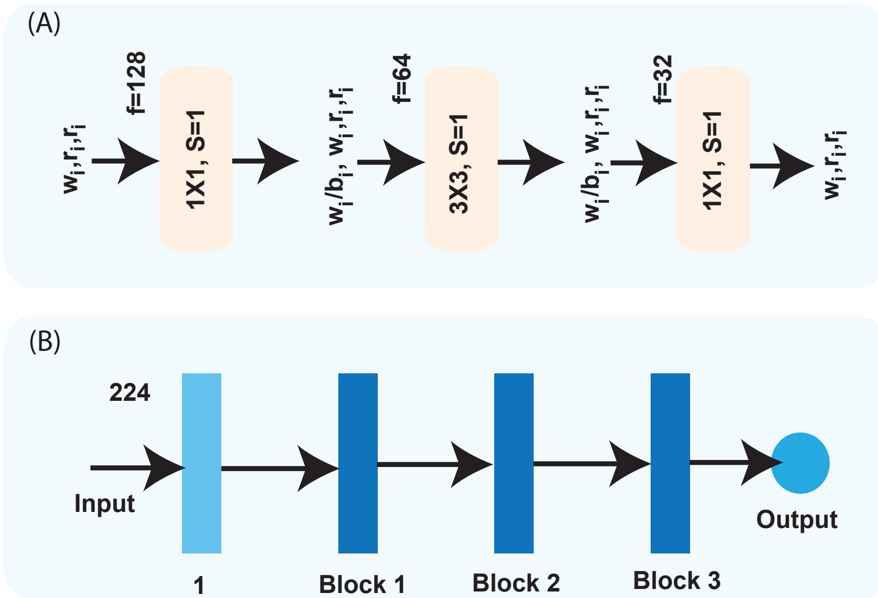

Fig. 3. Block diagram of the RegNet structured proposed model.

Table 2. Number of learning parameter of our proposed model for 224x224 image

Number of layer	Layer name	Output shape	Params
1	Conv2d	[224, 224, 128]	256
2	Conv2d	[222, 222, 64]	73792
3	Conv2d	[222, 222, 32]	2080
4	Conv2d	[222, 222, 128]	4224
5	Conv2d	[220, 220, 64]	73792
6	Conv2d	[220, 220, 32]	2080
7	Conv2d	[220, 220, 128]	4224
8	Conv2d	[218, 218, 64]	73792
9	Conv2d	[218, 218, 32]	2080
10	Flatten	[1520768]	0
11	dense	[128]	194658432
12	dense	[64]	8256
13	Linear	[1]	65
Total parameters			194,903,073

To validate our model, we used two distinct data set and k-10 fold validation. The primary purpose was to design a model with low-compute, low-epoch, and gain higher accuracy using a single network block. We just used five epochs to train our model. We obtain 99.02% validation accuracy for the first dataset, and for the second dataset, we receive 97.13% validation accuracy. The average accuracy is 98.075% which is promising compare to other deep learning models. The training and validation accuracy for both data sets are given below.

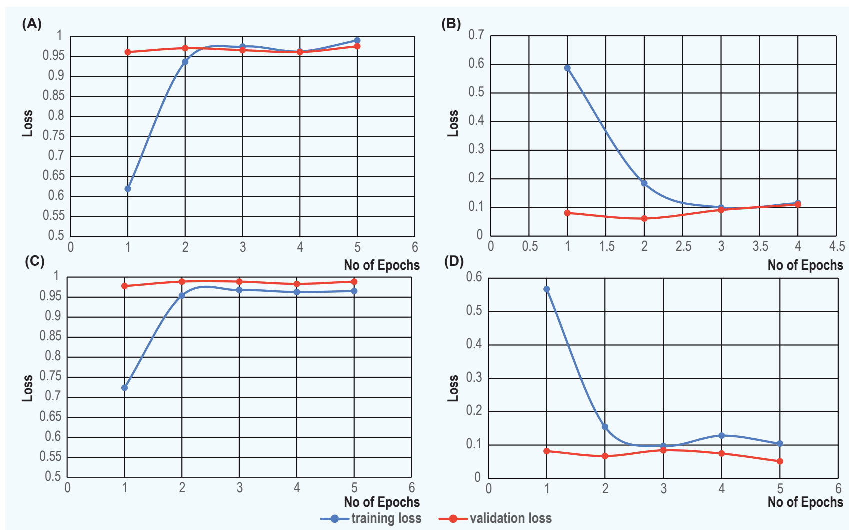

Fig. 4. Training/Validation Accuracy/loss. (A) the training and validation accuracy (B) training and validation loss as a function of epoch using for dataset named COVID-19 Radiography Database[34, 35] (C) the training and validation accuracy (D) training and validation loss as a function of epoch using for dataset named CoronaHack -Chest X-Ray-Dataset[36]

There were 1200 COVID-19 positive cases in the first data set and 1341 COVID-19 negative chest x-ray images. We split the data set into 70 and 30 ratios for training and validation. The training set consists of 960 COVID-19 positive CXRs and 1072 COVID-19 negative CXRs. The validation set contains 240 COVID-19 positive CXRs and 402 COVID-19 negative CXRs. We obtained 99.02% accuracy for this dataset, and we can see from Figure 4 the training and validation accuracy and loss for every epoch of our model.

There were 195 COVID-19 positive cases and 2000 COVID-19 negative chest x-ray images in the second data set. We split the data set into 70 and 30 ratios for training and validation. The training set contains 156 COVID-19 positive CXRs and 1400 COVID-19 negative CXRs. The validation set includes 58 COVID-19 positive CXRs and 600 COVID-19 negative CXRs. We obtained 97.13% accuracy for this dataset, and we can see from Figure 4 the training and validation accuracy and loss for every epoch of our model.

6 Result Analysis

In this section, we will present an analysis of our model and a comparison with other deep learning models presented in our literature review.

Intending to present more information on the performance of our classifiers on test images, we provide a receiver operating characteristic curve (ROC) curve figure 5 below. A receiver operating characteristic curve (ROC) curve is a graphical plot that illustrates the model performance evaluation. We have presented a ROC curve of 2 distinct dataset. AUC - ROC curve display estimation for the classification problems at various threshold settings. ROC is a probability curve, and AUC depicts the degree or measure of separability. It describes how much the model is proficient in differentiating between classes. The proposed classifier achieved the maximum AUC score (1.00) for the both dataset. The AUC score of our model for identifying COVID-19 is 1, which means our model has high-class separation capability whatsoever.

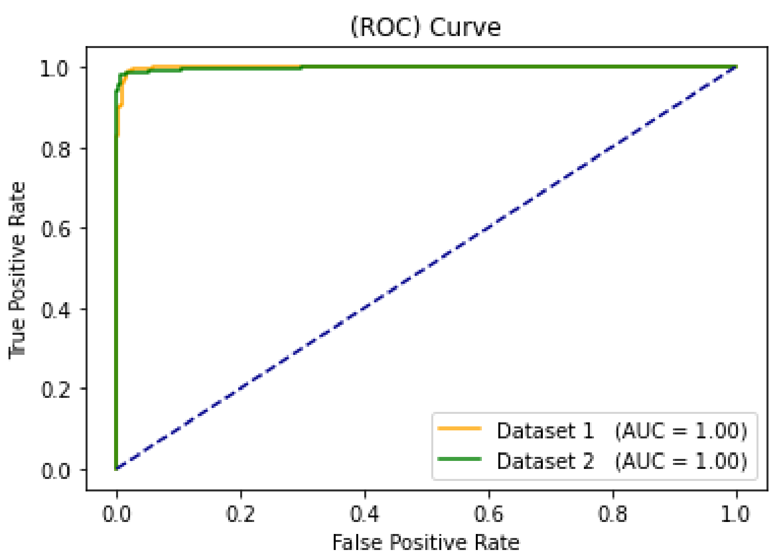

Fig. 5. ROC curve of proposed model.

From table 3, we can see our model achieved 99.02% accuracy, and the authors of [17],[20],[21] presented models have more accuracy than our model's accuracy. On the other hand author of [19],[22], [27], [31] presented models have less accuracy than our model. So we can conclude that our model gave a promising result for the detection of COVID-19 positive cases.

Table 3. Comparison table

Ref	Author name	Model Name	Accuracy Rate
[18]	Das et al.	Truncated Inception Net	99.96
[19]	Himadri Mukherjee et al.	CNN-tailored network	96.28
[20]	Himadri Mukherjee et al.	shallow CNN-tailored network	99.69
[21]	Mesut Togaçar et al.	Deep learning	99.27
[22]	Ali Narin1 et al.	ResNet	96.01
[27]	Li and Xia	Deep learning	96.10
[29]	Bassi & Attux	ImageNe	100.0
[30]	Majeed, T et al.	CNN transfer learning	97.86
[31]	Tulin Ozturk et al.	DarkCovidNet	98.08
[33]	Hussain et al.	CoroDet	99.10
[34]	Chowdhury, M. E. et al.	ImageNet	99.70
[35]	Rahman, T. et al.	Deep learning	99.65
[40]	P. M. Shah et al.	Deep GRU-CNN model	96.00
	Our proposed model	RegNet Structured	**99.02**

7 Conclusion and Future Work

In this paper, we propose a lightweight (12-layer) RegNet structured deep learning model for detecting COVID-19 positive patients using chest X-ray images.In this project, we used two types of images; one type was COVID-19 positive, and the other type was COVID-19 negative images. For validation, experimental tests were done on two different experimental datasets by combining COVID-19 positive and COVID-19 negative CXRs. We have trained and tested the proposed model, and we have achieved an overall accuracy of 98.08%. Besides, considering the number of parameters and the number of epochs used in our proposed model, it is computationally efficient compared to many other established models and other works presented in the literature review. It is important to note that our study has no clinical implications and has not been reviewed by any medical experts. We aimed to check whether our proposed RegNet structured model could detect COVID-19 positive cases using CXRs with high accuracy. Our developed model is only able to perform binary classification with an overall accuracy of 98.08%. In future, this work could be extended by fusing the decisions of multiple transfer learning models.

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