An Improved Detection Framework of COVID-19 Patients Using Machine Learning-Based Ensemble Techniques

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Abstract- *COVID-19, a novel coronavirus, is currently considered to be a more dangerous & lethal illness for the human body. In December 2019, the coronavirus, which is believed to have originated in Wuhan, China, traveled fast over the globe and killed a huge number of people. Early detection & correct diagnosis of COVID-19 may lower the patient's mortality, particularly in people with no apparent symptoms. X-ray pictures of the chest are the primary diagnostic tool for this condition. In this work, it was hypothesized that COVID-19 might be detected from chest X-ray images. This year's coronavirus illness may be detected utilizing chest X-ray pictures to save the lives of both patients and physicians by detecting SARS CoV-2, the virus which causes the severe acute respiratory syndrome. In addition, this becomes even more critical in nations where it is not possible to acquire laboratory kits for testing. These findings were intended to illustrate the ability of ML-based ensemble approaches to identify COVID-19 in chest X-rays with high accuracy. In this paper, we used two datasets. Using the transfer learning idea, the authors offer a new ensemble-based machine learning framework that combines parameters (weights) from many models to retrieve features from pictures that are then fed into a bespoke classifier for prediction. Class activation mapping with gradient weighting will reveal sick areas in CXR pictures.*

Keywords- COVID-19; coronavirus; detection of COVID-19; Ensembled model of MobileNetV2, InceptionResNetV2, Xception.

I. INTRODUCTION

Many people were shocked to discover that they were in the middle of a SARS CoV-2–related pneumonia epidemic, often known as coronavirus illness 2019. (COVID-19). Doctors combating COVID-19 are working with a limited set of tools since the illness has spread so far since it was first discovered in Wuhan, China. There have been more than 27,000,000 verified cases and more than 875,000 confirmed fatalities globally as of this writing. AI & DL research and applications have been launched to assist physicians in their efforts to cure patients and combat sickness.The number of cases with COVID-19 illness is rising every day because of the absence of rapid diagnostic tools. Many individuals perished from this illness over the globe in 2020. The virus may quickly spread via the respiratory system and lungs [1]. As a consequence, the air sacs might become inflamed, and fluid can leak out of them. When the procedure takes place, oxygen intake is hindered by an obstruction. Doctors and health care workers throughout the globe have a tremendous problem in identifying a virus quickly& accurately to lower the fatality rate caused by it.Even though point-of-care treatment is fast and convenient, even though clinical usage of COVID-19 testing is planned in the future, current turnaround times vary from three hours to more than 48 hours, and not all nations will likely have access to the test kits which provide findings quickly. Patients with COVID-19, according to a newly released international consensus statement by the Fleischner Society, should utilize chest radiography when access to computed tomography is restricted. In the battle against the disease, the high cost of diagnostic laboratory kits, particularly in poor & impoverished nations, is a major concern. Covid-19 may be detected using X-ray pictures, particularly in nations and hospitals that do not have access to a CT scanner or are unable to acquire one. Since there is presently no effective therapy for this, an accurate diagnosis is essential [2-4].In December 2019, the globe was struck by a massive epidemic of the new Coronavirus. To put it another way, this causes a highly contagious respiratory ailment that is rapidly spreading across the country. There are several crucial considerations to consider while dealing with a contagious condition, such as COVID-19. Droplets of a diameter of more than 5–10 nm, according to the World Health Organization, might be airborne carriers. This poses a grave danger to the public's health since close contact without the proper precautions may spread disease quickly. As a result, this illness has a high potential for development and a 2–5%mortality rate. Geometric progression demonstrates how quickly these spread. The seriousness of the problem may be seen in this graph[5]. On January 11, 2020, there were just 41 verified cases, but that number jumped by over one thousand times to 43,109 in only one month (11 February 2020)[6]. There were 4.04 million confirmed cases on May 11th, 2020, roughly 94 times the number on February 11th, 2020, when the sickness first appeared. A total of 12.32 million people were infected on July 11th, 2020, despite extensive measures including wearing masks and avoiding close contact with anyone who may have been infected[7]. We can only hope that the growth factor is diminishing with each passing day as a result of increasing public awareness.

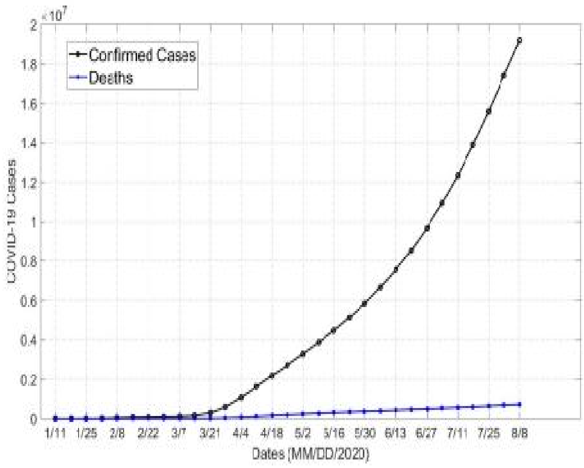

Figure 1: COVID-19 confirmed cases and fatalities throughout the globe are shown in a time-series graph [8].

Detection of COVID-19 patients at an early stage is critical for the virus's control[9-11]. In contrast, CNN may play animportant role in the automated identification of positive patients. This may save both time and money, which in the long run may save people's lives. In addition, as none of the currently used tests can guarantee 100% correctness, this may serve as an additional layer of validation.

The following are the remaining portions of this study: Chest X-ray picture categorization is discussed in Section 2 of the report. To detect COVID-19 from X-ray image datasets, the COVID-19 classification system is described in Section 3. Section 4 summarizes the study's findings and conclusions. Section 5 goes on to detail the proposed system's ability to identify COVID-19, as well as its limitations in terms of validation, comparative performance, and other factors. Section 6 concludes this investigation with a discussion of the findings.

II. LITERATURE REVIEW

Machine learning methods have recently been utilized to recognize COVID-19 in chest X-ray images. To assess their relevance to the current study and whether these words apply to the detection of covid images, a preliminary review of their content was required.The algorithm was trained using X-ray images of normal, pneumonia, & COVID-19 patients. There was a drawback to the study since only 285 photos were utilized to train a deep learning-based model for the COVID-19 prediction, and this limited number of images was not ideal.

K. Indihar et al. [2021]Aim to examine CoV-19 detection using CAD4COVID software and to evaluate the accuracy of the classifier performance utilizing Automated Machine Learning techniques. After analyzing the results from 70 photos, the likelihood scores for 39, 20 (36-65), 11 (66-100), and 11 (66-105) patients were all determined. AutoML detection has a sensitivity of 99 and an accuracy of 83 for detecting mutated RNA. With the finest optimizer, AutoML may be comparable to CAD4COVID when it comes to identifying Cov-19 [12].

Dasare and H. S [2021]system that can classify patients with or without the presence of pneumonia from a Chest X-ray picture using DL might be developed. Over 5000 chest X-ray pictures are used to train the deep learning model. An accuracy of 96.66% was reached when the trained model was evaluated and confirmed in the subsequent process. Medical accuracy cannot be guaranteed since the data isn't real-time. Validation plots have been created by regressing the training against validation loss and accuracy data. The best approach to deal with this public health catastrophe is to find the sickness as soon as possible. When the virus infects the majority of the lungs and results in pneumonia, the condition is considered severe. A chest X-ray is a most often used method for determining the presence of pneumonia. Computer-Aided Diagnosis (CAD) systems are essential for two reasons. As a first step, an enormous number of infected individuals have to be examined, which generates a large volume of X-rays. Second is the need for an accurate diagnosis. Radiologists have difficulty judging the seriousness of a tumor with their naked eyes and, as a result, often get the incorrect judgment, leading to a haphazard choice. Deep learning algorithms have shown to be the most suited as a result of their ability to achieve predicted accuracy and their capacity to handle a large amount of data. [13].

N. Nasser et al. [2021] DL-based classification technology, namely ResNet50, was used to identify and classify COVID-19. They evaluate the suggested system's dependability and effectiveness using two openly available datasets. 80% of the datasets were used to train the proposed system, while 20% of the datasets were used to test it. Tenfold cross-validation is used for performance assessment in this method. Accuracy (98.6%), Sensitivity (97.3%), Specificity (98.2%), and F1-score (97.87%) are all achieved by the proposed system in its current form. Research shows that our suggested system has excellent accuracy, specificity, sensitivity, and F1 and that it outperforms the current best-in-class systems. In medical diagnostic research and health care systems, the DL-based system is beneficial [14].

S. Jain et al. [2021]worked on developing a machine learning-based technique for screening patients for probable infection depending on their clinical data. To determine the likelihood of infection, the suggested technique makes use of a keyword-based technique. They can state that screening speed and accuracy will be enhanced by employing an ML-based strategy to reduce the time, which leads to the propagation of the Covid-19 virus. [15].

B. K. Umri et al. [2020]100 X-ray chest images of Covid-19 patients and 100 X-ray chest images of normal people will be evaluated for their quality. Both CLAHE and CNN algorithms were used to evaluate the dataset and arrive at detection findings using 2 distinct scenario-based analysis approaches. Covid-19's detection accuracy may be affected by the usage of CLAHE, according to the results of this investigation. The CNN basic model is superior to VGG16 transfer learning in terms of performance. [16].

M. K. Nath et al. [2020]COVID and NON-COVID pictures may be classified using the suggested approach, which uses a robust deep learning algorithm for both binary and multi-class classification. The use of a CNN network with 24 layers has been suggested. In terms of X-ray and CT image accuracy, it's a whopping 99.68 percent accurate. With a learning rate of 0.001, the Sgdm optimizer was employed to analyze both datasets. The World Health Organization declared the new coronavirus 2019 pandemic in March 2020 when the virus first appeared in Wuhan, China. When a Black Swan event occurs, all of a company's resources are put to work to minimize the damage. In humans, this virus may cause pneumonia and alter the respiratory rhythm (different from common cold and flu). Chest X-ray and computed tomography imaging may be more accurate and quicker to identify COVID-19 patients than RT-PCR in epidemic locations. [17].

A. K. Siddhu et al. [2020]Coronavirus infection was detected utilizing a collection of pictures from patients with common bacterial pneumonia, verified Covid-19 infection and also common cases Researchers wanted to see how well COVID-19 acquisition worked. Globally, the number of infected people skyrockets under the COVID-19 scenario. As a result, medical professionals and infected patients made the critical option to use many medical facilities in an acceptable length of time. [18].

B. Jabber et al. [2020]People must be screened to identify those who are affected and stop the spread of illness. Diagnostic testing for pathological conditions is often performed using real-time PCR. As a consequence of this tool's inaccuracies, it's necessary to find an alternative tool. The screening for COVID-19 is more accurately performed using chest x-rays rather than PCR. However, here, the accuracy of the findings is critical. In this paper, an image-based diagnostic recommender system for evaluating lung pictures is presented to help clinicians & relieve some of their workloads. An advanced neural network method. To get the highest level of accuracy possible, CNNs are used [19].

A. A. Khan et al. [2020]provide an automated screening technique for coronavirus patients based on 3D-Deep learning. Patients who test positive for COVID-19 may be quickly and easily weeded out with the help of our new technology. Three-dimensional deep learning approaches such as 3D ResNets, C3d, 3D Dense Net, I3D, & LRCN were tested extensively on two large databases: CC-19 and COVID-CT. Experiments reveal that our suggested strategy has a competitive advantage. [20]

III. RESEARCH METHODOLOGY

One of the most important aspects of our suggested Ensembled Model is its ability to extract prominent characteristics, such as COVID-19, normal, and pneumonia classifications using weighted averages of backbone CNN model weights. Using the CXR data as a starting point, we'll go through the different parts of our suggestedmodel& technology that underlies it.To identify COVID-19 in chest X-ray pictures, several key processes have to be taken, including gathering datasets, preprocessing, classifying, training models, & evaluating & analyzing results.

3.1 Material and Methods

In this article, we make use of two sets of data. The first set is a publicly available open dataset of X-ray and CT scans of the chest taken from patients of COVID-19 or other suspected viral or bacterial pneumonia. Data will be gathered from public sources as well as from hospitals and clinicians through the indirect collection. Using a normal chest X-ray, the second dataset (left panel) shows clean lungs with no regions of anomalous opacity. Viral pneumonia (right) has a more widespread "interstitial" pattern, while bacterial pneumonia (center) tends to be more concentrated in the right upper lobe of the lung. As part of their regular medical treatment, all patients had chest X-rays. As part of the quality control process, all of the chest x-ray pictures were first inspected to remove any low-quality or unreadable scans. Images were reviewed by two medical professionals for diagnosis before being sent into the AI system for training. The assessment set was verified by a third expert to ensure that there were no grading errors.

Type	Genus or Species	Image Count
Viral	COVID-19 (SARSr-CoV-2)	468
	SARS (SARSr-CoV-1)	16
	MERS-CoV	10
	Varicella	5
	Influenza	4
	Herpes	3
Bacterial	*Streptococcus* spp.	13
	Klebsiella spp.	9
	Escherichia coli	4
	Nocardia spp.	4
	Mycoplasma spp.	5
	Legionella spp.	7
	Unknown	2
	Chlamydophila spp.	1
	Staphylococcus spp.	1
Fungal	*Pneumocystis* spp.	24
	Aspergillosis spp.	2
Lipoid	Not applicable	8
Aspiration	Not applicable	1
Unknown	Unknown	59

Figure 2:The labels of Covid Chest x-ray Dataset[21]

It is our objective to build AI-based systems for infection prediction and understanding, as shown in the picture above. They will be released as soon as possible by our team.

Figure 3: The Normal(Left), Bacterial pneumonia (middle), and viral pneumonia (right)[22]

The dataset is organized into three main folders (train, test, and Val), each of which has subfolders for the various image categories (Pneumonia/Normal). There are 5,863 X-Ray images (JPEG) in two categories (Pneumonia/Normal) available for download. As part of this investigation, Guangzhou Women and Children's Medical Center provided images of anterior-posterior chest X-rays.

Table 1: Total no. of the image in the final dataset:

Category	**Label**
Pneumonia	0
Normal	1
Covid	2

The above table shows the 1848 total no. of images in the final dataset.Network designs must be similar to each other to support weight fusion. Multiple-label classification is performed on the fused parameters of the backbone architecture to identify coronavirus-infected patients.

3.2 Proposed Model

Proposals for various approaches were made at this phase. Our suggested approach for automatically detecting COVID-19 situations is shown in the following schematic design.

3.2.1 Data Augmentation

The act of adding new data to an existing dataset to feed the model-building process is known as "data augmentation. " To put it another way, it's a method for increasing the amount of data accessible to train a machine learning model. We didn't have to acquire any of these photographs by hand since they were created from the training data. This expands the training sample without having to go out and acquire this data. The label for each picture will be the same, and that is the original image that was used to make them. Vertical flip is enabled, rotation range is 33, shift ranges of width and height are 0,2, 0,2, 0,0, and shear range is 0,2, and zoom range is 0,2, and horizontal flip is enabled.

3.2.2 Splitting Dataset

Most data may be divided into training and testing sets by allocating two-thirds of the data points in each set. This method works well. Because of this, we use the training set to build the model and then apply it to the test set for evaluation. As a result, we can evaluate the model's performance. There are two sections to the Train Dataset: training and validation. The Training Dataset, the Validation Dataset, and the Testing Dataset each account for 80% of the total (10 percent).

3.3 Proposed Methodology

There are four different systems we propose to automatically identify instances of COVID-19 utilizing an ensemble model of parameters from MobileNetV2 and

InceptionResNetV2, as well as Xception. First, we combine the weighted parameters from the Ensembled models of MobileNetV2, InceptionResNetV2, and Xception to create a parameter (weight) fusion. For any backbone network, a custom-designed or off-the-shelf pre-trained model network architecture can be employed. Ensembled can only operate with identical network designs. A clone of the backbone architecture performs multi-label classification on the fused parameter of the Ensembled model for coronavirus-affected patients.

3.4 Proposed Algorithm

1. Gather two datasets
2. Split the dataset.
3. Apply data augmentation

   3.1 rotation range=33
   3.2 width shift range is set to 0.2.
   3.3 height shift range is set to 0.2.
   3.4 shear range is set to 0.2.
   3.5 zoom range is set to 0.2
   3.6 horizontal flipping is possible only if the following condition is true:
4. Apply Ensembledmodel of MobileNetV2, InceptionResNetV2, Xception.
   4.1 Epochs = 50
   4.2 Categorical Cross Entropy = Loss function.
   4.3 Rate of learning = 0.0001
5. Evaluate the Performance of the Model and predict the covid image.

3.5 Flow Chart

The flow chart for COVID-19 detection with ensemble model is presented in Figure 4 (see below). The first step is to collect and sort the data that will be used to train and test the model. The dataset titled "Chest X-ray Images (Pneumonia)" from Kaggle contains both normal and non-COVID-19 chest X-rays, which are required for training purposes [55]. Normal and Pneumonia photos make up the bulk of this collection, which includes 5863 photographs. It's also worth noting that we've also obtained 201 normal chest X-ray pictures as part of the training and validation process. Only 20% of the whole dataset is used for testing, while the other 80% is used for training. Two separate subcategories are included in the training and validation datasets for each group: 'normal' and 'COVID-19'.

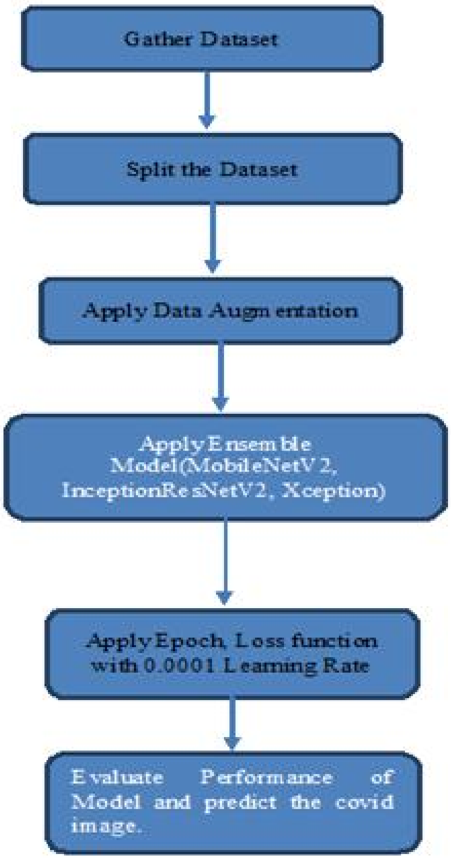

Figure 4: Flow Chart of Proposed Methodology

The above graph shows the Flow Chart of the Proposed Methodology. To keep the data consistent, they are shuffled, resized, and augmented. To classify data according to model categorization, this step follows. Using this approach, all models are trained and evaluated on a single set of data and in the same context.

IV. EXPERIMENT & RESULTS

The F-1 score, accuracy, and recall are all indicators of model performance. Confidence matrixes are used to derive these metrics from the validation dataset's potential results. In this level of the confusion matrix, the True Positive, True Negative, and False Negative are all analyzed.

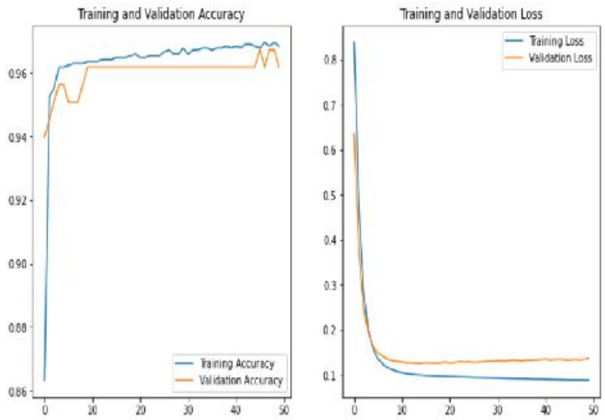

Figure 5: A graph showing the accuracy and loss during training and validation

The above graph shows the Training and validation accuracy and loss graph.

To commence, we use the learning curves generated by all of the backbone models in the ensemble during training and validation as a starting point for our investments. During the training phase, all models (as shown in Figure 4) demonstrate a moderate learning progression by experiencing a somewhat unstable drop in both kinds of losses. This demonstrates that the last model cannot have the optimal parameters or that the models generated after the training phase cannot be stable (weights). As a result of this, the tested models have a larger variation than expected, and training and validation losses fluctuate during the learning process.

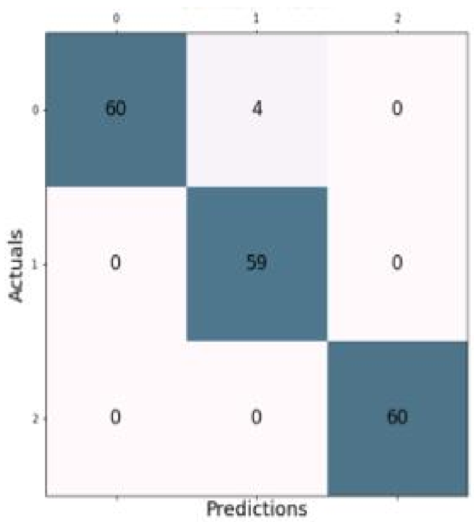

Figure 6: Proposed Model Confusion Matrix.

Confusion Matrix diagrams for the Proposed Model are displayed above. Normal & COVID-19 chest X-ray images totaling 59 are utilized to create confusion matrices for the two classes. There are only two circumstances in which the FN is zero in this model, and the TP and the TN are both found to have values of 59 for this model. As a result, it beats other models based on Dataset 2. To put it into perspective with comparisons to other models, we can see that the TN and FP cases had cases of 59 and 0, respectively.

Table 2: The Classification Report of Proposed Model

	Precision	Recall	F1-Score	Support
Pneumonia	1.00	0.94	0.97	64
Normal	0.94	1.00	0.97	59
Covid	1.00	1.00	1.00	60
Accuracy			0.98	183
Macro avg	0.98	0.98	0.98	183
Weighted avg	0.98	0.98	0.98	183

The table above shows the categorization report for the suggested model. Final models may not have optimum parameters, or they may not be as trustworthy as the model generated after training (weights). As a result of this, the tested models have a larger variation than expected, and training and validation losses fluctuate during the learning process. This problem is addressed by using the weights from various models of these backbone networks that were seen after training (around the final ten epochs). It is then applied to the clone model that was created for each of them.

Table 3: Table of Accuracy of Proposed Model

Model	**Loss**	**Accuracy**	**Validation Loss**	**Validation Accuracy**	**Testing Accuracy**
Ensembled Model	0.0754	0.9748	0.1363	0.9617	0.9781

The above table shows the Table of Accuracy of Proposed Model. We need to be clear about some of the existing limits of our work. Early infection, pulmonary phase, and hyperinflammation phase of COVID-19 disease development have been identified in recent investigations.

V. CONCLUSION

In this research, we provide a unique ensemble-based machine learningensemble architecture for automatically detecting COVID-19 from CXR pictures. As training advances, an ensembles architecture averages the weights from numerous backbone network models and utilizes that weight average to produce a single framework for retrieving features from images, which are then fed into a custom classifier for predictions. We get 0.97% accuracy,13.63 validation loss, validation accuracy is 96.17% and testing accuracy is 97.81 percentage.In addition, the model compares its findings to those of other notable studies in the area. More data and multi-class categorization are needed to further enhance this study. Last but not least, the ensemble model offers excellent chances of discovering COVID-19 in a short period and with little expenditure of resources. Despite encouraging findings, the suggested model has not been clinically tested. Even Nevertheless, the suggested approach may play a vital role in detecting COVID-19 early and quickly, thereby minimizing the testing time. Consequently, the price.As previously indicated, CXR images may not be the best tool for early COVID-19 detection, but other research results (published in peer-reviewed journals) show that radiography images give essential information about COVID-19 infection as it proceeds. Because our suggested fusion model is not a substitute for a radiologist, we can confidently say that it is not. We believe our findings to be a meaningful addition to the expanding acknowledgment and acceptance of AI-aided healthcare applications. CXR scans alone may not be enough to determine the best course of therapy for an individual, but an automated early screening may substantially assist health care providers in identifying and quarantining positive encounters until a more extensive test is completed.

VI. FUTURE SCOPE

By accurately detecting regions of CXR pictures associated with COVID-19 infection, our approach demonstrates excellent explainability qualities. We believe that the outcomes of our suggested fusion model will help doctors identify COVID-19 patients and lessen their effort. Additional research depending on the findings of this study would offer more information regarding the usage of ensemble architectures with COVID-19 chest X-ray pictures and enhance the findings. Currently, we intend to gather more COVID-19 photos as they become available to enhance our prediction findings soon. Feature concatenation from CXR pictures and multimodal COVID-19 information will be used to create a new fusion model in the future.

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