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PneuDetect: Pneumonia Detection using a Novel Two-Stage Deep Learning Pipeline from ChestX-Rays – A Review

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Abstract*:* Pneumonia, being a very critical infection of the lungs is fatal, especially in children. More children die from pneumonia than any other infectious disease. This disease is often identified by examining the Chest X-Ray Radiograph (CXR) images by highly trained medical experts. The procedure is time-consuming and frequently results in different diagnoses among radiologists. Recently, computer-aided diagnosis systems demonstrated the ability to improve diagnostic accuracy. Deep learning approaches generally tend to train a single model which can identify and localize this disease from Chest X-Ray images. This does not allow the model to learn task-specific features (different features for classification and object detection). Thus, we propose independently training and optimizing the classification and object detection models. Our approach utilizes the data obtained from a competition of Pneumonia Detection Challenge by a society of Radiology in North America on the Kaggle platform. Our results show a mean average precision (mAP) of 0.152 is attained by the proposed model.

Keywords: *Pneumonia, Chest X-Ray images, Computer Aided diagnosis, Kaggle Competition, Deep Learnin*

Introduction

Pneumonia disease is a serious illness where the lungs are infected by several microorganisms, like viruses, fungi, and bacteria. Approximately 16% of the untimely demise in young children (aged below 5 years old) globally are caused by Pneumonia. Roughly, around one million people in the USA (United States of America) must be hospitalized every year due to Pneumonia and, unfortunately, about 50,000 of the hospitalized people pass away because of the disease [1]. One of the major global concerns currently is the COVID-19 pandemic. The major cause of death due to COVID-19 is COVID converting into pneumonia. With recorded examples in 185 nations covering the major populated mainland continents, pneumonia caused by coronavirus is a serious global problem [2]. By the examination of Chest X-ray radiograph (CXR) images, Pneumonia disease is generally identified by highly trained medical professionals. It is usually recognized. when a region with abnormal opacity on CXR [3] is identified. Various other factors such as clinical history, vital signs, and laboratory tests are taken into consideration to validate the detection. The identification of this disease from CXR images is quite complicated as several other conditions like fluid surcharge, bleeding, lung cancer, post-radiation, or surgical changes may also cause some opaque regions in CXR images. Thus, CXR images of the past of that person are also considered for diagnosis. Also, while taking the X-ray some position misalignment or machine fault can further make the diagnosis more difficult.

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By the examination of the CXR image data, there is known variability among radiologists [4]. Examinations using Computer-aided methods for the detection of pneumonia disease are being increasingly used during the past decade to improve the effectiveness and precision of the detection methodologies [5–9]. An algorithm's abil- ity to recognize intrinsic patterns and function as an accurate predictor is extremely relevant and does depict sufficient utility [10]. Deep learning methods have consis- tently produced the best outcomes for nearly all computer vision tasks, including classification [11, 12] and segmentation [13].

1.1. Problem Statement

This study offers a practical approach corresponding to the Radiological Society of North America (RSNA) Pneumonia Detection Challenge for the identification of pneumonia regions on the Kaggle platform [14]. The objective of the problem is to locate and identify pneumonia from chest X-ray scans.

1.2 Objective:

The paper showcases a novel algorithm that can detect and localize pneumonia efficiently and quickly from Chest X-Ray. Most of the previous approaches perform the classification and localization task from a primary model architecture. This paper proposes a novel pipeline that pertains to a separate training setting for the classification and object detection models. The classification network would act as a rectifier network and assess an image for the presence of pneumonia; a positive sample would be further exploited by the object detection model to facilitate the bounding box generation. The separate architectures would function in a streamlined pipeline further enhancing pneumonia detection. The proposed methodologies are empirically validated on a plethora of performance metrics, allowing the accurate perception of their societal impact and utility.

2. Literature Review

Techniques that rely on the usage of deep learning algorithms are already being utilized in various fields [4–6, 15]. Several approaches to object detection in medical images have been previously presented in many papers. M.I.Razaak [16] addresses various difficulties along with the limitations of refining Biomedical image data. As per Dinggang Shen [17], models based on the usage of Artificial Intelligence techniques like Deep Learning (DL) are utilized for the identification and classification of various diseases. F.Milletari [18] proposed a methodology that used CNN for showing the prostrate in MRI volumes, and for the detection and classification of skin cancer at the dermatologist level, Andre [19] introduced a deep learning model. A technique using deep learning algorithms to detect and classify Diabetic Retinopathy from fundus images was proposed by Grewal [20], and Varun [21] suggested utilizing DL techniques to identify bleeding from ruptured blood vessels in the parts of the brain from the Computerized Tomography scan data. DL techniques utilized for the identification of chest pathology was covered by Y. Bar [22]. Various techniques have been used for the identification and examination of diseases from CXR image data [23–25]. S. Hermann [26] proposed an algorithm to eliminate any potential for diagnostic error, the chest X-ray pictures were submitted to a scan line optimization and review process.

In order to differentiate between pneumonia-disease-affected lungs from a healthy pair of lungs the paper [32] suggested using the Earth Mover's Distance (EMD) methodology. A model using Deep Learning (DL) techniques like CNN is utilized for pneumonia detection and categorization by Rahib et al. [33] and Okeke et al. [34]. Rajaraman et al. [35] and Cohen et al. [36] are two researchers who have demonstrated promising results. Rajaraman et al. [35] proposed a methodology to illustrate how pre-trained CNNs performed in pediatric CXRs to identify the pneumonia disease and categorize between the strains of microorganisms. Sirazitdinov et al. [37] proposed an R-CNN model for pulmonary image segmentation and custom image enhancement for the detection of pneumonia. Lakhani and Sundaram [38] proposed the use of pre- trained Deep Learning (DL) techniques like CNN models like AlexNet and GoogLeNet along with data augmentation for getting output with an accuracy of 0.94 to 0.95 of the a under the ROC curve. Rajpurkar et al. [7] introduced CheXNeXt, a 121-layer pre-trained Convolutional Neural Network algorithm that is based on DL techniques, to identify fourteen clinically significant diseases from Chest X-ray radiographs. The paper santosh2022advances offered a thorough scientific review of the current advances in Deep Learning specific to Tuberculosis Screening and Chest X-ray-based datasets. To diagnose pneumonia disease from a dataset of CXR scan images, the article [39] suggested a novel methodology based on an altruistic and adaptive Particle Swarm Optimization (PSO) dependent process to extract the attributes of the image in the deep layers of the CNN. The paper [40] suggested a novel methodology that is centric on the DL computing paradigm and CT scans for an accurate prediction of pneumonia.

The paper [41] successfully showcased the utility of Contrastive Learning and Radiomic features for the identification of pneumonia disease from CXR scan images. The research [42] presented a novel approach to diagnosing 14 chest illnesses using previously trained Deep Learning (DL) techniques like the CNN DenseNet-121 model and preprocessing techniques based on localization. Ayan et al. [43], Saraiva et al. [44], and Rahman et al. [45] utilized DL-based techniques in order to detect and categorize pneumonia. Xiao et al. [46] Xiao introduced a unique multi-dimensional (3D) CNN that incorporates multi-scale heterogeneity (MSH-CNN) to analyze chest computed tomography (CT) images. The paper [29] used models like Mask-region based convolutional neural networks which are incorporated with dropout layers and layers that have L2 regularization, using both global and local characteristics.

The author [47] developed a multi-dimensional artificial neural network (3D CNN) that incorporates short connections. The paper [48] presented a novel similarity learning pipeline and showcased a substantial improvement in predicting Covid-19 pneumonia. To merge the results of various neural networks and determine the final prediction, Vikash et al. [30] employed a majority voting technique. Of all the above-listed methodologies, none of them, except Vikash et al. [30] aimed toward merging the resulting predictions of several different models that used artificial neural networks.

Table 1 This table pertains to previously published highly impactful papers in this domain [31].

Reference	Dataset Used	Methodology	Description
[7]	ChestX-ray14 dataset	A 121 layer deep convolutional neural network	The CheXNet algorithm uses a 121-layer neural network to detect pneumonia in chest X-rays, exceeding radiologists' performance. It could improve healthcare in regions with limited access to radiologists and early pneumonia diagnosis is crucial to prevent complications and death.
[27]	CheXpert	Convolutional neural network	CheXpert is a large dataset of 224,316 chest radiographs with uncertainty labels to train convolutional neural networks. The best model outperforms at least two of three radiologists in detecting four clinically relevant pathologies. The dataset is released as a benchmark to improve healthcare delivery worldwide.
[28]	PASCAL VOC 2007 and 2012	Faster region-based CNN (F-RCNN)	The paper presents a Region. Proposal Network (RPN) that predicts object bounds and scores with high-quality proposals, improving the overall object detection accuracy. By sharing convolutional features, the RPN generates nearly. cost-free region proposals and achieves state-of-the-art accuracy on PASCAL VOC 2007 and 2012 with a frame rate of 5fps on a GPU.
[29]	RSNA pneumonia dataset	Mask R-CNN	This paper presents a deep-learning approach to identifying pneumonia in chest X-ray images using Mask-RCNN. The proposed architecture achieves better performance and robustness through critical modifications of the training process and a novel post-processing step.
[8]	ChestX-ray	Unsupervised fuzzy c-means classification learning	The paper describes a method. for detecting pneumonia using an unsupervised fuzzy c-means classification learning algorithm, which produces more accurate results than other methods. The approach involves analyzing chest X-rays and identifying changes in lung region absorption.
[30]	Guangzhou Women and Children's Medical Center dataset	4 CNN with transfer learning	This paper proposes a deep learning-based approach to simplify the detection of pneumonia in chest X-rays using transfer learning. The authors suggest a novel framework that extracts feature from images using different pre-trained neural network models, which are then fed into a classifier for prediction. They prepared five different models and proposed an ensemble model outperforming individual models.

3. Methodology

Most of the approaches discussed earlier solve this problem by combining classification and object detection models. Our novel approach focuses on training both networks independently and optimizing their performance. First, the classification network classifies the image and if it is detected as positive, it is sent to the object detectionmodel that predicts the bounding boxes. This approach gives the flexibility to use different architectures and training methods for classification and object detection. It is frequently observed that various deep learning approaches, such as categorization and image recognition, may call for the model to learn distinct characteristics. Thus, our approach gives flexibility to each model to learn distinct features which may help enhance the performance. The overall approach is described in Fig. 1.

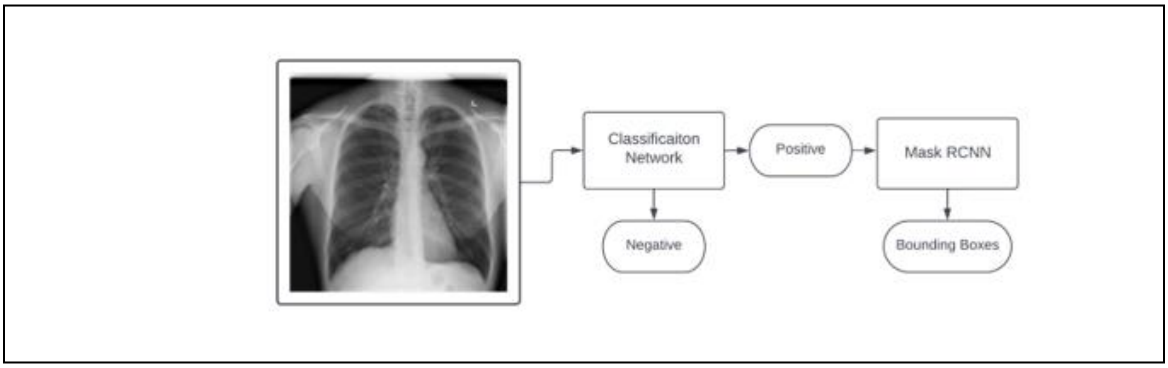

Fig. 1 The architecture of our proposed approach.

3.1 Classification

In our approach, we propose the utilization of transfer learning to train the classification neural network. Transfer learning is using the output of a model that has already been developed for a problem that is comparable. The dataset has a large and wide variety of images, thus transfer learning can help to learn the features better as it has already been trained once. During testing, we discover that the VGG-19 [49] network performs best when used as the core system. We add a few dense layers at the end to further refine the main model and make sure it learns the properties unique to our dataset. The dense layers are accompanied by a dropout layer and batch normalization to prevent overfitting. Fig. 3 shows the architecture of the classification model. Binary cross-entropy is used as the loss function in our proposed model, while Adam [50] is utilized as the optimizer. This loss function aids in calculating the classification's precise probability. The loss equation is mentioned below [51].

$$\mathcal{L}(y,\hat{y}) = -\frac{1}{M}\sum_{i=1}^{M}(y_i \cdot log(\hat{y}_i) + (1-y_i)\cdot log\,(1-\hat{y}_i)) \tag{1}$$

where yi is the ground truth label, yˆi is the predicted probability and M is the size of the dataset.

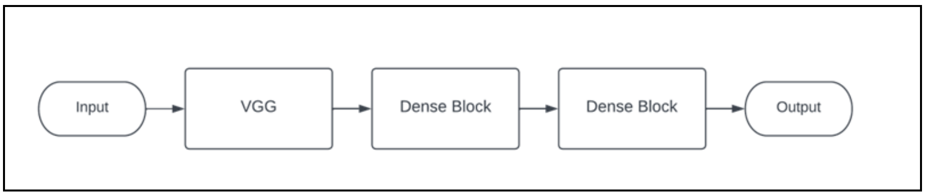

Fig. 2 Classification model architecture (The dense block is shown in detail in Fig. 3).

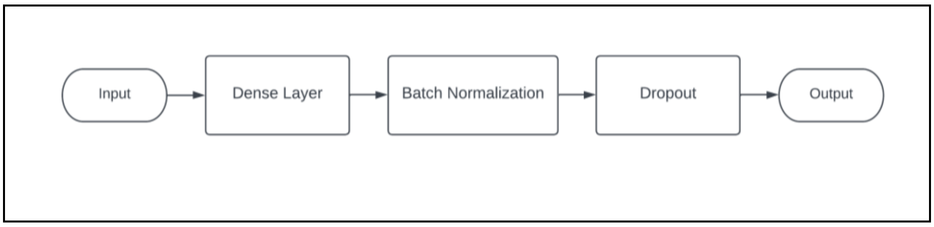

Fig. 3 The architecture of the dense block.

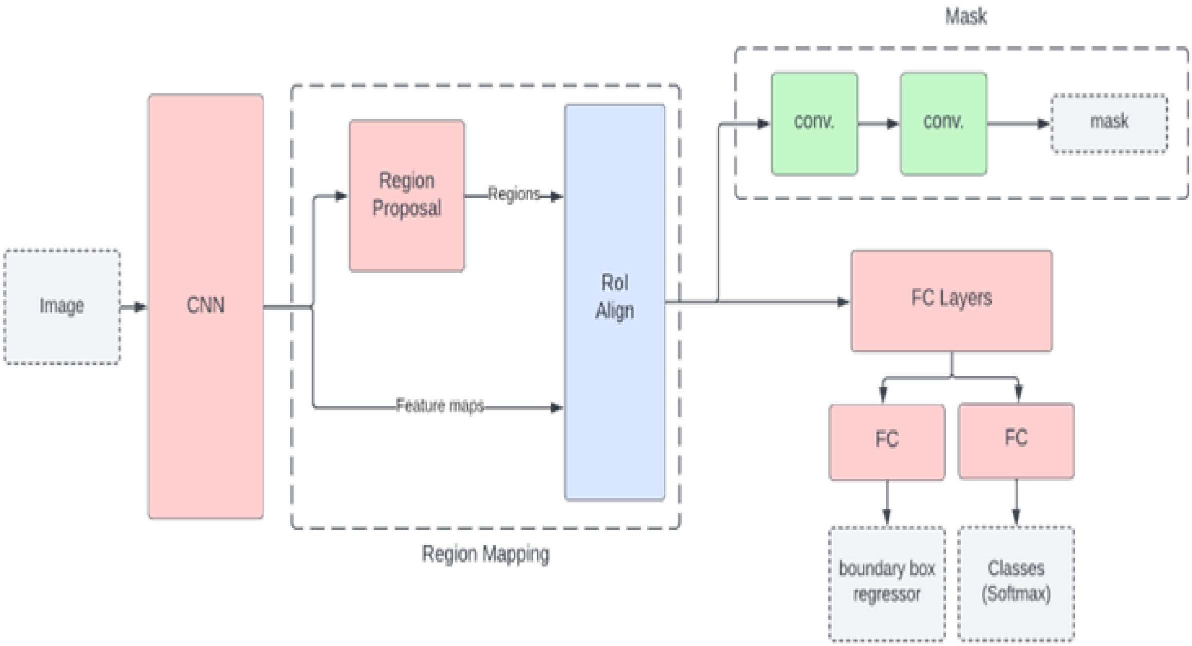

Fig. 4 The Mask-RCNN architecture

3.2 Object Detection

We use Mask-RCNN [52] for object detection. The Resnet-50 is the main system, and it has a pyramidal design. Mask region-based convolutional neural network is an advanced model, for example, integration, and it's created on top of faster CNN [28]. This is achieved by including a branch for object anticipation mask alongside the existing branch for bounding box recognition. Theoretically, a Mask region-based convolutional neural network can is an improved form of Faster R-CNN, however, its implementation depends on carefully constructing the mask branch [53]. Most importantly, the quicker region-based convolutional neural network failed to achieve detailed network input and output alignment. RolPool, which utilizes a coarse spatial quantization for feature extraction, serves as an example of this. By using the straightforward, quantization-free layer known as RolAlign, which consistently maintains precise spatial positions, Mask R-CNN rectifies the misalignment [53]. It is also to be noted that the object detection model is only trained on positive pneumonia images.

4. Dataset

The dataset was obtained from a past competition on Kaggle [14]. The Radiological Society of North America (RSNA), the US National Institutes of Health, The Society of Thoracic Radiology, and MD.ai collaborated with Kaggle to develop this dataset. The dataset contains 30,227 images (Fig. 6 shows the class distribution) of 1024x1024 resolution belonging to 26,684 unique patients. The images have two main classes- positive and negative. The positive images also have the bounding boxes of the region where lung opacities are present. When a person is infected with pneumonia, there is inflammation and fluid buildup in the air sacs of the lungs. The fluids contain bacteria and immune cells [6]. These regions appear opaquer than they should in the X-Ray and are termed lung opacities. To improve the performance of the models, we also applied various pre-processing methods. Scan images were downscaled from 1024x1024 to 256x156 and normalized. As evident from Fig. 6 the dataset is highly skewed towards negative images. Thus, while training the classification model the dataset was augmented with several techniques which are- horizontal and vertical flipping, width, and height shift, and random zoom [54]. It is noted that pixel level augmentations should be very carefully used as they may affect the region with opacities and thus may influence the model's performance.

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The ROI IoU, RPN IoU, and RPN NMS threshold in Mask-RCNN were 0.7, [0.3,0.75], and 0.9 respectively. We used Detectron2 [56] to train Mask-RCNN. The

5.1 Training Details

The proposed models were developed using the help of a system having an 8GB P100 GPU. The Adam optimizer having a learning rate hyperparameter set to 0.001 was applied in the classification model. Mask-RCNN is trained with a Cosine learning rate scheduler which reduces the learning rate starting from 0.02 as a cosine function

graphs of the training model networks are displayed below in Fig. 7.

6. Results

The classification models were evaluated using F1score. It is a statistical indicator used to evaluate the effectiveness of Artificial Intelligence models. It is the harmonic mean of the accuracy measures for classifiers, recall, and precision. It is the harmonic mean of the accuracy measures for classifiers, recall, and precision. The mean average accuracy (mAP) at various intersection over-union (loU) criteria served as the com- petition's final assessment statistic. The threshold ranges from 0.4 to 0.75 with a step. size of 0.05. The mAP is provided by [55] , where TP, FP, and FN denote true positive, false positive, and false negative respectively. The classification model obtained an F1-score of 0.822 and the overall mAP was 0.152. Table 1 shows the F1-score obtained by other base networks .

$$AP = \frac{1}{|threshold|}\sum_{t}\frac{TP(t)}{TP(t)+FP(t)+FN(t)} \quad (2)$$

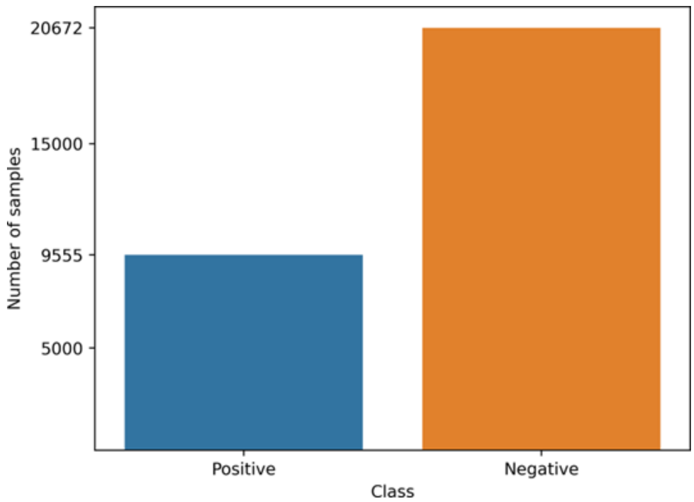


Fig 5: Class Distribution of Dataset

Model	F1-Score(%)
ResNet 50	78.1
DenseNet	77.4
EfficientNet B5	80.6
EfficientNet B7	79.1
VGG-19	**82.2**

Table 2: Comparative Study Between LRNet And Previous Works

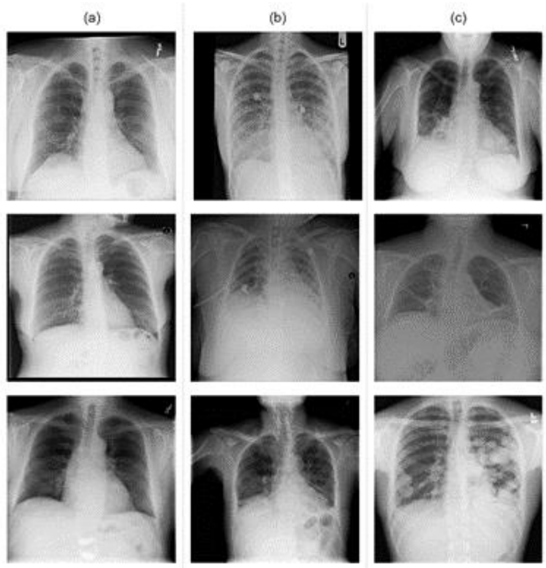
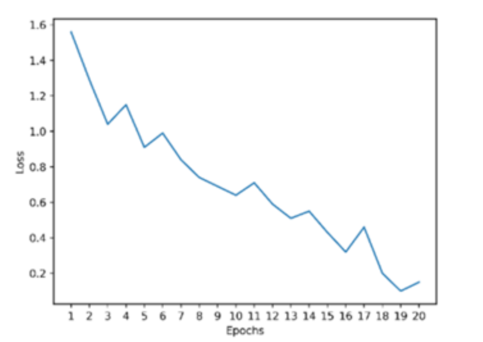


Fig. 6 Random samples from Dataset with classifications (a)Normal, (b)Lung Opacity, and (c)No Lung Opacity Not Normal

7. Conclusion and Future Work

Accurate and timely identification of pneumonia disease is very critical for successful diagnosis. We propose a novel methodology to detect and locate pneumonia disease from CXR image scans. The classification and object detection models would be trained separately using our suggested two-stage method. This approach mainly helps the different models to learn task-specific features and optimize the results. Future work may include advanced pre-processing techniques such as segmentation of only the lung part which may further improve the results by reducing the bias. Also, dif- ferent network architectures such as squeeze, and excitation blocks can be used with object detection models.



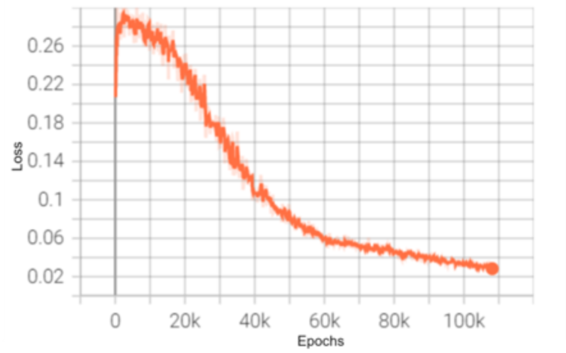


Fig. 7 The loss graph of a classification model (left) and Mask-RCNN (right).

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