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LViT: Vision Transformer for Lung cancer Detection

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***Abstract*— Lung cancer is one of the leading causes of mortality for males and females worldwide. Machine learning plays a crucial role in the automated detection, segmentation, and computer aided diagnosis of malignant lesions. In our study, we trained a vision transformer model using computer tomography (CT) scans. To establish if cancer is malignant or benign, the results are then compared to lung cancer images. Pre-classifying CT images from the initial dataset were the first stage. Since the entire image cannot be processed for the training model, we employed segmentation to break the image up into patches. To process the image through the transformer encoder and keep the training process on schedule and adjust to the variance in the images, the image has been separated into patches. The transformer's output is now the MLP head. Using the vision transformer model, we achieved the best accuracy of 91.93% after extensive training with 100 epochs.**

Keywords—Lung cancer, classification, segmentation, Vision Transformer.

I. Introduction

Lung cancer is one of the most frequently diagnosed malignancies and the primary cause of cancer deaths globally, with more than 2.29 lakh new cases being identified each year. Within five years of receiving their diagnosis, 75% of those people perish away. Lung cancer is the leading global cause of death for both men and women, to put it another way. Numerous studies have found that lung cancer is the most frequent cancer and the most common malignancy that kills men in India. Lung cancer is responsible for more than 9% of all cancer-related fatalities in adults of both sexes and around 7% of all newly diagnosed cancer cases. Lung cancer, by far the most prevalent type of cancer, is to blame for around one-fourth of all cancer-related deaths. Careful examination and surveillance are required for lung nodules that are still growing. The high intra-tumor heterogeneity (ITH) and complexity of cancer cells that cause drug resistance make cancer therapy more challenging.

The ongoing advancement of technology in cancer research over the past few decades has aided in the development of multiple clinical, medical imaging, and genomic databases as well as big collaborative cancer initiatives. Researchers may now more easily examine the whole patterns of lung cancer, including its identification, treatment, and clinical outcomes, thanks to these databases. Machine learning and Deep learning techniques for forecasting cancer growth and progression were used by the researchers in this study to analyze the development and progression of cancer. The prediction models provided in this article were created using a range of supervised machine-learning methods and different input and data samples. Images can be converted into arrays or images of integer labels, sometimes referred to as local binary patterns, using the image operator LBP. Further image processing, which is typically shown as a histogram, makes use of these labels. A variety of applications employ the LBP texture operator because of its specificity and convenience. Our research tools and capacities have expanded, particularly as a result of recent work on omics analysis, encompassing genomes, transcriptomics, proteomics, and metabolomics. In cancer research, the combining of many data types and vast amounts is becoming more common. For clinical activities, using numerous and highly dimensional data types still necessitates a large investment of time and knowledge, and analyzing the steadily growing databases of cancer-related data presents a significant challenge to researchers even with the aid of dimension reduction techniques like matrix and tensor factorizations [8–11]. To help doctors make decisions, Deploying Machine Learning (ML) models that automatically recognize the distinctive features of various data sources is more crucial than ever.

The histogram then analyses the image more thoroughly using these markers. the last three years, both men and women have died more frequently from lung disease than from breast or prostate cancer. The complexity and systemic nature of recently established prognostic models for prostate and breast cancer account for a considerable portion of this. To do this, an accurate forecast model for early-stage lung cancer must be created immediately if practicable.

The performance of classification algorithms that depend on conventional methods is subpar. In this study, we use a vision transformer machine learning model to classify the lung cancer dataset's CT images as malignant or benign. The transformer discovers new knowledge on its own by looking at the connections between input token pairs. Using patches of images as a token in computer vision is an approach. By emphasizing the network, one may locate this connection. The convolutional network's components may be replaced or used in conjunction with one another to achieve this. With the help of these network structures, photos may be categorized. However, a significant amount of work is necessary to create such a model. In the past, creating a multidimensional algorithm for picture processing required the human brain to work for hours or even days. Making a complex prediction model is significantly hampered by the high computing demands. Large and complex computations are now more easily accomplished because of the rising processing capability of chip technology and software optimization. When a large matrix can be created fast, it is possible to build models that are substantially more complex than logistic or linear regression.

II. Literature Review

Several initiatives share the similar goal of improving the precision of lung cancer diagnosis using machine learning technologies. The identification of lung cancer using imaging, deep learning algorithms, and data mining approaches has been the subject of several studies. In the last few years, a lot of algorithms have been developed that are related to the process used to diagnose lung cancer. In essence, processing methods are used on CT and X-ray pictures, algorithms are used, models are trained, and assessment is completed.

Mokled S. AL-TRAWEH (2012) [6], The author's goal was to find characteristics such as pixel percentage and mask-labeling for reliable picture comparison. Three phases were used by the researchers to provide more precise results. The first step is picture improvement, which entails improving the image and protecting it from interference, noise, or corruption. The Gabor filter approach produced the best results for this step. Image segmentation, the second stage, involves dividing and segmenting improved pictures. It applies algorithms to the image's ROI, and the techniques employed were the Marker-Controlled Watershed Segmentation and Thresholding approaches. Feature extraction employing a binarization and masking technique was the third and final stage. The proposed model's accuracy was 85.7%, although there is still room to utilize more advanced techniques and enhance accuracy.

Abeer Alsadoon, Suren Makajua P.W.C. Prasad, A. K. Singh, and A. Elchouemic (2017) [1], The author presented a paradigm that categorizes the findings of a lung CT scan into two groups: benign and malignant. In this model, the grayscale picture of CT scans was processed using a median filter during the first stage of image pre-processing. When CT images are being acquired, some noise is introduced, making mistakenly identifying modules easier. These noises have to be eliminated to properly identify lung cancer. The application of the Gaussian filter smoothed the picture and eliminated speckle noise. The segmentation procedure in the second step helps to identify items or boundaries that may be used to identify the region of interest in a picture. Watershed segmentation was used because of its ability to identify and separate touching elements in a picture. Characteristics including area, perimeter, centroid, diameter, eccentricity, and mean intensity are used as training features in the feature extraction step of the classification process. The identified nodule was labeled as benign or malignant in the final stage. Support Vector Machine, a supervised machine learning approach, was employed as the classifier for that categorization. The suggested model's accuracy was 92%, and the classifier's accuracy was 86.6%, but there is still room for development. Cancer is not divided into discrete stages like stages I, II, III, or IV; it is only classified as malignant or benign.

Parthasarathy G, Abirami S, Monica Santhana A, Nishali C, Pavithrasrisai V (2020) [2], to predict lung cancer, this author used a deep learning system. The initial phase was pre-processing, which comprised data cleansing, integration, and outlier analysis in addition to converting the raw data set into processed data. The author chose the sigmoid activation function in the second phase of the process. The third phase was creating a model using the deep learning technique convolution neural network (CNN). The ConvNet successfully captured spatial and temporal dependencies in an image and Rectified Linear Unit (ReLU) activation function was used for feeding input. Prediction and assessment included the final phase, which involved calculating the dependent variable using the trained model and assessing the proposed model using Mean Absolute Error (MAE). The suggested model has a 94% accuracy rate, although there is still an opportunity for accuracy growth.

In Yadav, S.P., and Yadav, S. (2018) [3], the researchers used wavelet transforms with discrete wavelet transforms to extract features from images and fuse them. The discrete wavelet transform employs the scaling and wavelet functions, two orthogonal functions. The quality of the images during implementation must not be compromised. The continuous wavelet transform was used in [16] for image fusion and the extraction of characteristics such as wavelet coefficients and frequency responses from images to gain access to a wide range of mathematical applications in the medical field. Through implementation, better treatment methods and reduced data transmission rates as a result of smaller data volumes were produced, which also controlled data loss. Additionally, [17] examines several medical picture fusion techniques with an emphasis on wavelet transform, independent analysis, and principal component analysis.

Convolutional neural networks and deep learning are combined by the author [5] for picture categorization. They trained a Double Convolutional Deep Neural Network (CDNN) and a Normal convolutional Deep Neural Network using computer tomography (CT) scans. These topologies were compared to lung cancer scans to determine the Tx cancer stage at which they may detect the possibility of lung cancer. To train the convolutional deep neural network, the dataset's CT images were first sorted using the k-means technique into groups of identical slice images (CDNN). A double convolution deep neural network with maximum pooling was created to conduct a more comprehensive search. In the end, they used CT scans of various lung cancer Tx phases to determine the Tx stage at which the CDNN would detect the chance of lung cancer and compared it to the regular CDNN. In comparison to a normal CDNN, which only achieved an accuracy of 87.6%, the suggested model of a double convolutional deep neural network generated 99.62%. Cancer’s Tx stage was identified with exceptional precision.

Lung Cancer Detection Using CT Images and CNN Algorithm, Sushama Garud, Dr. Sudhir Dhage 2021 [7], to detect lung cancer, this author employs CNN algorithms and CT scans. The input, which was also the initial phase, utilized CT scans. The second phase, pre-processing, was utilized to improve the image's quality by reducing unintentional distortions and enhancing some of the image's features. The third phase involved the photograph going through CNN. In that author used AlexNet architecture which had 25 different layers. The training procedure was completed with the assistance of this architecture. The ReLU activation function, also known as a rectified linear activation function, is a nonlinear activation function that was employed. The output that identified the image as benign, malignant, or normal was obtained as the final step. The total accuracy of the suggested model was 85.4%. Accuracy may still be improved, and the training set's size could be increased.

III. PROPOSED METHOD

A. *Vision transformer*

The guiding principles of the transformers used in the field of natural language processing serve as the foundation for the vision transformer (ViT), a transformer used in the field of computer vision.

B. *Workflow of Vision Transformer*

The working of the Vision Transformer (ViT in short) can be understood through the following workflow. We must first make patches from an image and then flatten the patches. The flattened patches must then be converted into a lower-dimensional linear embedding. After that, we add the positional embeddings and provide the sequence as an input to a conventional transformer encoder. In the next step, we create the model (supervised on a large dataset) and fine-tune the image classification dataset's downstream dataset by utilizing image labels.

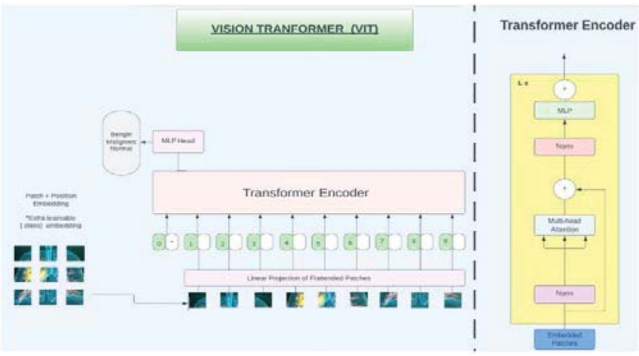

Fig. 1. The architecture of LViT

C. *How multi-head attention works in a vision transformer?*

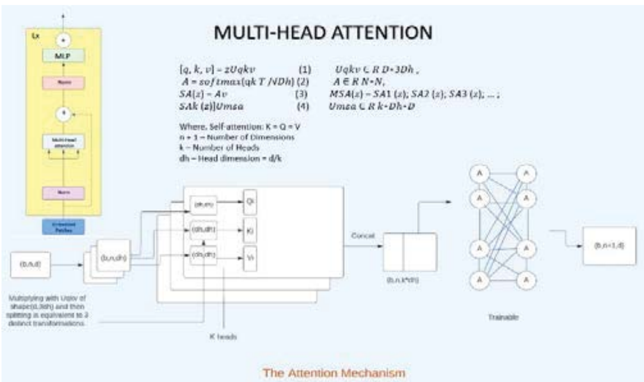

Fig. 2. The Attention Mechanism in the MLP

$[q, k, v] = zU_{qkv}$ (1)

$U_{qkv} \in R^{D*3Dh}$,
$A = softmax(qk^T/\sqrt{D_h})$ (2)

$A \in R^{N*N}$,
$SA(z) = Av$ (3)
$MSA(z) = SA_1(z); SA_2(z); SA_3(z); \dots; SA_k(z)]U_{msa}$(4)

$U_{msa} \in R^{k*Dh*D}$

Where, Self-attention: K = Q = V

n + 1 – Number of Dimensions

k – Number of Heads

dh – Head dimension = d/k

K feature tensors of the form (n, dh) are produced as a result of splitting the hidden state from the preceding encoder into K heads.

Each is multiplied by three trainable matrices of shape (dh, dh), Qi, Ki, and Vi. This is equal to equation 5, as there are precisely 3 matrices of shape (dh, dh)for each head in U = (d, 3dh).

The projection of the input is represented by Qi, Ki, and Vi in three subspaces. Each line in Q may be viewed as a learned projection of the patch that interests us, and lines in K can be seen as comparison patches for Q. To compute the final "attention," V and K are taught to indicate the significance of, or weights for, characteristics in V.

The scaled dot-product attention tensor (A) is then calculated for each head as a SoftMax of the multiplication of the Ki and Qi matrices, normalized with the square root of the head's dimension.

The self-attention is the form (n + 1, dh) of the product of A and V. The weighted average of feature J by the pdf online in A is the component at row l and column J.

The self-attention matrices are concatenated on the second dimension to produce an (n + 1, d) tensor, which is then effectively multiplied by a (d, d) trainable tensor before being sent through a single linear layer. This linear layer is particularly significant since it permits characteristics to be learned as aggregates from all the heads.

IV. EXPERIMENTS AND RESULT

In this section, we have used the vision transformer model and CT images as the dataset for the experiments to get a favorable result. We also present the proposed model experimental settings as well as the datasets used to test the model.

A. *Datasets*

The lung cancer dataset from the National Centre for Cancer Diseases (NCCD) and Iraq-Oncology Teaching Hospital (IQ-OTH/NCCD) was gathered over three months in the fall of 2019. Both healthy volunteers and patients with varying stages of lung cancer who have undergone CT scans are included. In these two hospitals, IQ-OTH/NCCD slides were labeled by oncologists and radiologists. The collection contains 1190 pictures depicting CT scan slices from 110 different instances (see Figure 1). There are three different case types: benign, normal, and malignant. Out of them, 40 are assessed to be malignant, 15 are assessed to be benign, and 55 are assessed to be normal cases. The initial collection of CT scan data took place in DICOM format. Siemens SOMATOM is the brand of the scanner. The following CT reading parameters were used: 120 kV, 1 mm slice thickness, 350–1200 HU window width, 50–600 HU window center, and complete intake and breath holding. All pictures underwent de-identification before analysis. The necessity for written consent was disregarded by the oversight review board. The institutional review boards of the participating hospitals' medical facilities gave their approval for the study. There are multiple slices in each scan. These slices range from 80 to 200 in number, and each one depicts the human chest from different perspectives. The 110 cases range in gender, age, educational level, place of residence, and mode of life. Others are farmers and gainers, while others work for the oil and transportation ministries of Iraq. They originate mostly from Baghdad, Wasit, Diyala, Salahuddin, and Babylon in central Iraq.

B. Experimental Settings

In our trials, we constructed the ViT model using Python, Google Collab, and TensorFlow extensions. Images used as input are normalized via a batch normalization layer. Layer resizing, a random flip of the model, a random rotation by a factor of 0.02, and a random zoom with height and width factors of 0.2 each compose the model's core support structure. To solve the underfitting issue, we set the learning rate to 0.001 and the weight decay to 0.0001. Furthermore, the batch size of 256, picture size of 72, patch size of 6, and projection dimension of 64 enable effective image processing for training the model, which is followed by 8 layers of transformer layer with 2048 and 1024 mlp head units. The number of heads was raised one at a time starting with 6 at the beginning of the 100 epochs. The generated tensor was then subjected to the model's application of the global average pooling layer.

C. Results and Discussions

TABLE I. RESULTS AND ANALYSIS OF DIFFERENT VIT MODELS BUILT WITH EVEN NUMBERS OF HEADS

Model Number	Number of heads	Test Accuracy	Loss
LViT$_{(h=6)}$	6	78.03%	0.6418
LViT$_{(h=)}$	8	81.61%	0.6747
LViT$_{(h=6)}$	10	78.92%	0.7077
LViT$_{(h=6)}$	8	91.93%	0.2816

TABLE II. RESULTS AND ANALYSIS OF DIFFERENT VIT MODELS BUILT WITH ODD NUMBERS OF HEADS

MODEL NUMBER	NUMBERS OF HEADS	TEST ACCURACY	LOSS
LViT$_{(h=7)}$	7	76.68%	0.6893
LViT$_{(h=9)}$	9	80.72%	0.7863
LViT$_{(h=11)}$	11	78.03%	0.7056

Based on table I, we can conclude that the model with 8 heads has the best accuracy among the head counts of 6, 8, and 10. Based on further analysis of the odd number of heads deduced from table II, we conclude that the accuracy in the model increases to 9 heads but is still comparatively less than the model with 8 heads. This research verifies our hypothesis that the model with 8 heads predicts the most accurately. In the beginning, we built the models with 16 epochs as the basis for determining the appropriate number of heads in our model. Furthermore, increasing the number of epochs improved the model's accuracy. Finally, with 100 epochs and 8 heads in our model, we get an accuracy of around 92%.

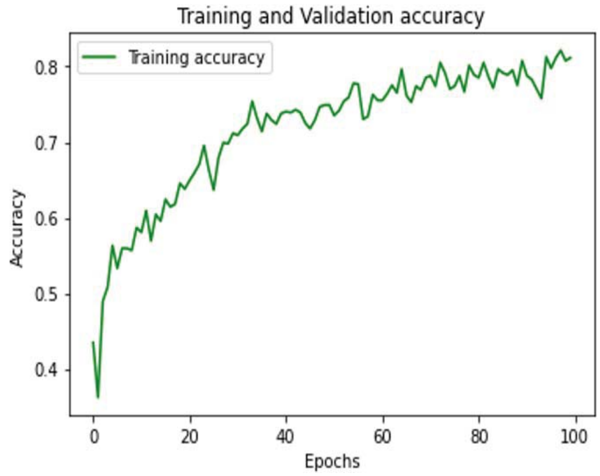

Fig. 3. Training and Validation accuracy for LViT

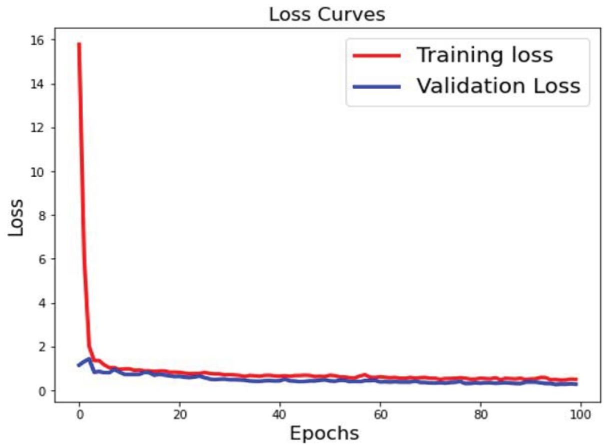

Fig. 4. Loss Curves of LViT

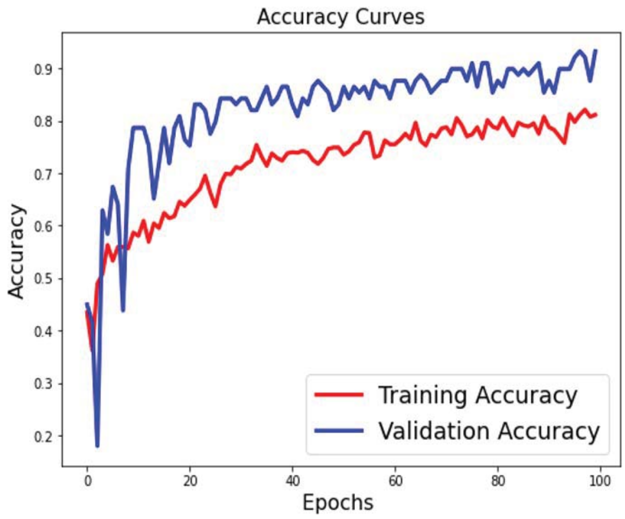

Fig. 5. Accuracy Curves for LViT

The very first model trained (Table I.) built using a single epoch and 4 heads resulted in 61.43% test accuracy, which is very low for the prediction models using imaging techniques, especially in the medical sector. In the further stages of the research, an increase in the validation accuracy was found when the number of epochs was increased, so for obtaining better results, we increased the number of epochs while training the model, this resulted in the drastic improvement of the prediction models in classifying the type of lung cancer detected through the image segments through the Vision Transformer. Furthermore, when the number of heads was increased, the trend of increase in the model accuracy was observed which resulted in improved validation accuracy with the best accuracy being 91.93%.

The first observation was made on choosing the number of heads for the model while training a pattern was observed that up to 8 heads, an increase was found and later with 9 or more heads a decrease in the model accuracy was observed. Furthermore, with 8 heads and more epochs for training the model, the accuracy increased, with the greatest test accuracy being 91.93%.

Benign	0.51	0.058	0.43
Malignant	0.0036	0.99	0.0089
Normal	0.039	0.021	0.94
	Benign	Malignant	Normal

Fig 6. Confusion matrix depicting a comparison of the cancer types withhigher accuracy in malignant cases and normal cases in the cancer types.

Using a confusion matrix to test our system on the dataset, we were able to detect certain behaviors but with subpar identification accuracy. Figure 6 illustrates that 99% of the time, predictions of cancer's malignancy are accurate, and up to 94% of the time, predictions of cancer's normality are accurate. However, projections based on the kind of benign cancer are only 51% accurate. Further analysis indicated that this issue remained because it was more challenging to differentiate benign cases from normal ones since the training dataset for this algorithm included fewer data points for the benign cancer category. Additionally, a benign tumor has a distinct, constant, smooth border, which may be the reason it's difficult to distinguish one from the normal one.

D. *Limitations*

The suggested system's first and most significant shortcoming is its lack of precision in comparison to other existing systems. This 92% accuracy can be enhanced further by increasing the number of epochs in the training model.

Another constraint of the proposed system is the compute cost of the function, which is larger than in systems developed with CNN.

Furthermore, the model trained for one image processing job does not adapt well to other tasks of a similar nature.

V. COMPARATIVE STUDY

TABLE III. COMPARISON ALONG WITH OTHER RELATED STUDIES

SR NO.	Reference	Dataset	Method	Result
1	Sreekumar Etal [14]	LIDC-IDRI	CNN	86%Senstivity
2	Baskar Et al [15]	CT images	Support vector machine	90.9%
3	Parthasarathy Et al [2]	CT images	CNN	94%
4	Sushama Et al [7]	CT scans	CNN	85.4%
5	LViT(our)	CT images	Vit Transformer	91.93%

Several well-known and widely used techniques have been created. Table III above illustrates a comparison between various research, comparing dataset type, technique, and outcome. To achieve an accuracy of 91.93% in our work, we employed CT scans as the dataset and the ViT transformer model. However, researchers in [2] used CNN to acquire an accuracy of 94% with a dataset as CT scans, on which they carried out extensive training and used the sigmoid activation function to acquire an accuracy of 94%. Furthermore, the researchers in [7], and [15] employed the same dataset, and the researchers in [7] got 85.4% utilizing Alex net CNN architecture for feature extraction. However, using the Delta Radiomics approach for feature extraction, researchers in [15] were able to achieve a higher accuracy of 90.9%. While utilizing the LIDC-IDRI dataset, researchers [14] achieved a sensitivity of 86% using the CNN technique.

VI. CONCLUSION

The most frequent cause of mortality and one of the most severe diseases, lung cancer is made more hazardous by the challenge of making an early diagnosis. It is feasible to raise the likelihood of survival if cancer is found and treated early enough. The development of lung cancer is foreseen in our work using the Vision Transformer. The suggested method makes optimal use of segmentation concepts for feature extraction from a collection of CT images before applying a vision transformation model. The proposed approach demonstrates that doctors may effectively use them to help in the detection of lung cancer and give remarkably beneficial results. If the prediction is true, the doctor may be able to provide a more effective medication and diagnose the patient more quickly.

For future work, we intend to further categorize malignant instances according to whether they are in the first stage, second stage, third stage, or final stage. In addition, the model's best accuracy was determined to be around 92%. Additionally, the model will provide the best results on increasing the number of epochs by the. However, since the trend of decrease was observed for heads greater than 8, increasing the number of heads does not guarantee an improvement in the accuracy of the model.

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The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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