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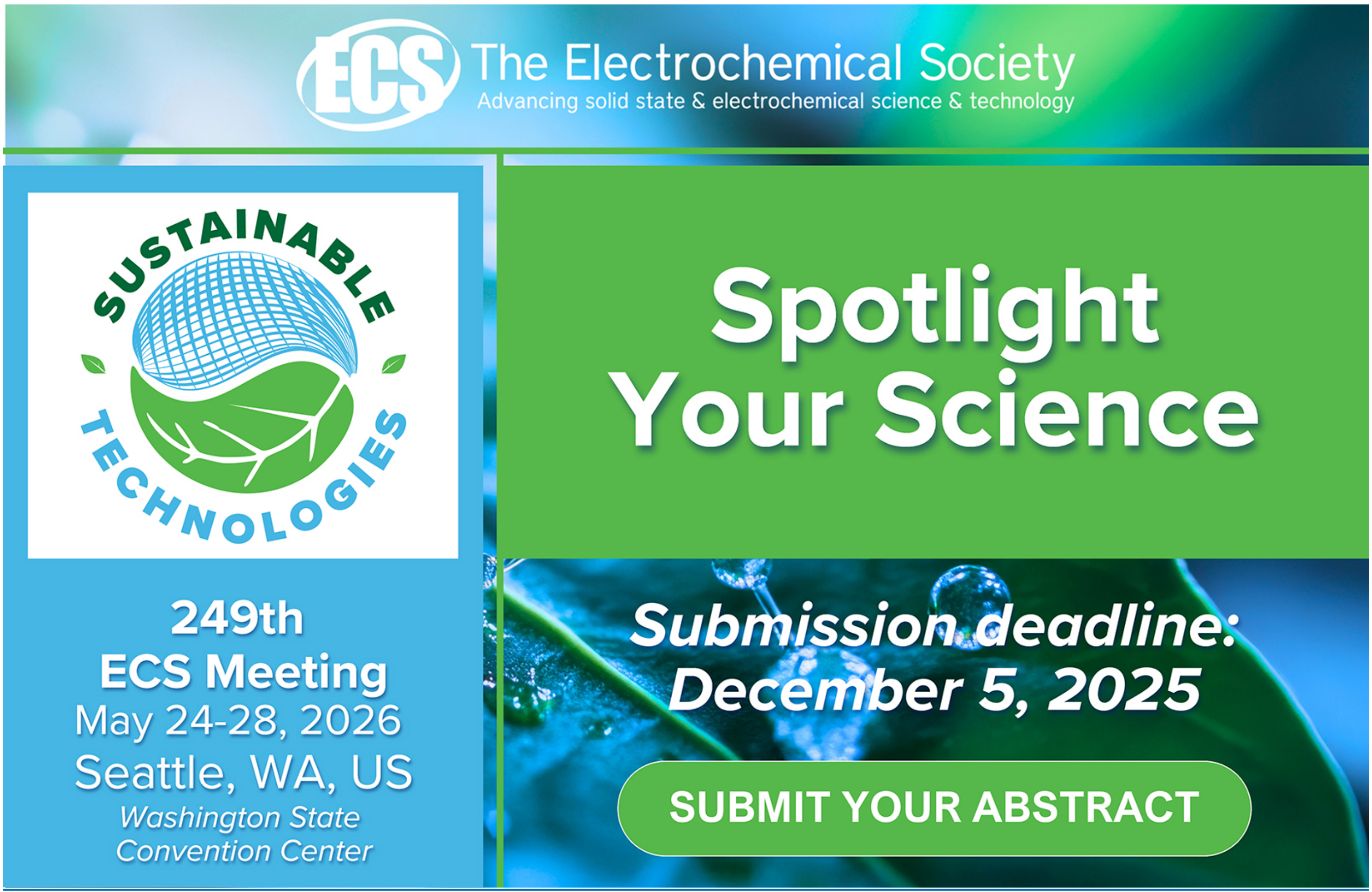

Deep Learning (CNN) and Transfer Learning: A Review

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Abstract. Deep Learning is a machine learning area that has recently been used in a variety of industries. Unsupervised, semi-supervised, and supervised-learning are only a few of the strategies that have been developed to accommodate different types of learning. A number of experiments showed that deep learning systems fared better than traditional ones when it came to image processing, computer vision, and pattern recognition. Several real-world applications and hierarchical systems have utilised transfer learning and deep learning algorithms for pattern recognition and classification tasks. Real-world machine learning settings, on the other hand, often do not support this assumption since training data can be difficult or expensive to get, and there is a constant need to generate high-performance beginners who can work with data from a variety of sources. The objective of this paper is using deep learning to uncover higher-level representational features, to clearly explain transfer learning, to provide current solutions and evaluate applications in diverse areas of transfer learning as well as deep learning.

1. Introduction

The term "deep learning" has recently become popular in the computer industry. Many real-time applications use it, and it is a division of Machine Learning as a whole. Deep Learning relies on a lot of data to make choices about fresh data, which is critical. Neural Networks classified as Deep Neural Networks are used to process data (DNN). Because neural networks are commonly used in deep learning methods, the term "deep neural networks" has gained currency. One of the most commonly used deep neural networks is the Convolutional-Neural Network (CNN) [1–2]. Traditional feature extraction techniques, such as SIFT, LBP, and others, require human feature extraction, but CNN does not. The features were extracted directly from a raw image dataset by CNN. When the networks are trained on a batch of photos, related features are not pre-learned. For computer vision tasks including object identification, classification, and recognition, this automated feature extraction method is the most accurate learning model. Machine Learning techniques that rely on human feature extraction and a different algorithm to categorize each object have been around for a long time. However, in Deep Learning techniques, the network itself extracts the features without involving the user and also classifies the items and Figure 1 depicts this.

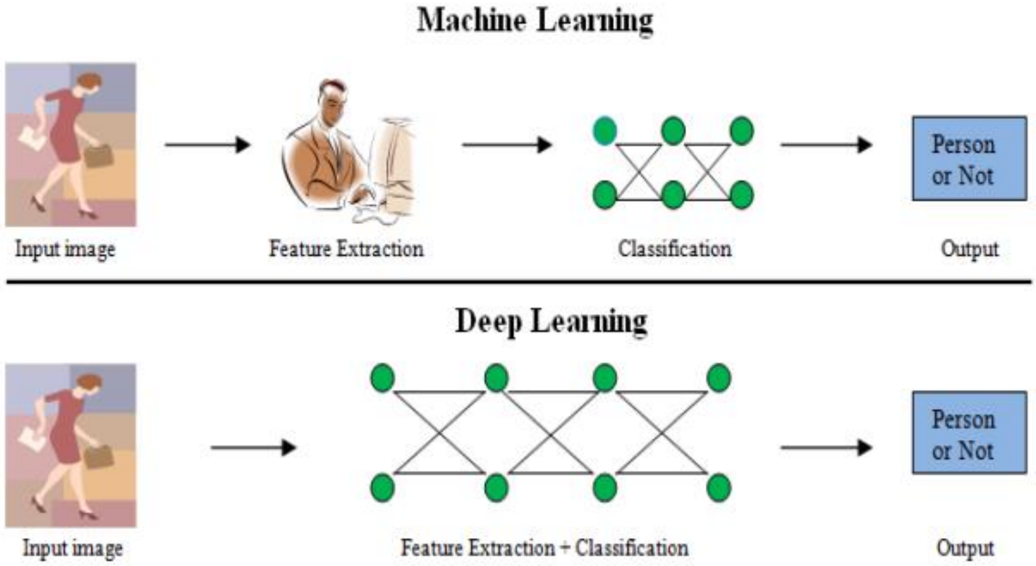

Figure 1: Machine Learning vs. Deep Learning [2]

Although it is based on the traditional neural network, deep learning outperforms it by a wide margin. Additionally, DL builds multi-layered learning models by combining transformations and graph technology. It has been found that the most modern DL approaches have performed well in a wide range of applications, including audio and voice, visual data, and natural language processing (NLP) [3], [4], [5], [6]. The integrity of the input-data representation is critical to the performance of an ML algorithm. In comparison to a poor data representation, an appropriate data representation has been found to deliver better performance. Thus, feature engineering has been a major study direction in ML for many years, which has influenced several studies. Features can be constructed from raw data using this method. That is not to mention how field-specific it is, and how labor-intensive it can be. In the computer vision environment, for example, numerous types of features have been created and contrasted, such as Histogram of Oriented Gradients (HOG) [7], Scale Invariant Feature Transform (SIFT) [8], and Bag of Words (BoW) [9]. There is no limit to how long a new study direction can be explored once it is discovered to be successful. Feature extraction is done in a rather automated manner by the DL algorithms. For researchers, this means employing the least amount of human work and field expertise possible to extract discriminative characteristics [9]. Multi-layer data representation architecture is used by these algorithms to extract low-level features while the high-level characteristics are extracted by the last levels. Notably, this form of architecture was first inspired by AI, which mimics the process that occurs in the brain's primary sensory regions. The human brain is able to automatically derive data representations from a variety of visual contexts. More specifically, the classification of objects is the result of this process, while the scene data collected is the input. This approach is modeled after how the human brain functions. However, it draws attention to the primary benefit of Deep Learning. Due to its enormous success, deep learning (DL) is presently most popular research trends in machine learning. The CNN is the largely fashionable and frequently used deep learning method. CNN's coverage of DL has made it a household name [10], [11]. Comparing CNN to its predecessors, the most notable advantage is that it mechanically finds the significant traits without any supervision of human, making it the most commonly utilized technology.

2. Related Work

The use of breast cytology pictures to automatically screen for and classify cancer has been the subject of numerous research proposals over the last few decades. Thus, researchers are researching nucleus analysis in order to gain more information on cell classification as either malignant or benign [12]. Similarly, cluster segmentation and categorization often make use of clustering related algorithms, circular Hough Transform, and a variety of statistical features [13], [14]. Histopathological image analysis methods are rapidly evolving in medical image investigations. As a result of this need, automated methods are sought for that are both effective and highly dependable [15], [16]. In order to ensure that qualitative diagnostics are carried out accurately, such procedures must be employed. The output and precision of the device are harmed by the dynamic presence of operations such as segmentation, reprocessing, and attribute mining in traditional process of machine learning. The standard of deep learning has been promoted in order to extract the important information from raw images and allow effective use for categorization method in order to overcome the challenges of conventional machine learning methods [16], [17]. Data sets are processed using a general learning approach rather than requiring changes to the functions [18]. Biomedical image processing has seen significant success in recent year’s credit to deep learning that focuses on different methods, such as determining mitotic cells from microscopic images, brain membrane segmentation, and skin condition classification. Researchers believe that the computational deep learning approaches utilized for transfer learning are applicable in the actual world. Computational deep-learning transfer learning is summarized in Table 1.

Research into visual anatomy, function, psychology, and computation has led to a major framework of vision that starts by retrieving local patterns of retinal images in lower visual cortex [e.g., the Lateral Geniculate Nucleus (LGN), V1] and afterwards incorporates the feature points to retrieve global pictures in better visual areas [e.g. V4 and IT] to start with [19], [20]. The visual pathways' local-to-global hierarchical organization is a major inspiration for Convolutional Neural Networks (CNNs). Different CNN levels have discrete receptive fields that are represented by similar visual neurons which encode specific features of a particular region of the field of vision (i.e., receptive fields). CNNs have been the most significant advancement in the study of artificial intelligence and computer vision because of their origins in biology, mathematics, and computer science (AI). Human-level classification accuracy can be achieved by training CNNs to recognize natural scenes. Facebook, Google's image search, and Amazon's product recommendations all use this system to properly tag images. Despite their commercial success, little is understood about how CNNs classify images and whether they have inherent limitations. This information is necessary in order to avoid catastrophic CNN application problems. The presentation of CNNs transfer learning depends on image classification has been reported in the literature [21], [22] however more research is needed. Geometric shapes were used as the datasets for training and testing the CNNs instead of actual photos [23, 40]. In addition to assisting the CNNs to conduct shape classification tasks, one of our primary goals was the transferring of CNN learning from trained data to new datasets (i.e. transferring datasets) with various shapes that shared local/global properties with the training datasets.

Table 1. previous research on deep learning in transfer-learning experiments is reviewed

Author	Title	Method	Result	Year
[34]	Time-Independent Prediction of Burn Depth using Deep Convolutional Neural Networks	Deep learning techniques of pretrained deep CNNs like ResNet-101, ResNet-50, Google Net, and VGG-16	Precision Average = 81.66% Minimum = 72.06% Maximum = 88.06% Accuracy =90.54% Sensitivity = 74.35% Specificity = 94.25%	2019
[35]	Domain Adaptation for Large-Scale Sentiment Classification: A Deep Learning Approach	deep learning method	Sentiment Classifiers produce better outcomes than existing state-of-the-art method.	2011
[36]	Deep convolutional neural networks with transfer learning for automated brain image classification	Deep learning method	Recall = 96.7% F1-score = 92.7%	2020
[37]	Bi-Transferring Deep Neural Networks for Domain Adaptation	BTDNN (Bi-Transferring Deep Neural Network)	Achieves good Precision	2016
[38]	Clean Net: Transfer Learning for Scalable Image Classifier Training with Label Noise	Clean Net	Label Noise Reduction = 41.5% Performance of Image verification = 47% Classified Images = 3.2%	2018

3. Deep Learning
In this discipline of Machine Learning, neural networks are used as a replica of the human brain. It is based on the human brain's most fundamental unit, the neuron. Deep learning is a term utilized to explain about the study of how neurons work together to form a model of a neural network. A deep learning model is the final product of a neural network. Most of the time, in deep learning, unstructured data is used from which the deep learning model pulls characteristics on its own by repeatedly training on data. Transfer Learning refers to the use of pre-built models developed for a

certain collection of data as a jumping-off point for building a new model using a different set of data and attributes. This is a frequent strategy in which a model generated for one task is utilized as a starting point to develop a model for a different activity.

3.1. Convolution Neural Networks

Recent times have seen a surge in the use of Convolutional Neural Networks (CNNs). In a CNN, there is an, a last output layer, input layer, and a variety of further hidden layers. Convolutional layers, fully connected layers, normalization layers, and pooling layers are the most common types of hidden layers in a CNN (ReLU). For increasingly sophisticated models, additional layers might be used. There are numerous examples of a standard CNN described in [24] and Figure 2.

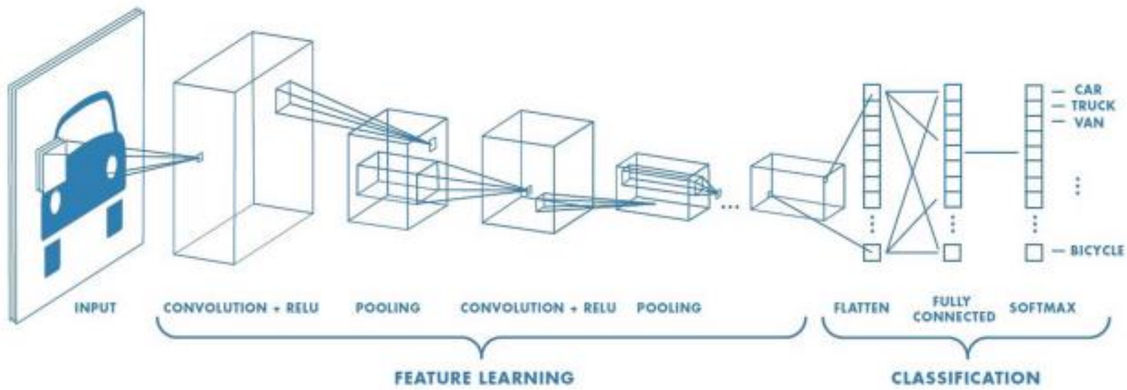

Figure 2: Typical CNN architecture [39]

For a wide range of computer vision and machine learning challenges, CNN architecture has proven to be an outstanding choice. The details of CNN's training and prediction are saved for subsequent sections. Modern Machine Learning applications use this CNN model widely because of its record-breaking performance. These CNNs are built on a foundation of linear algebra. Data and weights are represented via matrix vector multiplication [25]. For a picture set, each layer has a different set of attributes. Using a facial image as an input, for example, a CNN learns the basic characteristics of the image in its initial layers, such as edges, bright spots, dark spots, and other geometrical features. The image's recognizable features, such as the eyes, nose, and mouth, will be added to the following set of layers. Following that, the network may define a human face using forms and objects that resemble genuine human faces. The image classification process is broken down into smaller segments by CNN, which matches bits of the image rather than the entire image (features). Features extracted by the CNN are represented by a 3x3 grid. Line the feature up with the picture patch in the next step, known as filtering.

Once all the pixels have been multiplied by their corresponding feature pixels, the values are added up and separated by the entire amount of pixels in feature space. This process is repeated for each and every pixel. The feature patch contains the final value for the feature. Following that, the remaining feature patches are subjected to a similar procedure, which includes applying the convolution filter repeatedly until one matches perfectly.

In the following layer of a CNN, called "max pooling," the image stack is reduced. When attempting to pool an image, it is necessary to specify the window size (often 2x2/3x3 pixels) as well as the stride (e.g. frequently 2 pixels). The maximum value is afterwards recorded for each window as the window is filtered over the image in steps across. Data can be reduced in dimension while still maintaining significant information by using max pooling. A CNN's normalization layer, also known as the Rectified Linear Unit (ReLU) procedure, entails setting all of the filtered image's negative values to 0. When applied to all images that have been filtered, the ReLU layer increases the model's nonlinear properties. Convolution, pooling, and ReLU are all used in the CNN's subsequent layering process, where each layer feeds the next. "Deep stacking" is possible when layers are repeatedly applied. The fully connected layer, often identified as classifier, is the final layer of the CNN design. All of the values in this layer play a role in deciding the classification. Each intermediary layer votes on phantom "hidden" categories, resulting in multiple levels of fully connected layers being layered on top of one another. Furthermore, each new layer of neural networks improves decision-making by allowing the network to learn increasingly more complex features combinations [26]. For the convolution layer and also the values of the fully - connected layer, back propagation is utilized by the deep neural network.

3.2. Transfer Learning
With the help of Transfer Learning, a model can be taught and refined for one activity and then applied to a different one which is closely connected to it. An example of this is when what has been discovered and learned in one context is used to increase efficiencies and performance in another. Pre-trained models were applied to data sets that are smaller than the actual training datasets [27]. Image Net was used to train the Inception-v3 model and now it is being repurposed to learn (or shift) features so that it can be skilled on a fresh dataset (CIFAR-10 and Caltech Faces). Initial training can be done using the Image Net dataset and Transfer Learning instead of beginning from scratch with random weight initialization, allowing us to use the learnt features and model structure to better fit the new dataset/task. Transfer learning of the pre-trained CNN representation is made easier with Tensor Flow. The topology of the CNN model is examined for picture categorization via Transfer Learning. In order to identify which variables influence classification accuracy, researchers must test and adjust the network topology and dataset features.

3.2.1. Transfer Learning Applications. The review shows that significant structures have been used to transfer learning. Document classification, multilingual text categorization, emotion classification, and spam email detection are just a few of the many uses for natural language processing (NLP). Classification of films, photos, papers, and other artefacts is a part of these procedures. Muscle tiredness categorization, Wi-Fi location categorization, human actions categorization, pharmaceutical efficacy categorization, machine defect categorization, and cardiac arrhythmia categorization are some of the applications discussed by [28]. For the most part, the solutions evaluated could be applied to a wide range of situations. Natural language processing and image processing are two of the most commonly used application-oriented technologies. The use of suggestion systems can benefit from a number of different types of transfer learning. For a certain field, recommendation services provide users grades or ratings (e.g., books, movies). With only a few examples from the past (epidemiological data), the method lacks dependability. Information from another domain can be used in cases where there is insufficient domain data for reliable forecasts (for example, a recent release of a film) (for instance, using books). Using transfer learning methods and studies raised concerns [29].

4. Case Studies

4.1. *Image classification to predict whether it's a nude or non-nude image*
Transfer learning is a concept where we train a model on one problem and then we can fine-tune and apply it on another similar kind of problem. Transfer learning is beneficial in terms of reducing training time, also need for huge datasets is eliminated. We have used transfer learning for image classification using a neural network library named Keras. With the help of web scraping 5600 training images and 1000 testing images were scraped from the internet to create the dataset. Two existing models, VGG-16 and VGG-19 were applied on the dataset. VGG-16 model has 16 Convolution layers with 3x3 filter size, stride-1 and padding-same for all the layers and all the max pooling layers have 2x2 filter size and stride-2 .VGG-19 model is very much similar to VGG-16 model but with 3 additional conv layers. As pre-processing all the images are resized to 224x224. Both

the models were trained for 15 epochs with SGD as optimizer, sigmoid as activation function and batch size as 128.For the said parameters VGG-16 gives 84.28 % accuracy while VGG-19 gives an accuracy of 85.39%. In this case VGG-19 is performing better than VGG-16 as with the increase in no of layers in CNN, model's ability to fit more complex functions also increases.

4.2. *Image classification to predict whether it's food image or not*

A dataset name Food-5K which consist of 5000 images with classes as food and non-food is used to perform image classification task. After pre-processing the images, ResNet-50 model was used where the final layer of the model was changed according to our dataset specifying no of classes. ResNet-50 model has 5 stages and every stage consists of a convolution block and an identity block. Each convolution block and identity block has 3 conv layers. This model reached up to 95 percent in performance for 20 epochs. Because we used transfer learning we don't have to implement CNN model from scratch and it saves training time.

5. Discussion

Data and model perspectives have been summarized in terms of the implementation procedures and strategies for the transition of learning. Transfer learning applications have been tested in a number of research initiatives since their inception. In a wide range of contexts and activities, it was clear that transfer learning had made significant strides. Real-world research assignments, on the other hand, may have dealt with specific obstacles or issues. There may have been a resolution to some of these issues while others remained unaddressed. Self-supervised learning is a relatively new approach to education. By creating and executing artificial tasks that serve no purpose, self-supervised learning can generate labels from scratch using unlabeled source data with no human annotation. If you use self-supervised learning, a typical and useful challenge is to compare patch locations and estimate the picture's rotation angle [30]. Automatically created labels can be acquired using this synthetic learning technique without the involvement of humans. Another technique for obtaining higher-quality image data is smart imagery. Image noise and artifacts can be minimized, image resolution improved, and shadows can be detected [31]. All of these factors enable deep learning algorithms to perform more accurately and quickly. Convolutionary neural networks have been utilized for transfer learning for many years, along with other deep learning methodologies, in a variety of experiments. For unsupervised domain adaptation, an adversarial network and training procedures were used to implement adversarial network and training methods (GAN). The mixture of deep learning method with transfer learning is exemplified here. Transfer learning has been attempted by numerous researchers in order to improve the learning process [32]. Even though there have only been a few studies published on medical image in this subject, we expect there will be more in the near future. According to one theory, the original algorithms' default parameter choices may not be appropriate for the data set selected. When GFK was first developed, it was intended to be used for object identification, which meant that it could be directly integrated into the text categorization [33]. However, this resulted in an unsatisfactory outcome. Based on these findings, it appears that some algorithms may not be suitable for use with data from these fields. As a result, it is critical to select the right algorithms to begin the research process. In addition, a useful algorithm must be found for practical applications.

6. Conclusion

The implication is that the effect of deep learning on transfer learning has been reported for machine learning diagnostics. Intelligent data-driven diagnostic approaches have piqued the interest of both the academic community and industry. A number of machine learning techniques have been implemented to predict the life of machines and track their condition in order to detect faults. Since these accomplishments, deep transfer learning has developed into the fundamental subject of deep learning diagnostics science. To diagnose deep learning, transfer learning methods such as mutual parameters and features are widely employed in diagnostics. For a variety of purposes, a variety of transfer learning architectures have been developed. Deep transfer learning is the subject of this research, which focuses on recent developments and a variety of other criteria. It is nevertheless suitable to say that deep-seated learning diagnostics have previously reached their testing restrictions, even though the efficacy of these approaches has not been properly examined. Heterogeneous transfer learning solutions must be upgraded because of the wide variety of data being collected. Transfer learning solutions can benefit from using big data systems in conjunction with larger data sets. The range and size of data sets used to transfer learning systems is an important subject for future research. This is not the only area of study that deals with the issue of label space. This topic has the potential to become increasingly important as fresh data sets are collected and create publicly available. This is a promising field for further research, as there are only a few examples of transfer learning algorithms in the literature that deal with the unlabeled source and unlabeled goal data condition.

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