Classification of Power Quality Events Using Deep Learning

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***Abstract*— Power Quality (PQ) can be defined as a clean supply voltage that stays within the prescribed range in a smooth curve waveform. A power quality problem is defined as any problem that causes voltage or frequency deviations in a power supply, and it may result in failure or maloperation of a network. Therefore, continuous monitoring is also required in case of malfunction in these cases. In this paper, we have presented a deep learning-based power quality event classification method. We have used the proprietary electric relay wave-form data from The Turkish Electricity Transmission Corporation (TEIAS), as well as generated wave-form from MATLAB-Simulink, to train our model, using Convolutional Neural Networks (CNNs). The results proved to be effective, and can open the path to further research in this direction.**

Keywords*— *Power Quality, Deep Learning, Neural Networks, Convolutional Neural Networks, Electrical Distribution System.

I. INTRODUCTION

A power quality problem is defined as any problem that causes voltage or frequency deviations in a power supply, and it may result in failure or maloperation of a network. Power quality may also be described as the Load's ability to function properly. Without good power quality in an electrical network, Load's electrical and mechanical equipment may overheat, malfunction, fail prematurely, require high maintenance, and in many cases they may not operate at all. Power quality has various effects, and it is important to understand what equipment causes poor quality issues in electrical networks. Most of the poor quality issues are generated by devices in buildings. Non-linear loads are the major cause of poor quality issues. There are 10 power quality problems that need to be concentrated upon: Over-voltage, surges, spikes, transients, frequency variation, under-voltage, sags, blackouts, noises, and harmonics. An extensive literature survey suggests that there is no generally accepted method for characterization of these disturbances and suitable limits are not yet found in any international standard. One of the reasons for the lack of characterization methods is the difficulty of defining suitable site indices for each discrete disturbance type [1]. A diagram of power quality problems is shown in Fig. 1.

Power quality can be defined as a clean supply voltage that stays within the prescribed range in a smooth curve waveform. Over-voltage conditions can be defined over the range of a normal voltage or whatever normal voltage defines. Nominal voltage is a reference voltage, used to describe the batteries, cells, or electronic systems such as a 12 or 24 volt batteries. Under-voltage is under the lower boundary. The peak is the extreme condition of over-voltage, and blackout is the extreme condition of under-voltage. We can describe the clean power or high power quality voltage as a steady smooth sine wave. It is what we want for any computers, servers, or other Computing devices in a data centre. The first issue of power

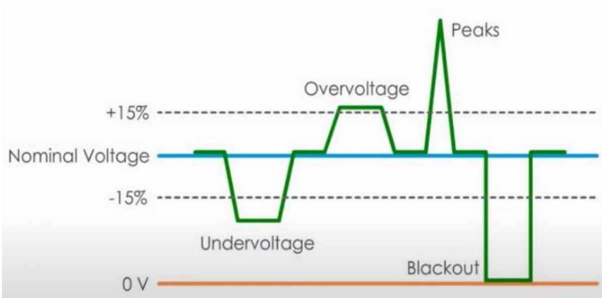

Fig. 1. Effects of PQ events on waveform.

quality that we discussed is over-voltage. Over-voltage refers to the power supply above the normal voltage range. Over-voltage can last for minutes to several days. It includes several different conditions such as surges, spikes, and transients. Surges occur over the short-term and they may be caused by lightning strikes or switching off heavier loads. In most situations, power surges are not a strong enough to interrupt or damage devices, but they can be very harmful sometimes. In a small office or home office, surge protectors are good enough. Spikes are and very short duration of voltage increases. They may be caused by lightning strikes or power outages. Transients are very fast voltage increase in terms nanoseconds. Frequency variations are a change in frequency. Voltage involves wavelengths. The longer the wavelength, the lower the frequency, and vice versa. The US electrical grid operates at 60 Hz, or 60 cycles per second. Anything but 60 Hz is considered frequency variation. Now, under-voltage is the opposite of the over-voltage. It is defined as a condition where the applied voltage drops to about 90\% of the normal range or nominal voltage value. They are also known as brownouts. This condition can last for a few minutes to days. Sags, or commonly referred to as dips, is the under-voltage condition over the short-term. It may be caused by switching on heavy loads. Sags also rarely damage electronic devices. A common cause of sags for industrial customers is turning on large loads such as large motors [2]. Blackouts are the total loss of power, which brings down the whole network, and interrupts normal business operations. Many times, blackouts become a a matter of life and death to a business. Noise is a term well known by most people. It is a high-frequency distortion of the voltage waveform caused by disturbances related to the Electromagnetic Interference (EMI) or Radio Frequency Interference (RFI). Finally, harmonics are unwanted frequencies, which superimposed on the fundamental waveform creates a distorted wave pattern. They are a recurring distortion of a normal wavelength.

II. Motivation and Previous Works

These power quality problems are not equally dangerous. Some of them may just affect the best performance of electronic devices, while some would damage devices, data, or even kill a business overnight. For a large datacentre, problem quality problems means potential disasters. The steady, clean and uninterruptible power supply, is the minimum requirement for business continuity. Power quality has a direct impact on electrical consumption and electrical demand. Bad power quality increases the current/amperes required in electrical networks. Good power quality decreases the current required in electrical networks. Therefore it is important to understand that not only has a damaging impact on all the electrical and mechanical equipment, it also has an impact on your electricity bills. This is why it is important that poor quality issues are addressed on a timely manner. A lot of actions have been taken to ensure efficient power quality. Many solutions in the form of devices have been presented. The approach that we have taken is with the perspective of Computer Vision.

Previously many works have been done with respect to power quality solutions. Regarding the deep learning solutions, Balouji and Salor [3] presented an image recognition method on the PQ event waveform images using a Multi-layer Convolution Neural Network (MLCNN). Their approach seemed to be very effective as their test data of power quality events classified with 100% accuracy. They used input images of dimensions (220x220x3). Their approach is quite similar to us, however, the specific amount of data they have used is not specified. This raises a doubt that their model has enough experience to tackle the future power quality events that may rise in the power system. Ahajjam et al. [4] have also done PW event classification using deep learning, however the difference that we have their work is that they have used temporal-spectral images to train teir CNN model. Their simulation results show that they are able to detect power quality disturbances with good accuracy, and are able to detect and distinguish between several number of power quality events in an image. Working on temporal-spectral images proved to give good results in power quality event classification.

Apart from deep learning based approaches, Saini and Kapoor [5] have presented a review of power quality events analysis. It mostly includes signal processing, and optimization techniques for power quality analysis. Mahela et al. [6] have also done a comprehensive review on power quality event analysis. This review includes Neural network based classification and also Support Vector Machine (SVM) based classification. The review of Saxena et al. [7] is somewhat dated, however they have performed good analysis on the key issues of power quality event analysis and presented some of the still well-known classification methods. An innovative approach to classify power quality events was presented by Chintakindi et al. [8], where they have proposed to use an improved version of the S-transform for the classification. They have simulated their proposed method on MATLAB software in accordance with IEEE Standard 1159. The effectiveness of the algorithm proved to identify multiple events at once. Similarly, Dash and Subudhi [9] have used S-transform for classification, however, they have combined a technique called Whale Optimization Algorithm (WOA), and SVM with it as well. They validated the proposed technique on real time signals obtained from the circuits.

III. Deep Learning Overview

The vision behind Deep Learning, and hence more accurately, Convolutional Neural Networks (CNN). CNNs are mostly used for problems like images recognition or speech recognition. The reason for this is that are CNNs outperform normal artificial neural networks in these types of problems. In fact, the accuracy of some CNN models at image recognition is even better than humans. The limitation in a normal artificial neural network is such that, as we understand an artificial neural network gets the data of each pixel as input, into the first layer of neurons. So if we have a 16x16 pixel image and we want to find what is in that image, all 256 pixels would be fed into the first layer. The problem in this case is that we would see the pixels randomly with no order and won't be able to identify the image. This is because we are not considering the effect of neighbouring pixels. If we consider the order of the pixels, only then we are able to identify what is the object in the image identifying the object. As the human brain works, we do not look at individual points or pixels, we recognize pattern in group of points or pixels. In fact, cells in our visual cortex respond to different patterns. Some respond to horizontal lines, some respond to vertical lines, and some respond to other complex patterns. The output of the lower-level neurons is then processed by higher-level neurons, to identify object in our visual field. CNNs are inspired from this concept. In, CNNs, instead of looking at each individual pixel, we look at a group of pixel. If you look at a group of pixels, we are more likely to pick up different features of the object in the image. So once we know the features, it is more likely that we can predict the object in the image.

As shown in Fig. 2, this concept is implemented in the way that the image is at the bottom, which is the input image to our Network. As seen on top of it, we will have a convolutional layer. This is the most important concept in CNNs. We have a convolutional layer which comprises of neurons, which take in information from a group of pixels in the previous layer. So in the first layer above the image, a neuron gets information stored in the pixels within the corresponding rectangular box as shown in the figure. This rectangular window is also referred to as the receptive field of the specific neuron. Similarly, the same process happens in the next layers with respect to the previous layers. This architecture allows the network to concentrate on lower-level features in the first layer, and then assemble these features into larger higher-level features in the next hidden layer, and so on.

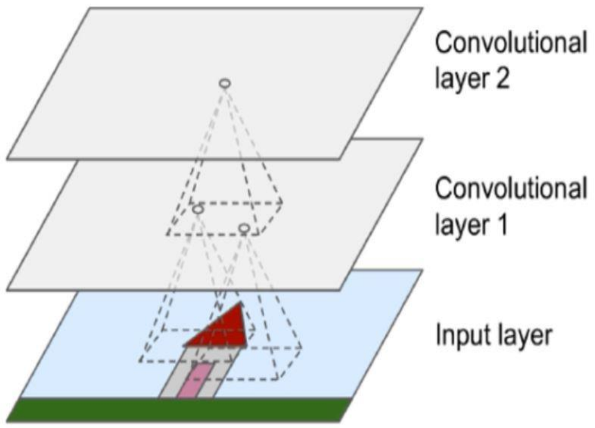

Fig. 2. Windows/Receptive fields in convolutional layers.

The concept of stride is such that the first neuron in the convolutional layer would be looking at a specific set of pixels. The next neuron in the convolution layer will have a slightly shifted receptive field/ rectangular window. This shift in the view from one neuron to another is referred to as stride. There is overlap between receptive fields if the stride is too small. Hence, there is small overlap if the stride is large, and large overlap if the strike is small. One thing to note from this is that if the stride is small, and overlap will be less, then fewer neurons will be required in the upper layer. Hence, the stride will determine the size of the upper layer as well.

As mentioned before, a cell in the convolutional layer gets information from a set of pixels in the previous layer. In case we have 25 pixels in a receptive field, we convert the 25 pixel values to one value using a filter. A filter is a matrix of the same dimensions as our receptive field. Therefore in case of 25 pixels, the 5x5 receptive field will have a 5x5 filter. We multiply each window pixel value with the corresponding filter value and add all of these products up. This product will represent information in the 25 pixels now. What we get after applying a filter is called a feature map, as shown in Fig. 3. Each feature map has some particular feature highlighted. We always use many types of filters, so that each filter creates different feature maps containing different features. This means that the convolutional layer is going to be a bundle of feature maps, and each feature map has some particular highlighted feature. As seen in Fig. 3, each cell on convolutional layer 2 will be getting information of all the feature maps in the previous layer, because only then can the cells in the convolutional layer 1 combine the different features to find more high-level features.

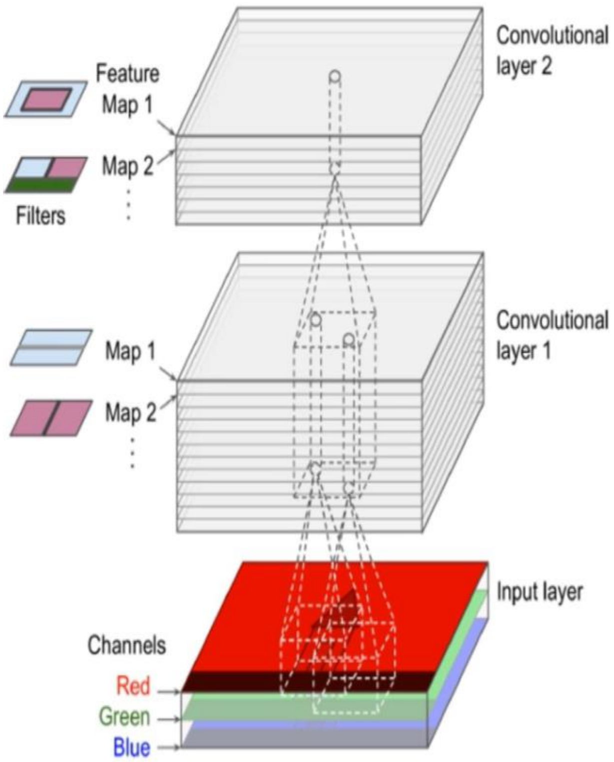

Fig. 3. Feature maps in convolutional layers.

A pooling layer is another concept used in our convolutional network to reduce the computational load, memory usage, and the number of parameters to be estimated. It basically subsamples i.e. shrinks the input image. We have the option of applying two kinds of pooling: Max pooling and average pooling. Commonly, max pooling works better because it highlights the main features, instead of averaging them out. It is trade off basically. We give away some extra information in the previous layer, to reduce the computational load on our system.

IV. Data Preparation

The data that we have used in this research work are the current waveform images of the practical electric relays at the Turkish Electricity Transmission Corporation (TEIAS). The data that we have is 3 years' worth of real-time data, which includes hundreds of power quality event occurrences. In this paper, we have used a few of the images, as well as generated wave-form data from MATLAB-Simulink, in order to present a general idea of the training and accuracy of the proposed overall work. After this, we will use all of the proprietary data obtained from TEIAS to train our deep learning model, so that it can detect and rectify all kinds of power quality events in the future using past 3 years' worth of experience from an actual power transmission company.

We have all of our data in the form of .JPEG images. In terms of data preparation, we have three folders: Training, validation, and testing. Each of these folders contain two sub-folders: Fault and no fault. In these folders, we have added images of our wave-forms that have noise and cause fault in the power equipment, and the ones that have no fault. Fig. 4 shows some samples of the input images that have noise in the wave-form, whereas Fig. 5 shows the ones that don't have any noise. This is the data we used for a the deep learning model. We have used 15 images in each of these folders. The dimensions of these images are not standardized, therefore we re-scaled the dimensions of all the images data into 255x155 pixel value. Fig. 4 shows some samples of the input images we have fed into our model.

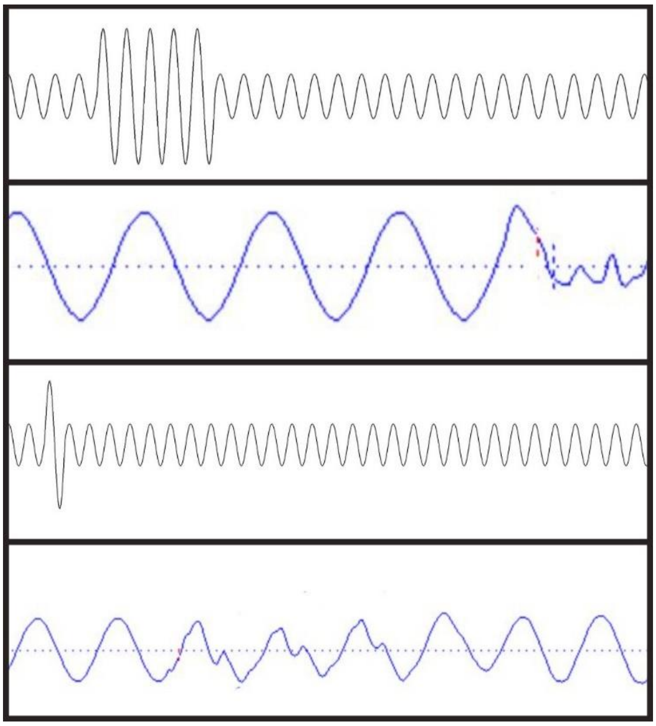

Fig. 4. Input image data of wave-forms with noise.

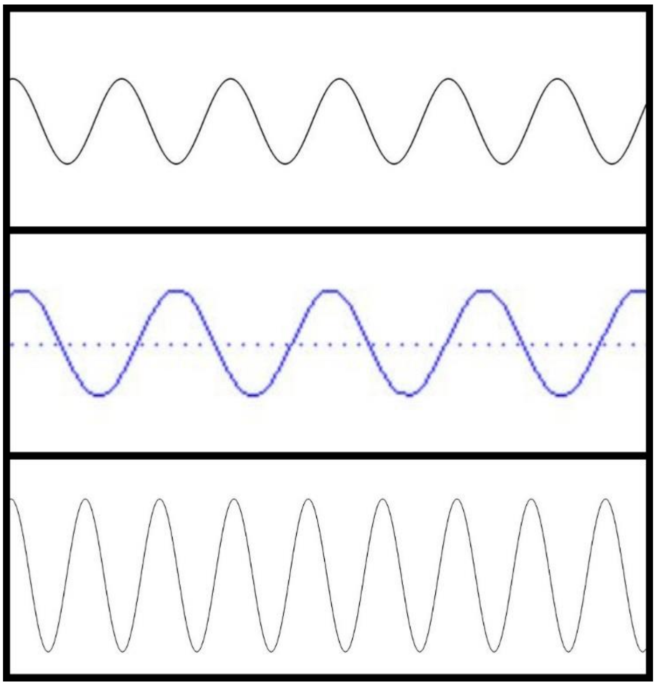

Fig. 5. Input image data of wave-forms without noise.

V. Proposed Method

In this section, we have described the approach that we have used in building and using our Python-based deep neural network model, for the recognition of power quality events, and then classifying them. As discussed before, power quality events consist of several different cases. The event that we focused upon in this paper is Noise.

Python has been used to design and train our CNN [10]. As mentioned before, the dimensions of the input images are not standardized, therefore we re-scaled the dimensions of all the images data into 255x155 pixel value. Before inputting the data into our model, we converted the images to the form of values. We read the picture files, decoded the .JPEG content to RGB grids of pixels, getting the three channels red blue green in our input. Then we converted these RGB floating-point values into values between 0 and 1.

Data pre-processing has been performed using the Keras image generator module. We have fed the waveform images directly from our folders to this module, and re-scaled the images inside this module as well. Using this module, we have the set the batches to be fed to the training in each epoch, to be 15. After the pre-processing of the images, we created the structure of our CNN model. We used 4 different convolutional layers with Max pooling. After that we applied a dense layer and finally the output neuron. For our first layer, we have a convolutional layer with 32 filters and 3x3 window. As we mentioned our input images dimensions before, our input size is 255x155x3. After this we have a max pooling layer with a window of 2x2. Another convolutional layer is added after this with 64 layers and the same 3x3 window. Following this layer, we add 2 more convolutional layers with 128 filters, 3x3 window, and a max pooling layer with a window of 2x2, each. We used Flatten after these convolutional layers, followed by a single dense layer with 512 neurons, and finally, the output layer with neuron, since we want to predict between 2 options.

VI. Results and Discussion

Initially, we compiled our model with the loss of binary cross-entropy [11][12], and used the RMSprop optimizer [13]. RMSprop has an advantage when dealing with image processing. We used the learning rate of 0.001, and trained our model for 40 epochs. As shown in Fig. 6, we have achieved a good accuracy score and low loss.

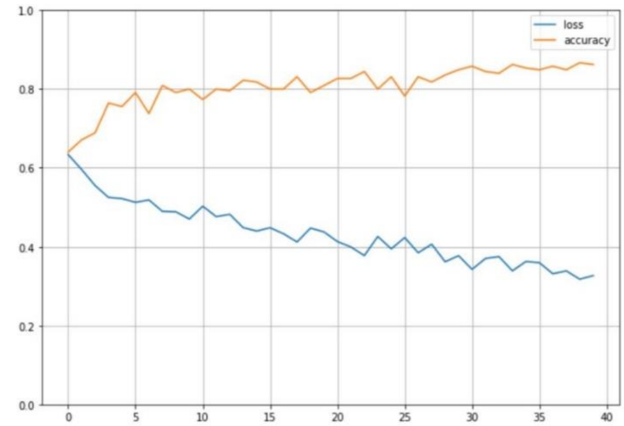

Fig. 6. Model training results (40 epochs).

The validation accuracy and as well as the loss has been plotted in Fig. 7. We are achieving good accuracy here as well, but according to the behaviour of the validation accuracy graph, it shows signs of over-fitting in our model. In order to fix this overfitting, we created dummy data. We did this by modifying our existing data into different forms by applying transformations like zoom, shear, rotation, height shift, width shift, and horizontal flip. Shearing means that we pull an edge of our picture, which makes the shape of the picture like a rhombus. Width shift means that we are shifting our whole image left or right, and height shift means shifting it upwards or downwards. One more change we made was adding a dropout layer to our model architecture. The dropout layer randomly deactivates 50\% of the neurons during each epoch. The model was then trained with the remaining different 50\% neurons at each epoch. Adding the dropout layer is very effective in removing overfitting in models. We trained our model again after making these changes.

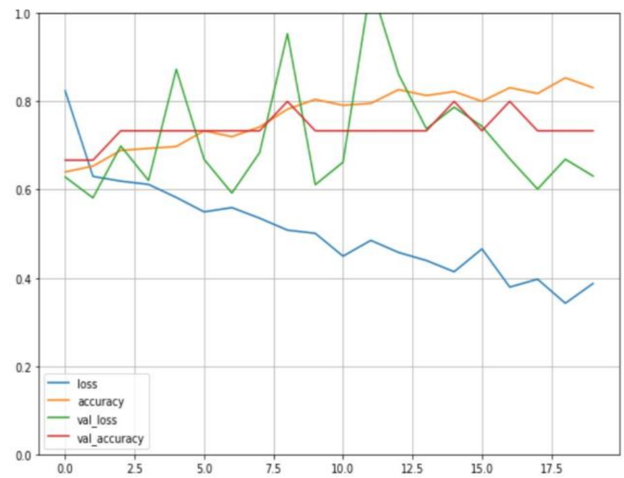

Fig. 7. Model training results with Overfitting (20 epochs).

The model was trained many times by changing several parameters, and Fig.8 shows how the results varied with each training. As seen in the figure, beyond 55 epochs, there is not room for much change or more accuracy. The accuracy that we achieved in detecting noise and disturbances in the wave-forms is very high. The results did not vary significantly after the training was performed with 55 epochs. The maximum possible accuracy was achieved at 60 epochs, and the results are shown in Table I.

TABLE I. BEST ACHIEVED RESULTS

Epochs	Results		
	Train. Accuracy	***Loss***	***Vald. Accuracy***
60	95.2%	5.6%	86.7%

This deep learning-based power quality event detection approach is to be used with an electric relay or other power equipment wave-forms would greatly prevent even minuscule power quality events to be overlooked. Human error is significant in observation and detection, which is why this approach can be further built upon in order to replace human effort completely in this respect.

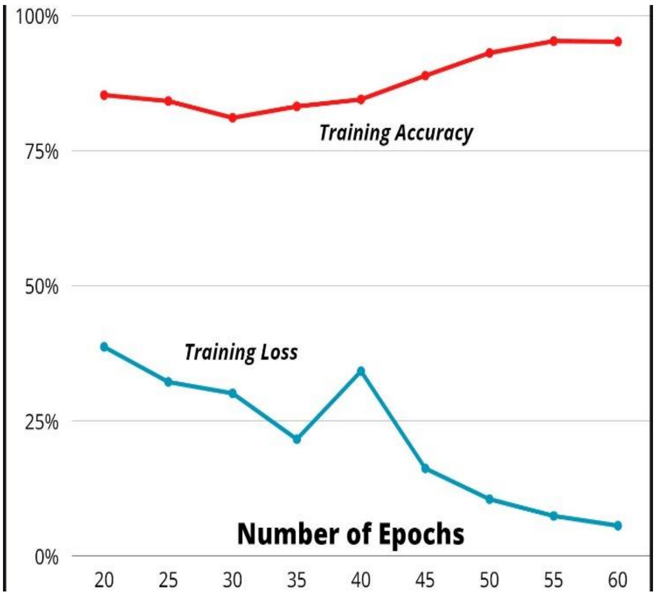

Fig. 8. Results achieved with each training performed.

VII. Conclusion

This paper presented an issue that is faced in power transmission and power quality field. Without good power quality in an electrical network, Load's electrical and mechanical equipment may overheat, malfunction, fail prematurely, require high maintenance, and in many cases they may not operate at all. In order to avoid this, many solutions are being provided in different perspective. We provided a deep learning image recognition based solution. The efficiency of the proposed approach proved to be good, which is further work will definitely be done in this direction, in order to not just minimize, but completely finish the issue at hand.

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