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Handwritten Hindi Character Recognition using Deep Learning Techniques

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***Abstract* -** In this paper we present a handwritten Hindi character recognition system based on different Deep learning technique. Handwritten character recognition plays an important role and is currently getting the attention of researchers because of possible applications in assisting technology for blind and visually impaired users, human–robot interaction, automatic data entry for business documents, etc. In this work, we propose a technique to recognize handwritten Hindi characters using deep learning approaches like Convolutional Neural Network (CNN) With Optimizer RMSprop (Root Mean Square Propagation) , Adaptive Moment (Adam) Estimation and Deep Feed Forward Neural Networks(DFFNN). The proposed system has been trained on samples of large set of database images and tested on samples images from user defines data set and from this experiment we achieved very high recognition results. Experimental results are compared with other neural network based algorithm.

Keywords: DFFNN, CNN, Softmax classifier, RMSprop and Adam Estimation, Deep Learning.

I. INTRODUCTION

Deep learning Techniques have been effectively applied to various areas like image classification, speech recognition, Medical Images detection, face detection, satellite images, recognizing traffic signs and pedestrian detection and so on. The outcome of deep learning techniques is also prominent, and in some cases the results are superior to human experts [1,2] in the past years. From last few years most of the problems are also being re-experimented with deep learning techniques with the view to achieving improvements in the existing findings. Different architectures of deep learning have been introduced in recent years, such as convolutional neural networks, deep networks, and recurrent neural networks. The entire architecture has shown the expertise in different areas. Character recognition is one of the areas where machine learning techniques have been extensively experimented. The first deep learning technique, which is one of the leading machine learning techniques, was proposed for character recognition in 1998 on MNIST database [3].

The deep learning techniques are basically composed of multiple hidden layers, and each hidden layer consists of multiple neurons, which compute the suitable weights for the deep network. A lot of computing power is needed to compute these weights, and a powerful system was needed, which was not easily available at that time. Since then, the researchers have drawn their attention to finding the technique which needs less power by converting the images into feature vectors. In the last few decades, a lot of feature extraction technique have been proposed such as HOG (histogram of oriented gradients) [4] and many others techniques are used as prominent feature extraction methods, which have been experimented for many problems like image recognition, character recognition, face detection, etc. Feature extraction [5] is one type of dimensionality reduction technique that represents the important parts of a large image into a feature vector. These features are handcrafted and clearly designed by the research community. The robustness and performance of these features depend on the skill and the knowledge of each researcher. There are the cases where some vital features may be unseen by the researchers while extracting the features from the image and this may result in a high classification error. Deep learning inverts the process of handcrafting and designing features for a particular problem into an automatic process to compute the best features for that problem. A convolutional neural network has multiple convolutional layers to extract the features automatically. The features are extracted only once in most of the shallow learning models, but in the case of deep learning models, multiple convolutional layers have been adopted to extract discriminating features multiple times. This is one of the reasons that deep learning models are generally successful. And also in Deep feed forward neural networks the features

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are compute automatically by using different number of hidden layer in it.

The LeNet [3] is an example of deep convolutional neural network for character recognition. Recently, many other examples of deep learning models can be listed such as AlexNet [2], ZFNet [6], VGGNet [7] and spatial transformer networks [8]. These models have been successfully applied for image classification and character recognition. Owing to their great success, many leading companies have also introduced deep models. Google Corporation has made a GoogLeNet having 22 layers of convolutional and pooling layers alternatively. Apart from this model, Google has also developed an open source software library named Tensorflow to conduct deep learning research. Microsoft also introduced its own deep convolutional neural network architecture named ResNet in 2015. ResNet has 152-layer network architectures which made a new record in detection, localization, and classification. This model introduced a new idea of residual learning that makes the optimization of different data.

Character recognition is a field of image processing where the image is recognized and converted into a machine-readable format. As discussed above, the deep learning techniques and especially convolutional neural networks have been used for image detection and recognition. It has also been successfully applied on Roman (MNIST) [3], Chinese [9], Bangla [10] and Arabic [11] languages. In this work, a convolutional neural network and Deep Feed Forward neural network is applied for handwritten Hindi characters recognition.

Rest of the paper is organized as follows; Section 2 contains related work. The proposed algorithm is presented in Section 3. The experimental details and results obtained are presented in Section 4. Section 5 contains the conclusion part.

II. RELATED WORK

Amit Choudhary et al. [12] proposed an Off-Line Handwritten Character Recognition using Features Extracted from Binarization Technique. This work is to extract features obtained by Binarization technique for recognition of handwritten characters of English language. The recognition of handwritten character images have been done by using multi-layered feed forward artificial neural network as a classifier. This algorithm delivers outstanding classification accuracy of 85.62 %.

Baheti M. J et al. [13] proposed a comparison of the offline handwritten character recognition system for the isolated Gujarati numerals. They used affine invariant moments based model for the feature extraction. They used KNN classifier and PCA to reduce dimensions of feature space and used Euclidean similarity measure to classify the numerals. KNN classifier obtained 90 % as recognition rate whereas PCA obtained recognition rate of 84%. After the comparison it is observed that KNN classifier has shown better results as compared to PCA classifier.

Sonu Varghese K et al. [14] proposed a Novel Tri-Stage Recognition Scheme for Handwritten Malayalam Character Recognition. In the first stage we are grouping characters into different classes based on the number of corners, bifurcations, loops and endings. In the second phase we are identifying exact character in the class based on the different feature extraction technique specially defined for each class. In the third stage we are checking the probability of occurrence of the current character in the given position based on defined rules for the formation of words. we are implementing a three stage feature extraction technique which uses structural, statistical and moment variant features of the character. Recognition conducted in different stages improves the efficiency, recognition rate and accuracy of the given system.

Parshuram M. Kamble [15] proposed a method for handwritten Marathi character recognition using R-HOG Feature. The system has been evaluated on a large amount of handwritten Marathi characters. From the results as shown it can be concluded that the use of R-HOG based feature extraction method and FFANN based classification will be more effective with increased processing speed and accuracy.

Verma [3] used radial basis function and multilayer perceptron neural networks for recognizing the handwritten characters of Devanagari script. Back propagation error algorithm is also used to improve the recognition rate. In this proposed system, they compare the results obtained from radial basis Function (RBF) networks and multi-layer perceptron. Dataset consists of 245 samples written by five different users. The results so obtained show that multilayer perceptron (MLP) networks performs better than that of radial basis functions. But MLP networks training time is more as compared to radial basis function networks. Highest recognition rate so obtained using radial basis function and multilayer perceptron (MLP) networks are 85.01% and 70.8% respectively.

III. PROPOSED APPROACH

The proposed method is mainly consists of 4 phases steps. In the primary phase, collecting the characters data from kaggle dataset and gathering images from different users. After collecting the character data of gray scale images will be pre-processing by checking null and missing values. Using the normalization techniques to convert the gray level values to range of 0 to 1 values, and then labelling Hindi characters from 0 to 35 with one hot coding which will generate vector

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form of data. In the 3rd phase, we extracted the features atomically from Different Deep learning algorithm like Convolutional Neural Network (CNN) and Deep Feed Forward Neural Networks (DFFNN) for recognition of handwritten character system. In finally phase we applied an optimization technique like Optimizer RMSprop (Root Mean Square Propagation), Adaptive Moment (Adam) Estimation to get very promising results. The proposed method block diagram is shown below in Figure 1.

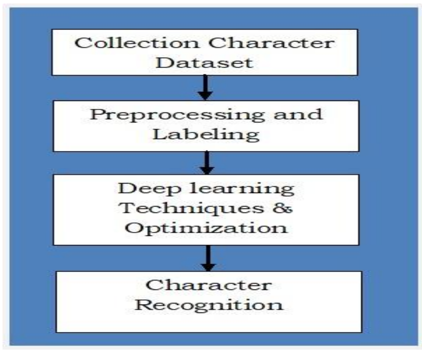

Figure 1: Block diagram proposed handwritten digit recognition system

A. Convolutional neural network

Computer Vision and pattern recognition is a major growing field in area of image processing. In that Convolutional Neural Network (CNNs) plays major role in computer vision. CNNs is working on many applications in Image Classification and it is the core of most Computer Vision and pattern recognition systems today, from automatic tagging of photo in Facebooks to self-driving cars, recognizes digits, alpha-numerals, traffic signal boards, and the other object class[7]. We used five layered Convolutional Neural Networks (CNN) model. On them one layers for convolutional, one layers for max pooling or sub sampling, one Flatten layer which converts 2D array into 1D array and finally two fully connected layers for classification. The initial layer is convolutional (Conv2D) layer has 32 output mapping and the next max pooling layer has 14 output mapping.

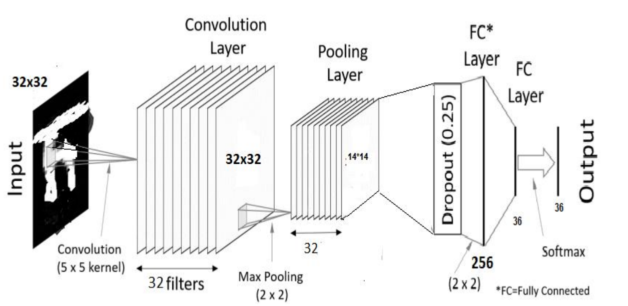

Figure 2: The overall structural design of the CNN Model of our proposed system with different layer.

Adam and RMSProp, as two of the most influential adaptive stochastic algorithms for training deep neural networks. Many attempts, such as decreasing an adaptive learning rate, adopting a big batch size, incorporating a temporal decorrelation technique, seeking an analogous surrogate, etc., In addition, we illustrate that Adam is essentially a specifically weighted AdaGrad with exponential moving average momentum, which provides a novel perspective for understanding Adam and RMSProp. At last, we validate the sufficient condition by applying Adam and RMSProp to tackle the counterexamples and train deep neural networks.

B. RMSprop Optimizer

The RMSprop (Root Mean Square Propagation) optimizer is similar to the gradient descent algorithm with momentum. The RMSprop optimizer restricts the oscillations in the vertical direction. Therefore, we can increase our learning rate and our algorithm could take larger steps in the horizontal direction converging faster. It has shown success for training Recurrent Models.

$$S_{dw} = \beta s_{dW} + (1-\beta)\left(\frac{\partial J}{\partial W}\right)^2 \quad (1)$$

$$W = W - \alpha \frac{\frac{\partial J}{\partial W}}{\sqrt{\left(s_{dW}^{corrected}\right)+\varepsilon}} \quad (2)$$

ss - the exponentially weighted average of past squares of gradients

$\frac{\partial J}{\partial W}$ - cost gradient with respect to current layer weight tensor

W - weight tensor

β - hyperparameter to be tuned

α - the learning rate

ϵ - very small value to avoid dividing by zero

RMSprop as well divides the learning rate by an exponentially decaying average of squared gradients.

C. Adam Estimation Optimizer

Adaptive Moment (Adam) Estimation is another method that computes adaptive learning rates for each parameter. Adam, an algorithm for first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments. The method is straightforward to implement, is computationally efficient, has little memory requirements, is invariant to diagonal rescaling of the gradients, and is well suited for problems that are large in terms of data and/or parameters.

$$m_t = \beta_1 * m_{t-1} + (1-\beta_1) * g_t \quad (3)$$
$$v_t = \beta_2 * v_{t-1} + (1-\beta_2) * g_t^2 \quad (4)$$

m_t and v_t are estimates of the first moment (the mean) and the second moment (the uncentered variance) of the gradients respectively, hence the name of the method. As m_t and v_t are initialized as vectors of 0's, the authors of Adam observe that they are biased towards zero, especially during the initial time steps, and especially when the decay rates are small (i.e. β_1 and β_2 are close to 1). They counteract

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these biases by computing bias-corrected first and second moment estimates:

$$\widehat{m_t} = \frac{m_t}{1-\beta_1^t} \quad (5)$$

$$\widehat{v_t} = \frac{v_t}{1-\beta_2^t} \quad (6)$$

They then use these to update the parameters just as we have seen in Adadelta and RMSprop, which yields the Adam update rule:

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{v_t+\varepsilon}} * \widehat{m_t} \quad (7)$$

D. Deep Feed-Forward Neural Network

This neural network is known as feed-forward networks, this network is simplest to analyze. The feed-forward Neural Network input layer contains n-dimensional vector as input to the network and contains L-1 hidden layers as middle layers mostly two hidden layers are used and may increase based upon the requirement. Finally there is one output layer containing k number of output classes. Each neuron in the hidden layer and output layer can be split into two parts: pre-activation and activation. In Deep feed-forward network is the hidden layer are taken of size m- dimensional vector size which quite larger than the normal hidden layers of feed-forward network, so that the hidden layer can generated a huge network of features. From this huge number of features we can extract right match for predicated classes [17][18]. A deep feed-forward network is used to extract features of image automatic to recognition the classes of testing image of the data set. Figure 3 is shown below how the DFFNN used in this work.

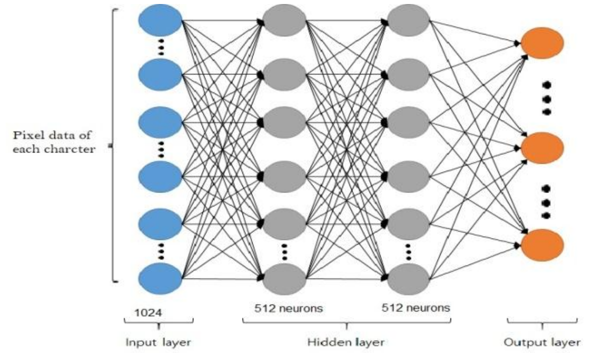

Figure 3: The overall structural design of the DFFNN Model of our proposed system with different layer.

IV. RESULTS AND DISCUSSION

In general Feed forward Neural Network consists of different hidden layer. In most of FFNN will have two hidden layers with 16 or 32 neurons and more, Hidden layers are multiplied with different random weight of image pixel data which is between 0 to 1. But in Deep Feed forward Neural Network was design with same two hidden layers and each hidden layers consists of large set of neurons i.e. we used 512 neurons are taken and this are multiplied with random weights. By using this deep network we got promising results. Here we displaying some labeling of characters in Table 1.

Table 1: Sample data representation of labeling.

Layer Type	layer Operation	No of feature Maps	feature maps Size	window Size	Total parameters
C1	Conv2D	32	32×32	5×5	832
MP1	Max-pooling2	32	32×32	2×2	0
FL1	Flatten	6272	1×1	N/A	0
F1	Fully connected	256	1×1	N/A	1605888
F2	Fully connected	36	1×1	N/A	9509

In this testing phase we used five layered Convolutional Neural Networks (CNN) model with Adam Optimization. On them one layers for convolutional, one layers for max pooling or sub sampling, one Flatten layer which converts 2D array into 1D array and finally two fully connected layers for classification. All the parameters with respect to the corresponding layers are stated in Table 2.

Table 2. Parameters setup for CNN with Adam Optimization.

Layer Type	layer Operation	No of feature Maps	feature maps Size	window Size	Total parameters
C1	Conv2D	32	32×32	5×5	832
MP1	Max-pooling2	32	32×32	2×2	0
FL1	Flatten	8192	1×1	N/A	0
F1	Fully connected	256	1×1	N/A	2097408
F2	Fully connected	36	1×1	N/A	9252

In this testing phase we used five layered Convolutional Neural Networks (CNN) model with RMSProp Optimization. On them one layers for convolutional, one layers for max pooling or sub sampling, one Flatten layer

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which converts 2D array into 1D array and finally two fully connected layers for classification. All the parameters with respect to the corresponding layers are stated in Table 3.

Table 3. Parameters setup for CNN with Adam Optimization.

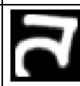
bha	ra	dhaa	dha	ta
				

Table 4: Individual results of the test database DFFNN

Labeled number	Hindi Character	No. of images	Correctly Classified	Not Correctly Classified	% Accuracy
0	Ka	396	383	13	96.72
1	kha	413	401	12	97.09
2	ga	418	403	15	96.41
3	gha	402	387	15	96.27
4	kna	368	352	16	95.65
5	cha	396	370	26	93.43
6	chha	394	374	20	94.92
7	ja	427	413	14	96.72
8	jha	389	370	19	95.12
9	yna	430	415	15	96.51
10	taa	438	421	17	96.12
11	thaa	405	389	16	96.05
12	daa	413	400	13	96.85
13	dhaa	402	390	12	97.01
14	adna	430	414	16	96.28
15	ta	395	384	11	97.22
16	tha	380	358	22	94.21
17	da	409	394	15	96.33
18	dha	378	353	25	93.39
19	na	405	383	22	94.57
20	pa	393	370	23	94.15
21	pha	407	393	14	96.56
22	ba	395	379	16	95.95
23	bha	401	372	29	92.77
24	ma	398	387	11	97.24
25	yaw	410	387	23	94.39
26	ra	421	409	12	97.15
27	la	405	390	15	96.30
28	waw	378	352	26	93.12
29	mot	418	404	14	96.65
30	pet	422	406	16	96.21
31	pat	391	368	23	94.12
32	ha	383	354	29	92.43
33	chhya	430	418	12	97.21
34	tra	378	360	18	95.24
35	gya	382	360	22	94.24
Average recognition percentage					95.57

Table 5: Individual results of the test database using CNN-Adam Estimation

Labeled number	Hindi Character	No. of images	Correctly Classified	Not Correctly Classified	% Accuracy
0	Ka	396	383	13	96.72
1	kha	413	401	12	97.09
2	ga	408	403	5	98.77
3	gha	402	387	15	96.27
4	kna	368	352	16	95.65
5	cha	396	370	26	93.43
6	chha	394	374	20	94.92
7	ja	417	413	4	99.04
8	jha	389	370	19	95.12
9	yna	420	415	5	98.81
10	taa	428	421	7	98.36
11	thaa	405	389	16	96.05
12	daa	403	400	3	99.26
13	dhaa	402	390	12	97.01
14	adna	420	414	6	98.57
15	ta	395	384	11	97.22
16	tha	380	358	22	94.21
17	da	409	394	15	96.33
18	dha	378	353	25	93.39
19	na	405	383	22	94.57
20	pa	393	370	23	94.15
21	pha	407	393	14	96.56
22	ba	395	379	16	95.95
23	bha	401	372	29	92.77
24	ma	398	387	11	97.24
25	yaw	410	387	23	94.39
26	ra	421	409	12	97.15

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27	la	395	390	5	98.73
28	waw	378	352	26	93.12
29	mot	408	404	4	99.02
30	pet	412	406	6	98.54
31	pat	391	368	23	94.12
32	ha	383	354	29	92.43
33	chhya	420	418	2	99.52
34	tra	378	360	18	95.24
35	gya	382	360	22	94.24
Average recognition percentage					96.02

Table 6: Individual results of the test database using CNN-RMSProp

Labeled number	Hindi Character	No. of images	Correctly Classified	Not Correctly Classified	% Accuracy
0	Ka	430	427	3	99.30
1	kha	396	392	4	98.99
2	ga	433	426	7	98.38
3	gha	401	386	15	96.26
4	kna	391	375	16	95.91
5	cha	405	397	8	98.02
6	chha	369	349	20	94.58
7	ja	365	355	10	97.26
8	jha	419	410	9	97.85
9	yna	392	387	5	98.72
10	taa	387	384	3	99.22
11	thaa	401	395	6	98.50
12	daa	405	402	3	99.26
13	dhaa	390	378	12	96.92
14	adna	406	400	6	98.52
15	ta	394	393	1	99.75
16	tha	395	373	22	94.43
17	da	420	415	5	98.81
18	dha	401	386	15	96.26
19	na	420	408	12	97.14
20	pa	399	386	13	96.74
21	pha	410	396	14	96.59
22	ba	360	354	6	98.33
23	bha	406	391	15	96.31
24	ma	387	376	11	97.16
25	yaw	408	385	23	94.36
26	ra	407	395	12	97.05
27	la	421	416	5	98.81
28	waw	411	407	4	99.03
29	mot	411	395	16	96.11
30	pet	377	370	7	98.14
31	pat	406	393	13	96.80
32	ha	384	365	19	95.05
33	chhya	402	384	18	95.52
34	tra	416	407	9	97.84
35	gya	375	360	15	96.00
Average recognition percentage					97.33

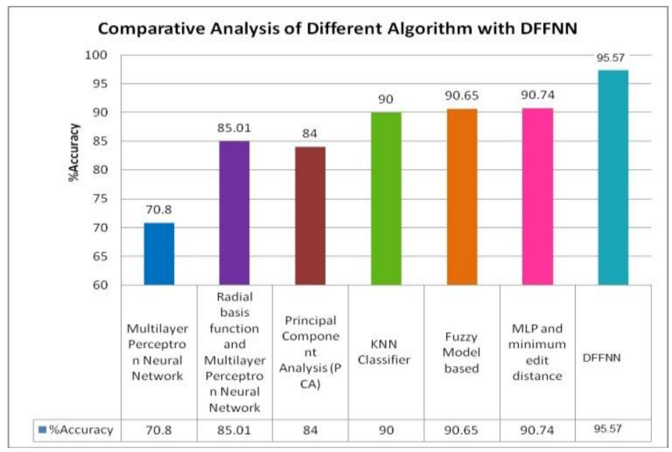

Figure 4: Graphical representation of the % recognition of the DFFNN and other existing method

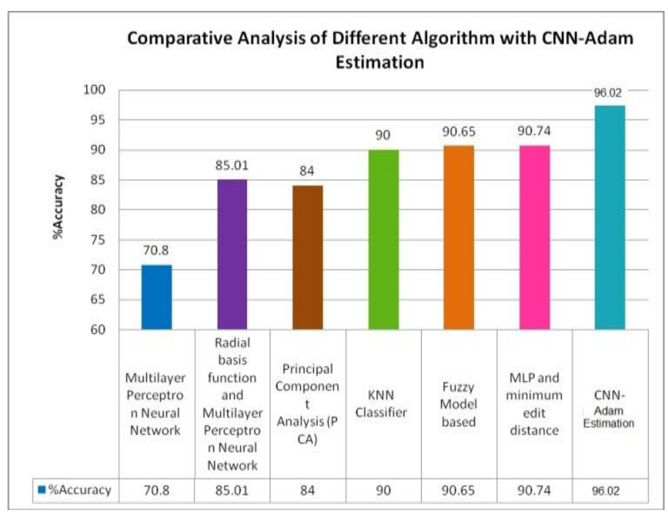

Figure 5: Graphical representation of the % recognition of the CNN-Adam method and other existing method

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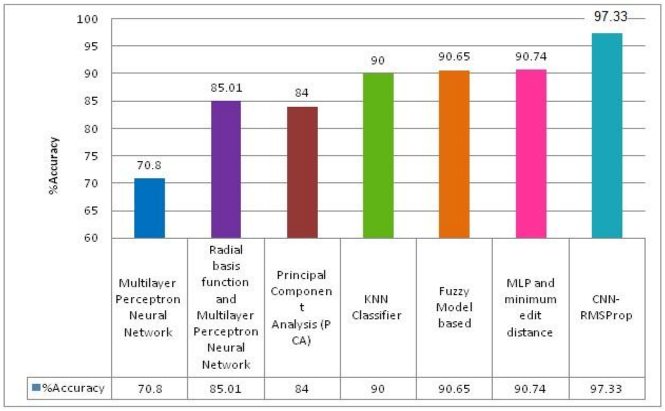

Figure 6: Graphical representation of the % recognition of the CNN-RMSProp method and other existing method

V. CONCLUSION

In this paper we proposed different neural network approach for Recognition of Handwritten Hindi characters. We evaluated the performance using Convolutional Neural Network (CNNs) with optimization techniques and Deep Feed Forward Neural Network. These techniques are train and test on a standard user define dataset which is collect from different users. From experimental results, it is observed that DFFNN, CCN-Adam and CNN-RMSprop yield the best accuracy for Handwritten Hindi characters compared to the alternative techniques. We achieved promising results from proposed method with high accuracy rate.

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