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Back Propagation ELM based Multilayer Feature Extraction for Image and Text

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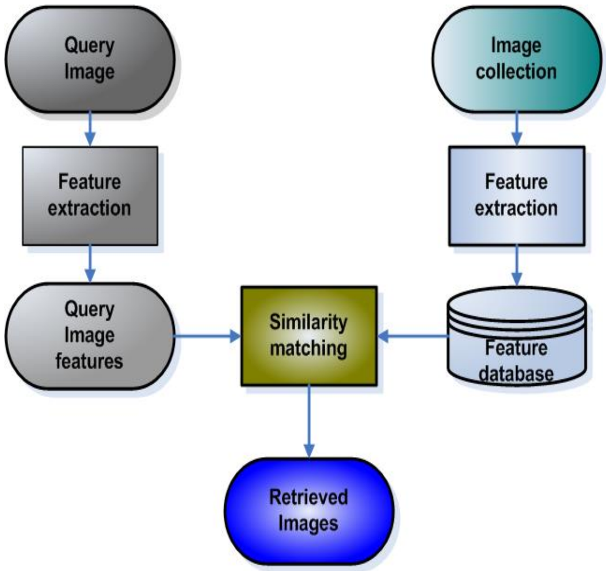
Abstract--ELM-based hierarchical learning framework for multilayer perceptron in which it has self-taught feature extraction followed by supervised feature classification and they are bridged by random initialized hidden weights is built in a multilayer manner. H-ELM training is divided into two separate phases: 1) unsupervised hierarchical feature representation and 2) supervised feature classification. A new H-ELM-based auto-encoder is developed to extract multilayer sparse features of the input data. The original ELM-based regression is performed for final decision making. H-ELM-based feature extraction and detection algorithms are developed for practical computer vision applications, such as object detection, recognition, and tracking. Since the supervised training is implemented by the original ELM, the unsupervised building blocks of the H-ELM architecture. The hidden layers of the framework are trained in a forward manner. Once the previous layer is established, the weights of the current layer are fixed without fine-tuning. The advantages of ELM random feature mapping, the hierarchically encoded outputs are randomly projected before final decision making, which leads to a better generalization with faster learning speed. To overcome this, in the proposed system, these issues are overcome by implementing with image and text using Back-Propagation–Extreme Learning Machine algorithm (BP-ELM) and then classified both text and image by using Support Vector Machine algorithm. Hence the proposed system detects the image and text in the form accuracy and efficiency of an image.
Keywords:Feature Extraction; Image Detection; Image Retrieval; BackPropagation-ELM; Hierarchical Extreme Learning Machine (HELM); Image and Text.

I. INTRODUCTION

Feature extraction is a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval. Feature detection, feature extraction, and matching are often combined to solve common computer vision problems such as object detection and recognition, content-based image retrieval, face detection and recognition, and texture classification. Feature extraction starts from an initial set of measured data and builds derived values intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. This process is called feature extraction. ELM-based hierarchical learning framework for multilayer perceptron in which it has self-taught feature extraction followed by supervised feature classification and they are bridged by random initialized hidden weights is built in a multilayer manner. A new H-ELM-based auto-encoder is developed to extract multilayer sparse features of the input data. The original ELM-based regression is performed for final decision making. H-ELM-based feature extraction and detection algorithms are developed for practical computer vision applications, such as object detection, recognition, and tracking. Since the supervised training is implemented by the original ELM, the unsupervised building blocks of the H-ELM architecture. The hidden layers of the framework are trained in a forward manner. Once the previous layer is established, the weights of the current layer are fixed without fine-tuning. The advantages of ELM random feature mapping, the hierarchically encoded outputs are randomly projected before final decision making, which leads to a better generalization with faster learning speed. An object is extracted from the image by using Hierarchical Extreme Learning Machine algorithm (H-ELM). The image is detected and classified as efficiency and accuracy of an image.In the existing system the feature extraction and detection of an image is showed by using the dataset in the form of shape and size and classified by using SVM algorithm whereas the accuracy is less described in Fig.1

The paper proposes these issues are overcome by implementing with image and text using BackPropagation–Extreme Learning Machine algorithm (BP-ELM) and then classified both text and image by using Support Vector Machine algorithm, Hence the proposed system detects the image and text in the form of accuracy and efficiency. Section 2 discusses about the literature survey emphasizing the research activities and related works in feature extraction analyses, image detection and classification. Section 3 presents the existing system and its drawbacks. The proposed system and the algorithm used for the image and text are discussed.

FIGURE.1 DETECTION OF IMAGE



Section 4 explains the details of project implementation with front end and back end description and the individual module explanations. Section 5 mentions the concluding remarks about the project.This Section 6 entails the objective of the proposed system which is used to extract the Object features using HELM and Text using BP-ELM Algorithm and classify the images using SVM. The existing system includes Feature Extraction and it is done along with Classification using SVM.

II. RELATED WORK

H-ELM-based auto-encoder is developed to extract multilayer sparse features of the input data. The original ELM-based regression is performed for final decision making. H-ELM-based feature extraction and detection algorithms are developed for practical computer vision applications, such as object detection, recognition, and tracking. Since the supervised training is implemented by the original ELM, the unsupervised building blocks of the H-ELM architecture.The author (Guang-Bin Huang, Jiexiong Tang, 2012) proposedExtreme Learning Machine (ELM) is an emerging learning algorithm for the generalized single hidden layer feed-forward neural networks, of which the hidden node parameters are randomly generated and the output weights are analytically computed. However, due to its shallow architecture, feature learning using ELM may not be effective for natural signals even with a large number of hidden nodes. To address this issue, a new ELM-based hierarchical learning framework for multilayer perceptron is divided into two main components: 1) self-taught feature extraction followed by supervised feature classification and 2) they are bridged by random initialized hidden weights. ELM-based sparse auto-encoder is developed constraint. By doing this more compact and meaningful feature representations than the original ELM by exploiting the advantages of ELM random feature mapping, the hierarchically encoded outputs are randomly projected before final decision making, which leads to a better generalization with faster learning speed.

It achieves better and faster convergence than the existing state-of-the-art hierarchical learning methods. H-ELM achieves high level representation with layer wise encoding, and outperforms the original ELM in various simulations. Moreover, compared with other MLP training methods, the training of H-ELM is much faster and achieves higher learning accuracy. To attain these three features the author (A. A. Mohammed, R. Minhas, Q. M. J. Wu, and M. A. Sid Ahmed, 2013) proposes theA Fast and Accurate Online Sequential Learning Algorithm for Feed forward Networks. This methodOnline sequential learning algorithm for Single Hidden Layer Feed-forward Networks (SLFNs) hidden nodes in a unified framework. The activation functions for additive nodes in OS-ELM can be any bounded nonconstant piecewise continuous functions and the activation functions for RBF nodes can be any integral piecewise continuous functions. Detailed performance comparison of OS-ELM is done with other popular sequential learning algorithms on benchmark problems drawn from the regression, classification and time series prediction areas. The OS-ELM is faster than the other sequential algorithms and produces better generalization performance.

A fast and accurate Online Sequential Learning Algorithm (OS-ELM) has been developed for SLFNs with both additive and RBF hidden nodes in a unified way, no other control parameter has to be chosen. Performance of OS-ELM is compared with other well-known sequential learning algorithms on real world benchmark regression, classification and time-series problems. This indicates that OS-ELM produces better generalization performance with lower training time.the author(Brenden M. Lake, Gautam K. Vallabha, and James L. McClelland,2014)The learning of speech sounds and other perceptual categories, category labels are not provided, the number of categories is unknown, and the stimuli are encountered sequentially. One fundamental difficulty in learning the model is to deal with significant noise and clutter background factors. Learning meaningful features of digit character is a crucial step towards building general system that can be easily employed in higher level tasks such as identity verification, digital signature , and converting subtitle data into text format .The author (Gao Huang, Shiji Song, Jatinder N. D. Gupta, and Cheng Wu,2013) proposed Restricted Boltzmann Machines (RBM) and auto-encoders, learns to represent features in a dataset meaningfully and used as the basic building blocks to create deep networks. It introduces Extreme Learning Machine based Auto Encoder (ELM-AE), which learns feature representations using singular values and is used as the basic building block for Multi-Layer Extreme Learning Machine (ML-ELM). However, ELMs are primarily applied to supervised learning problems. Only a few existing research studies have used ELMs to explore unlabeled data. In this paper, we extend ELMs for both semi-supervised and unsupervised tasks based on the manifold regularization, thus greatly expanding the applicability of ELMs.

This provides new perspectives for understanding the mechanism of random feature mapping, which is the key concept in ELM theory. Empirical study on a wide range of data sets demonstrates that the proposed algorithms are competitive with state-of-the-art semi-supervised or unsupervised learning algorithms in terms of accuracy and efficiency.The representation capability of ELM-AE may provide a good solution to multilayer feed forward neural networks. ELM based multi-layer network seems to provide better performance than state-of the-art deep networks. This algorithm is for image retrieval is compared with the previous existing algorithms and proves that the proposed algorithm beats the existing algorithms.

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III. DETECTION AND RETRIEVAL OF IMAGE AND TEXT

A. Image Retrieval

Machine Learning Training which determine the use of unsupervised learning techniques to discover features in large data sets and supervised learning techniques to build predictive models. Feature detection, feature extraction, and matching are often combined to solve common computer vision problems such as object detection and recognition, content-based image retrieval, face detection and recognition, and texture classification.

The extracted features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data. Feature extraction a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. The output of each hidden layer can be represented as

$\mathbf{H}_i = g(\mathbf{H}_{i-1} \cdot \beta)$

Where $\mathbf{H}_i$ is the output of the ith layer, $\mathbf{H}_{i-1}$ is the output of the $(i-1)$th layer, $g(\cdot)$ denotes the activation function of the hidden layers, and β represents the output weights. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval The process of Feature Extraction is shown in the below

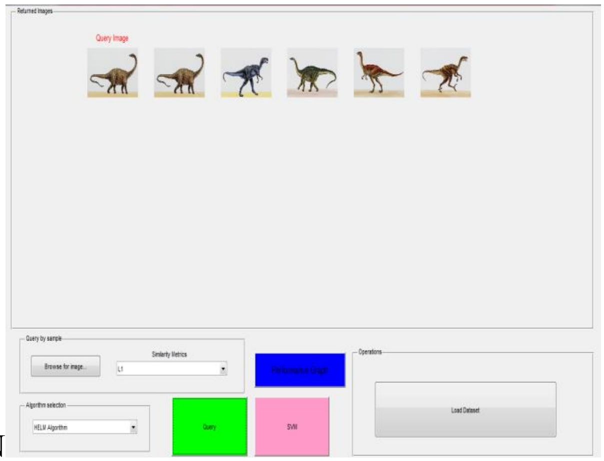


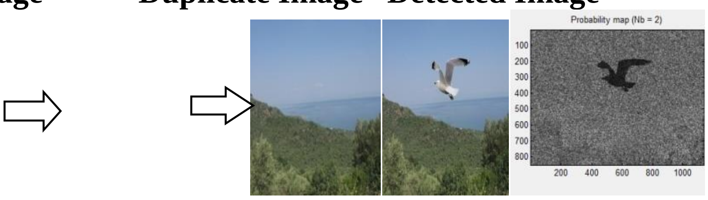
FIG 2.FEATURE EXTRACTION

B. Image Detection

Object detection is a computer technology related to computer vision and image processing that deals with detecting instances of semantic objects of a certain class (such as humans, buildings, or cars) in digital images and videos. Images are been classified and detected which are been unrelated to an original images and then classified by an H-ELM Algorithm. The process of Image Detection is shown in the below Fig.

FIG.3 SUPERVISED AND UNSUPERVISED IMAGE DETECTION OF OBJECT

Original Image **Duplicate Image** **Detected Image**



View point is to check the distance and the comparison between the two images. It will test the images of unsupervised data of objects. Detection of object from an image set of data.

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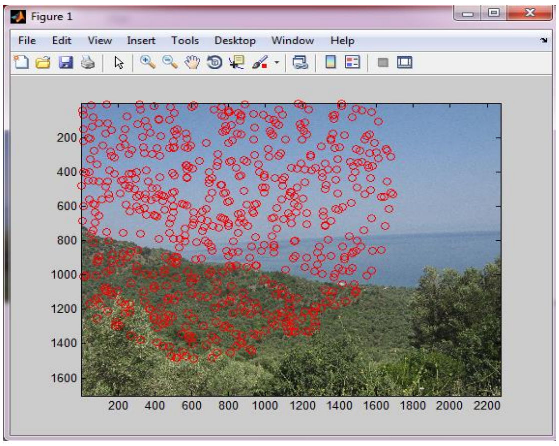
FIG.4 UNSUPERVISED IMAGE DETECTION



C. Feature Extraction for image and text using BP-ELM

Extracting the features from an image and text which is loaded dataset, with the help of BP-ELM Same set of similar features will be extracted from image and text .then classifying the image and text whether it is an original or duplicate image it identify it by SVM. At last detection of image and text will be taken place.

Text present in digital images can provide useful information about the image and the group of images it belongs to. On this page we present some results of automatic detection and character recognition of text in natural scenes. connected-component analysis to find all components in the image. Now using information about the character size from the previous approach,

we filter out (blacken) all the non-character components based on aspect ration and area of characters, and retain (whiten) all the character components. The results for this binarize image is show in the next image from left. This can be fed to and Optical Character Recognition (OCR) engine if need be to read tex

D. Classification Using SVM

In this module, implements the existing feature extraction and classification using SVM

Support Vector Machine algorithm

Support Vector Machines are also knows as Support Vector Networks (SVM) which is a supervised learning model with associated learning algorithm that analyzes the data and recognize the patterns, used for classification and regression analysis. Single-class Support Vector Machines, which solve an unsupervised learning problem related to probability density estimation. Multiple-class support vector machines, which solve a supervised learning problem related non-probabilistic binary classifier or binary linear classifier, to nonprobability density estimation.

SUPPORT VECTOR MACHINE

- Input/Output sets X,Y
- Training set(x1,y1)….(xm,ym)
- "Generalization", given a previously seen x ε X ,find a suitable y ε Y.
- i.e., want to learn a classifier, y=f(x,α),where are the parameters of the function.
- Eg., if we are choosing our model from the set of hyperplanes in "R", f(x,{w,b})=sign(w.x+b)

➢ **Sliding Window Classifier Algorithm f(x) = wTx + b**

f(x) = $\sum \alpha_i y_i (x_i^T x) + b$

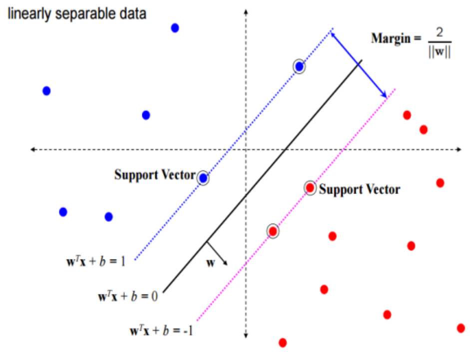
w = weight of vector

α = Parameter of the Function

b = Bias

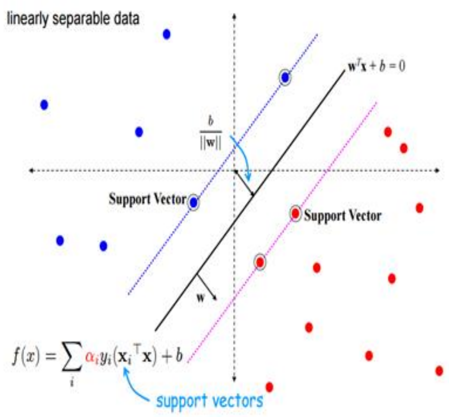
- **Then the margins given by** $\frac{w}{\| w \|}.(x_{+} - x_{-}) = \frac{w^{T}(x_{+} = x_{-})}{\| w \|} = \frac{2}{\| w \|}$

FIG.6 GRAPH PERFORMANCE OF LINEARLY SEPARABLE DATA



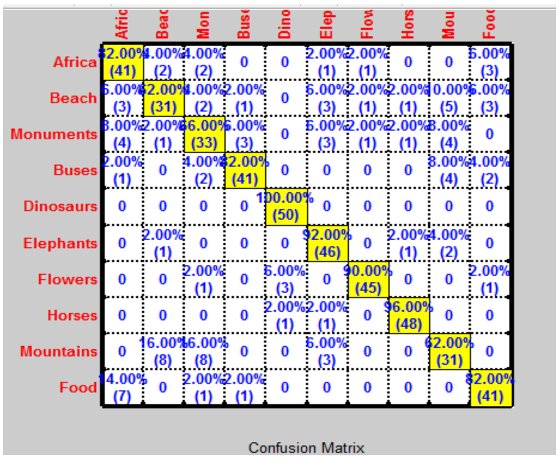
Analyzing the supervised and unsupervised data of an images with modulo functions which are in linearly separated data with support vector of margins

FIG.7 CALCULATING THE WEIGHT OF LINEARLY SEPARABLE DATA



SVM classification six datasets are been classified with each other , which dataset we are using that datasets will be shown a 100% classification through SVM functions

FIG.8 FEATURE EXTRACTION CLASSIFICATION



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HELM Sparse Auto-encoder

The input weights of the H-ELM sparse auto-encoder are established by searching the path from a random space. The ELM has demonstrated that the training of HELM with random mapped input weights is efficient enough to approximate any input data.

- Confusion Matrix:

37	0	2	0	0	2	0	1	1	7
2	38	4	0	0	1	0	0	5	0
5	6	31	1	0	3	0	0	3	1
1	1	3	41	0	0	0	0	4	0
0	0	1	0	47	0	0	0	0	2
0	2	1	0	0	45	0	0	2	0
0	0	2	0	0	0	47	0	1	0
0	0	2	0	0	2	0	46	0	0
0	11	7	0	0	1	0	0	31	0
1	1	3	1	0	0	0	1	0	43

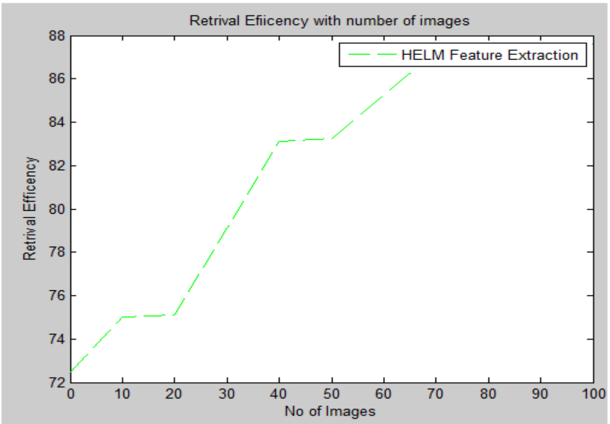
- Predicted Query Image Belongs to Class = 4

In order to generate more sparse and compact features of the inputs, L1 normalization is performed for the establishment of H-ELM auto-encoder, and this is different from the proposed L2-normalize whereas the single value is calculated for feature representation

IV.RESULT ANALYSIS

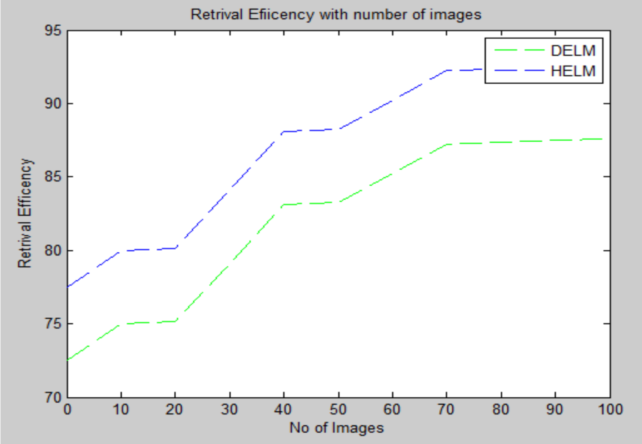
The important techniques used in the proposed system are evaluated in this section. The Support Vector Machine (SVM) is used for classifying the data as sensitive and insensitive. The figure 2 shows that the SVM classifier maintains the efficiency with consistent degree. From the experimental result, even though the database has more insensitive data than the sensitive data, the SVM maintains constant accuracy and that is shown in the figure 2. This figure also depicts that the SVM provide better performance even when the number of data to be classified is increased.The extracted features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

FIGURE.9SVM CLASSIFIER EFFICIENCY



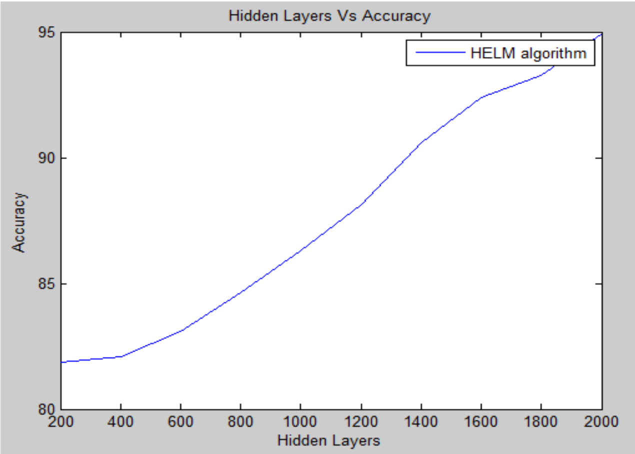
Feature extraction a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vectorThe Backpropagation-Extreme Learning Machine (BP-ELM) in the proposed method is compared with the previous Hierarchical Extreme Learning Machine technique. In the HELM, the retrieve an image and is easy to compute from the detection. Hence the BP-ELM is performing better than the existing HELM. The figure 3 shows the comparison graph for both the HELM and theBP-ELM that shows the BP-ELM proves better efficiency than the existing retrieval method

FIG.10COMPARISON OF ACCURACY AND EFFICIENCY(DELM-SVM)



Object detection is a computer technology related to computer vision and image processing that deals with detecting instances of semantic objects of a certain class (such as humans, buildings, or cars) in digital images and videos.

FIG.11SVM CLASSIFIER ACCURACY



Images are been classified and detected which are been unrelated to an original images and then classified by an H-ELM Algorithmin Fig.11

- **Accuracy Computation**

Accuracy Value of an image detection for a and b

a = 200 400 600 800 1000 1200 1400 1600 1800 2000

b =81.8800 82.0700 83.0900 84.6200 86.2800 88.1200 90.6100 92.4100 93.2500 94.9300

Accuracy of an image detections can be represented by image by image set of format which calculate how set of images are been detected and represented in accuracy form of graph representation .

IV. CONCLUSION

The paper proposed Hierarchical Extreme Learning Machine (HELM) algorithm is used for feature extraction of an image and classifying image by using SVM algorithm. Multilayer Perceptron (MLP) training dataset is based on the universal approximationcapability of the original ELM (Extreme Learning Machine). The H-ELM achieves high level representation with layerwise encoding, and outperforms the original ELM in various simulations.Moreover, compared with other MLP training methods, thetraining of H-ELM is much faster and achieves higher learning accuracy and is also verified the generality and capability of H-ELM for practical computer vision applications. In these

applications, H-ELM functions as a feature extractor andclassifier, and it achieves more robust and better performance than relevant state-of-the-art methods.
Support Vector Machine (SVM) is used for classify the current image with other image and also it identifies the similarities between the images using BPELM. SVM are supervised learning models that analyze data and recognize patterns used for classification and regression analysis whereas BPELM-SVM training algorithm build a model that assign with one category making it with a non-probabilistic binary linear classifier performing linear classifications, SVM's can efficiently perform a nonlinear classifications.

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