Hybrid deep learning with pelican optimization algorithm for M2M communication on UAV image classification

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Article Info

Article history:

Received Feb 11, 2024
Revised Mar 26, 2024
Accepted Apr 15, 2024

Keywords:

Artificial intelligence
Deep learning
Machine-to-machine
Pelican optimization algorithm
Unmanned aerial vehicle

ABSTRACT

Machine-to-machine (M2M) communication for unmanned aerial vehicle (UAVs) and image classification is essential to current remote sensing and data processing. UAVs and ground stations or other linked devices exchange information seamlessly using M2M communication. M2M connectivity helps UAVs with cameras and sensors communicate aerial pictures in real time or post-mission for image categorization and analysis. During flight, UAVs acquire massive volumes of picture data. Image classification, commonly using deep learning (DL) methods like convolutional neural network (CNN), automatically categorizes and annotates photos based on predetermined classes or attributes. This work uses UAV photos to produce hybrid deep learning with pelican optimization algorithm for M2M communication (HDLPOA-M2MC). HDLPOA-M2MC automates UAV picture class identification. GhostNet model is used to derive features in HDLPOA-M2MC. The HDLPOA-M2MC approach leverages pelican optimization algorithm (POA) for hyperparameter adjustment in this investigation. Finally, autoencoder-deep belief network (AE-DBN) model can classify. The HDLPOA-M2MC method's enhanced outcomes were shown by several studies. The complete results showed that HDLPOA-M2MC performed better across measures.

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1. INTRODUCTION

Integrating unmanned aerial vehicle (UAV) photos with machine-to-machine (M2M) communication is a dynamic merging of technologies with major ideas across disciplines [1]. This combination enables real-time data collection, decision-making, and analysis in risky remote sensing and rapid data delivery circumstances [2]. UAVs have improved imaging systems that can take high-resolution images and video from previously unattainable angles [3]. Environmental monitoring, disaster management, surveillance, and infrastructure inspection benefit from these visualizations. The emergence of UAV remote sensing offered new and effective crop data collection methods. Today, precision agriculture, such as site-specific crop arrangement using remote sensing, is more popular. Creating detailed crop distribution maps is becoming more important [4]. The rapid development of UAV technology adds to data collection. This aircraft network can swiftly gather 3-D data with low atmospheric effects and short return time [5]. Many commercial UAVs have inexpensive digital cameras. However, crop identification sometimes requires several spectrum data.

Small and medium-sized businesses need UAV remote sensing [6]. More accurate crop distribution data is crucial for agricultural monitoring methodology growth [7]. UAV remote sensing has quick data capture, cheap cost, easy operation, and excellent resolution. It may capture images for a specific location and incorporate ground measurement data to quickly and accurately observe agricultural planting data [8]. It may also supplement satellite and airborne remote sensing and verify large-scale remote sensing accuracy. Most researchers nowadays have researched drone-based crop identification and utilized numerous methods. AI is essential to everyone [9]. It can alter perceptions and environment. With these technologies, the labor was restricted to the least developed industries that now contribute to several segments [10].

Hybrid deep learning with pelican optimization algorithm for M2M communication (HDLPOA-M2MC) is developed for UAV photos in this study. HDLPOA-M2MC automates UAV picture class identification. GhostNet model is used to derive features in HDLPOA-M2MC. The HDLPOA-M2MC approach leverages POA for hyperparameter adjustment in this investigation. Finally, autoencoder-deep belief network (AE-DBN) model can classify. The HDLPOA-M2MC approach was shown better by several studies.

2. LITERATURE SURVEY

A method to trace missing transmitting fracture sections is devised [11]. Postprocessing used 1D deep learning (DL) and image processing (IP) used a pre-processor. IP-aided DL, DL's predecessor, avoids planar structural background and tedious labeling without unique features. Local IP post-processor for DL paths without crash section thin snaps-iterative variance sliding window. Hamza *et al.* [12] developed UAVDL-ICM for DL image categorization. DL models DenseNet, inception with residual network-V2 (ResNetv2), and ResNet are employed. It tunes hyperparameters via genetic programming. Final detection uses fully-connected deep neural networks (FCDNN) and oppositional water wave optimization (OWWO). Zhou *et al.* [13], an autonomous strawberry ripeness framework was described.

Effective DL and YOLOv3 models recognize simple items. These algorithms were trained to recognize strawberry blossoms and fruit at various ages. DL-IP equaled strawberry picture capture from ground and air. Highly effective recognition model by Mittal *et al.* [14] incorporates influential feature extractor. Fusion is one of several improved feature maps employing enhanced VGG16 and ResNet50 algorithms. The fusion improves low-altitude aerial image identification using semantic data. Performance was estimated using many benchmarks low-altitude aerial datasets.

Chudhari *et al.* [15] note Bayesian DL-based crop type classification (BODLD-CTC) model optimization. Crop category perception is evaluated with UAV images. Features are retrieved via Xception. Uses long short-term memory (LSTM) for recognition. LSTM hyperparameters are optimized and classification improved by BO. Albattah *et al.* [16] designed a 3-stage DL-automated. A CornerNet basic system adapted for DenseNet100 is also constructed. Model remarks for method instruction are of interest. Key addition with DenseNet-100 is followed by a normal CornerNet. Last, one-stage sensor CornerNet classifies and recognizes various insects.

3. THE PROPOSED METHOD

In this study, a developed HDLPOA-M2MC technique on UAV images. The objective of HDLPOA-M2MC method lies in the automated identification of different classes that exist in the UAV images. It contains three most important processes namely GhostNet-based feature extraction, POA-based hyperparameter tuning, and AE-DBN-based classification. Figure 1 represents the workflow of HDLPOA-M2MC algorithm.

3.1. GhostNet feature extraction module

GhostNet suggested a state-of-the-art ghost model that yields further mapping features via realistic process [17]. This elementary neural network (NN) unit creates image feature with inputs and less computations. There exist 2 features to these implementations of the model. First, GhostNet performed the traditional convolution for constructing mapping features with other channels. Next, it performed a basis process to make other feature mappings. Lastly, it concatenated some feature maps to construct new output.

Ghost bottleneck is the significant portion of GhostNet that includes two ghost modules. The process of making M mapping features from the ghost model was expressed as (1).

$$\gamma = X * f + b \tag{1}$$

Now, the width and height of inputs are w & h correspondingly; c displays the channel sums, b specifies the bias term, and the convolution operation is $*$; $f \in R^{c\times k\times k\times m}, X \in R^{h\times c\times w}$ refers to the convolution kernels. k^*k denotes the convolution size f. Initially, the W x H x C size-based input feature map was rationalized by the standard convolutional layer. Next, cheap linear procedure is applied on W' x H' x C mapping features with the k x k lesser kernel convolution function that produces substantial volume of ghost features. Finally, the outcomes of process are combined to create outcome feature map of dimension W' x H' x c. The typical linear and convolution adjustment utilized in ghost model enables to excellent conservation of novel features. In conclusion, the mapping features are transformed as the latter 1280-dimension features applying the global average pooling and convolutional layers. The computational cost is lower when compared to traditional convolution directly.

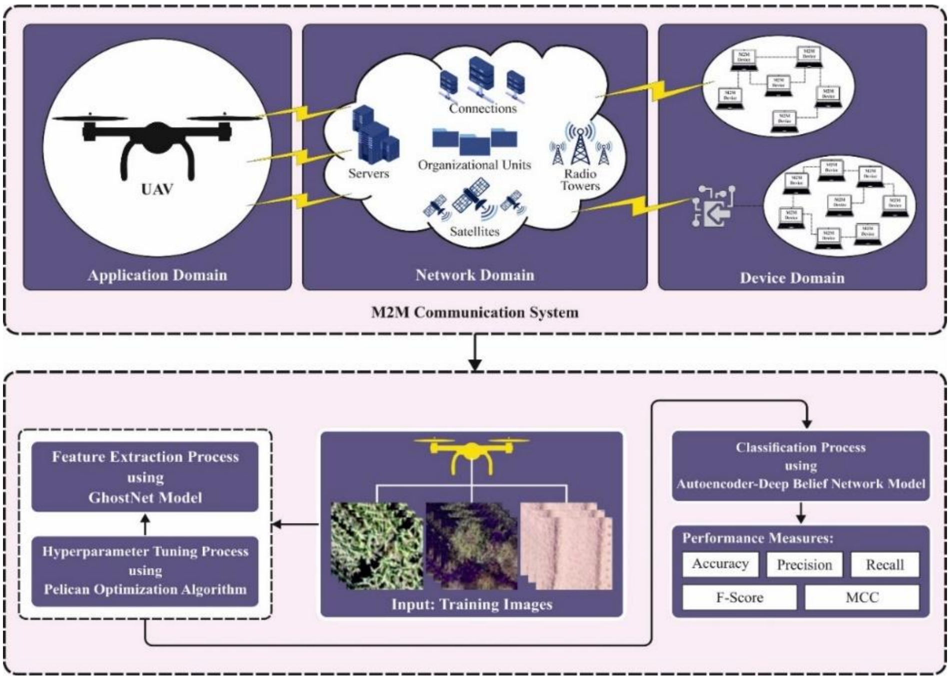


Figure 1. Workflow of HDLPOA-M2MC system

3.2. POA-based parameter tuning module

The POA stimulates the normal strategy of pelicans in the hunting method, which can split into 2 major phases such as approaching prey and surface flight phases [18]. In first phase of POA, it arbitrarily describes the prey place as well as moves close to its decided area. The mathematical equation for the pelican function at first step can be given by:

$$P_i = X_k, i = 1,2, \dots, N, k = 1,2, \dots, N \tag{2}$$

$$x_{i,j}^{P1} = \begin{cases} x_{i,j} + rand \cdot (p_j - I \cdot x_{ij}), & F_p < F_i \\ x_{i,j} + rand \cdot (x_{i,j} - p_j), & else, \end{cases} \tag{3}$$

$$X_i = \begin{cases} X_i^{P_1}, F_i^{P_1} < F_i; \\ X_i, \quad else, \end{cases} \tag{4}$$

Where, F_i indicates the value of important function, as the value of the adaptation degree; P_i represents the place of target nominated by i pelican; x_{ij}^{P1} signifies the new position of i pelican with the j dimensional; k symbolizes the arbitrary value generated from 1 and N; $F_i^{p_1}$ describe the modification values equal to it. $rand$ represents the arbitrary numbers in the range of 0 to 1, then the value of I is both 1 and 2. $rand$ and I indicates the arbitrary numbers employed to making arbitrary POA function from search and upgrade.

In the second phase, if the individual pelican acquires the surface, they could extend their wings into water and change the fish upward early finding the victim from their throat pockets. Modelling these behavioral techniques of pelicans allows for convergence to the optimal position at the hunting area that enhances the local search capability and exploitation of POA. During the scientific models, this approach checks the places near to pelican place so this technique could be converged to the optimal place.

$$x_{i,j}^{P_2} = x_{i,j} + R \cdot \left(1 - \frac{t}{T}\right) \cdot (2 \cdot rand - 1) \cdot x_{ij} \tag{5}$$

$$X_i = \begin{cases} X_i^{P_2}, & F_i^{P_2} < F_i; \\ X_i, & else, \end{cases} \tag{6}$$

Additionally, t denotes the present round counts; T stands for the maximum round counts; R describes the constant gaining the value of 0.2; $x_{i,j}^{P_2}$ denotes the novel status of i^{th} pelicans from the j^{th} dimensional from the 2nd hunting step; $F_i^{P_2}$ indicates the equal fitness values from the new conditions.

3.3. Classification module

DBN is a collection of unsupervised models such as RBM that are implemented as the latent status of each subnet and the visible state of succeeding layer [19]-[21]. The DBN architecture takes an effective function which describes how variable is based on variable from the abovementioned layer. The proposed DBN model includes multiple latent and visible layers of restricted Boltzmann machines (RBM) and logistic regression (LR) for the classification from the last layer. At first, feature space of vector was mapped, and later each layer of RBM model was correspondingly trained in unsupervised fashion to retain the feature information. Next, fine alteration is adjusted. AE is 3-layer unsupervised NNs. It is noted that the simple process of NN is applied for the learning representations such as functional series (FS) or reducing the dimension and attempting to reconstruct the input pattern from the resulting layer. Consider X is dataset with m features and n instances. Y shows the encoding outcome. The calculated expression of encoded and decoded operations for simplest AE are correspondingly shown in (7) and (8).

$$Y = f(wX + b) \tag{7}$$

$$\acute{X} = g(\acute{w}Y + b) \tag{8}$$

Here w and b indicates the adjustable variables, the activation function represents f and g, W shows the weighted $(\acute{X})$ transpose, and $\acute{X}$ refers to the reconstruction input vector from the resulting layer. The proposed AE-DBN architecture includes 2 different components. At first, the AE is applied as a DL technique for extracting features in the input dataset. Figure 2 portrays the infrastructure of DBN.

Next part is described by the DL method reliant on DBN to update the RL. The encoded portion is in charge of extracting features of the input dataset. This enables to DBN of the proposed model that forecast the RUL. Mainly, the AE is individually trained to accomplish the weighted matrix priory trained in the DBN prediction mechanism [22]. The decoded portion of AE is applied to confirm the validity of feature extraction to regenerate the new dataset. The suggested machine learning solutions for UAVs and their network capabilities will dominate this study. UAV roles, collaboration, cooperation, and shifting situations in the network will also be considered. The drone's 3D position is optimized to maximize coverage, and network resources are prioritized for delay-sensitive M2M data. UAVs, blockchain, and mobile edge computing (MEC) being studied as potential technologies for secure M2M communication networks that can protect data even if compromised. Optimising blockchain systems with a Markov decision process improves computational power and performance [23]-[25].

4. PERFORMANCE VALIDATION

The M2M transmission outcomes of the HDLPOA-M2MC method can be investigated on the test dataset, encompassing 6450 samples as depicted in Table 1. Figure 3 shows the classifier analysis of the HDLPOA-M2MC method under test dataset. Figures 3(a) and 3(b) illustrates the confusion matrices given by the HDLPOA-M2MC technique at 70:30 of TR Phase/TS Phase. The outcome indicated that the HDLPOA-M2MC approach has appropriately recognized and classified 6 classes. Additionally, Figure 3(c) exhibits the PR investigation of the HDLPOA-M2MC technique. The figure shows that the HDLPOA-M2MC model has gained higher PR performance with every class. Besides, Figure 3(d) represents the ROC analysis of the HDLPOA-M2MC method. This figure revealed that the HDLPOA-M2MC system leads to proficient outcomes with greater ROC values with various classes.

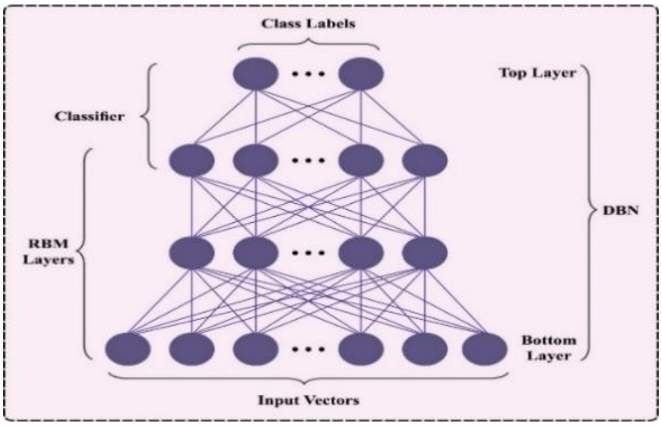
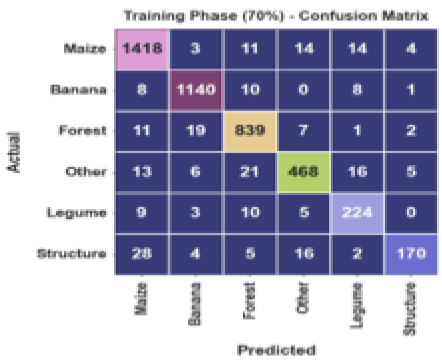


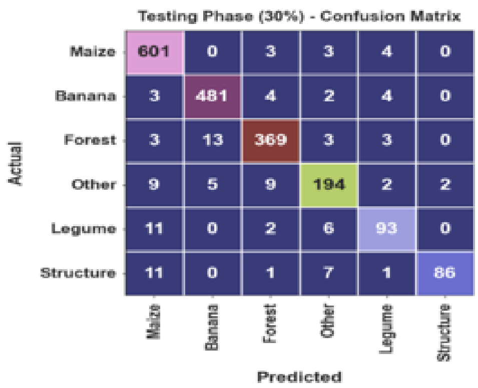
Figure 2. DBN structure

Table 1. Details of dataset

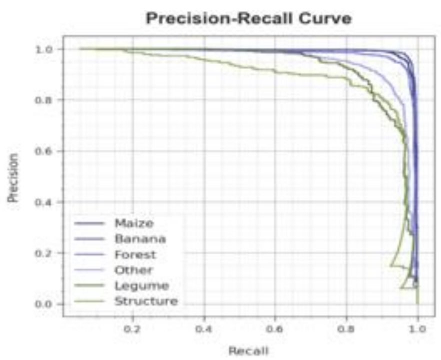
Class	No. of images
Maize	2075
Banana	1661
Forest	1270
Other	750
Legume	363
Structure	331
Total images	6450



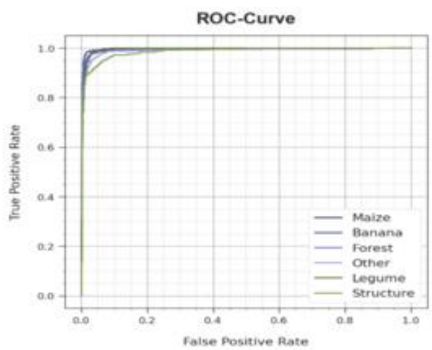
(a)



(b)



(c)



(d)

Figure 3. Classifier outcome of; (a)-(b) confusion matrices, (c) PR curve, and (d) ROC curve

The M2M communication results of the HDLPOA-M2MC method are inspected in Figure 4. The outcomes indicated that the HDLPOA-M2MC technique attains 6 classes effectually. With 70% of TR Phase, the HDLPOA-M2MC method offers average $accu_y$ of 98.11%, $prec_n$ of 92.62%, $reca_l$ of 90.54%, $F1_{score}$ of 91.41%%, and $G_{measure}$ of 90.33% respectively. Also, based on 30% of TS Phase, the HDLPOA-M2MC system provides average $accu_y$ of 98.09%, $prec_n$ of 93.43%, $reca_l$ of 90.34%, $F1_{score}$ of 91.74%, and $G_{measure}$ of 90.64%, correspondingly.

To determine the efficiency of the HDLPOA-M2MC method, we have produced accuracy curves for both the training (TR) and testing (TS) phases, as demonstrated in Figure 5. These curves give valuable insights into the model's proficiency and learning process to generalize. As we increase the count of epochs, an obvious expansion in both TR and TS $accu_y$ curves become marked. This improvement implies the model's capacity to recognize patterns within both the TR and TS databases. Figure 6 also presents an overview of the model's loss values across the training process.

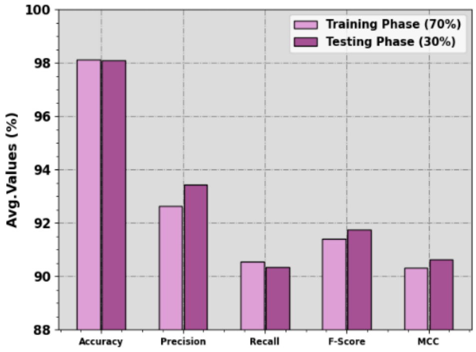


Figure 4. Average of HDLPOA-M2MC method on 70:30 of TR phase/TS phase

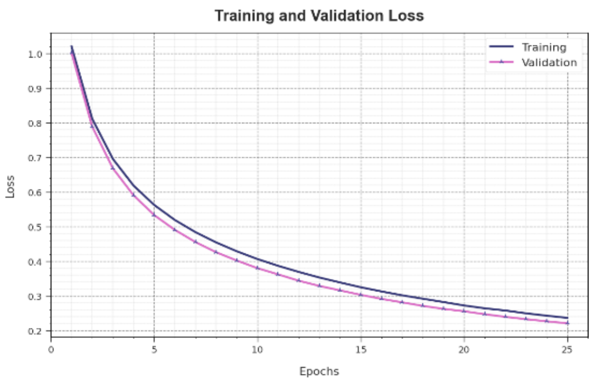


Figure 5. $Accu_y$ curve of HDLPOA-M2MC model

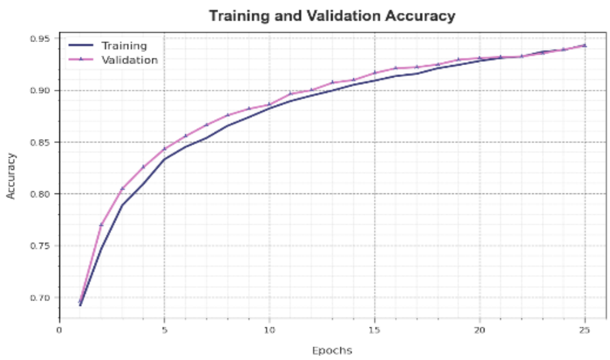


Figure 6. Loss curve of HDLPOA-M2MC model with TR and TS phase

In Table 2 and Figure 7, the comparison performance of the HDLPOA-M2MC method is examined. The outcomes depicted that the HDLPOA-M2MC method offers improved outcomes. Based on $accu_y$, the HDLPOA-M2MC method attains maximum $accu_y$ of 98.11% while the SBODL-FCC, DNN, AlexNet, visual geometry group (VGG-16), ResNet, and support vector machine (SVM) methods attain reducing $accu_y$ values of 98.11%, 97.56%, 86.37%, 90.61%, 87.84%, and 86.81% correspondingly. Also, with $prec_n$, the HDLPOA-M2MC method achieves raising $prec_n$ of 92.62% whereas the SBODL-FCC, DNN, AlexNet, VGG-16, ResNet, and SVM methods get reduced $prec_n$ values of 89.16%, 86.24%, 87.82%, 85.42%, 86.54%, and 88.14%. Meanwhile, on $reca_l$, the HDLPOA-M2MC method accomplishes raising $reca_l$ of 90.54% whereas the SBODL-FCC, DNN, AlexNet, VGG-16, ResNet, and SVM techniques get reduced $reca_l$ values of 85.14%, 84.53%, 81.84%, 81.47%, 81.29%, and 83.76%.

Table 2. Comparative outcome of HDLPOA-M2MC method with other algorithms

Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
HDLPOA-M2MC	98.11	92.62	90.54	91.41
SBODL-FCC	97.56	89.16	85.14	86.87
DNN model	86.37	86.24	84.53	86.43
AlexNet model	90.61	87.82	81.84	83.47
VGG-16 model	90.48	85.42	81.47	85.83
ResNet model	87.84	86.54	81.29	83.15
SVM model	86.81	88.14	83.76	84.32

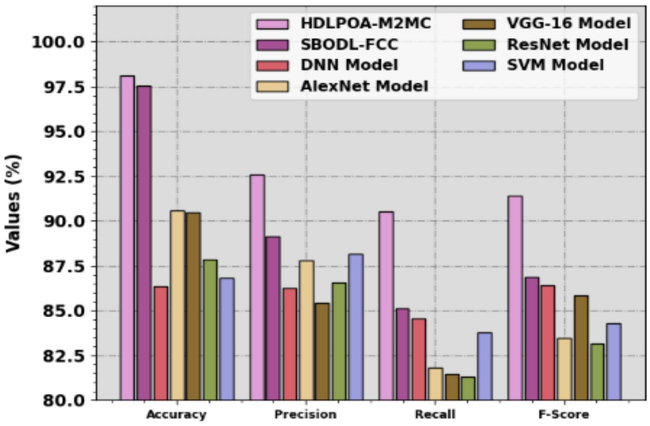


Figure 7. Comparative outcome of HDLPOA-M2MC algorithm with other approaches

5. CONCLUSION

In this study, a developed HDLPOA-M2MC technique on UAV images. The objective of HDLPOA-M2MC method lies in the automated identification of different classes that exist in the UAV images. In the HDLPOA-M2MC technique, GhostNet model is initially executed to derive features. For hyperparameter tuning process, the HDLPOA-M2MC technique uses POA in this study. At last, AE-DBN model can be exploited for classification process. An extensive set of experiments were performed to establish the improved results of the HDLPOA-M2MC method. The comprehensive outcomes inferred the superior performance of the HDLPOA-M2MC algorithm under various metrics.

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