Deep Rule-Based Aerial Scene Classifier using High-Level Ensemble Feature Descriptor

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Abstract—In this paper, a new deep rule-based approach using high-level ensemble feature descriptor is proposed for aerial scene classification. By creating an ensemble of three pre-trained deep convolutional neural networks as the feature descriptor, the proposed approach is able to extract more discriminative representations from the local regions of aerial images. With a set of massively parallel IF…THEN rules built upon the prototypes identified through a self-organizing, nonparametric, transparent and highly human-interpretable learning process, the proposed approach is able to produce the state-of-the-art classification results on the unlabeled images outperforming the alternatives. Numerical examples on benchmark datasets demonstrate the strong performance of the proposed approach.

Keywords— deep rule-based, deep convolutional neural network, ensemble feature descriptor, aerial scene classification

I. INTRODUCTION

Aerial images are an important source of information for people to understand the Earth [1]. Aerial scene classification is currently a hot research topic because it is instrumental for many real-world applications [2]. Meanwhile, this task is very challenging due to the highly complex semantic contents and spatial patterns of such images.

There have been many approaches proposed for classifying the aerial images. In general, they can be divided into three main categories [3]: *1)* low-level methods; *2)* middle-level methods; and *3)* high-level methods.

Low-level methods attempt to distinguish aerial scenes based on the low-level visual features extracted from the images [4]–[6]. Middle-level methods, in general, encode the low-level visual features extracted from the local regions of the aerial images into holistic middle-level representations for scene classification [7], [8]. High-level methods are, mostly, based on deep convolutional neural networks (DCNNs) [2], [9], [10]. In comparison to the former two categories, high-level methods can perform classification with the highest accuracy and are the state-of-the-art in the remote sensing domain. Nonetheless, practically all of the existing high-level methods lack transparency in the approximate reasoning process, and the reasons for making a particular decision are often not interpretable for humans [11]. These demerits largely influence the applicability of the high-level approaches in real-world scenarios.

As a recently introduced generic approach for image classification, deep rule-based (DRB) classifier [12], [13] is a powerful alterative to the DCNN models. The DRB approach expands the traditional fuzzy rule-based (FRB) systems with a massively parallel multi-layer structure that DCNNs benefit from [13]. Thanks to the prototype-based nature, the system structure of the DRB approach is fully transparent, and the learning and decision-making processes are autonomous, nonparametric and highly interpretable for humans [11].

The DRB classifier may employ different types of descriptors for visual feature extraction, which can be low-level [14], [15], middle-level [8] or high-level [16]–[18]. In reality, however, using one type of feature is often not enough for classifying different scene categories that share similar appearances. Different feature descriptors have different merits and demerits, and they have different descriptive abilities. Therefore, fusing multiple features into more descriptive representations usually results in a stronger classification performance [1], [19], [20].

Following this principle, in this paper, a deep rule-based (DRB) approach using multiple features is proposed for aerial scene classification. The proposed approach uses an ensemble of different high-level feature descriptors for extracting highly distinctive semantic representations from sub-regions of aerial images locally. The DRB system identifies a number of prototypes during the training process, and self-organizes a set of massively parallel prototype-based IF…THEN rules for classification in an autonomous, nonparametric manner [11]–[13]. Numerical examples demonstrate that the proposed DRB approach is able to produce the state-of-the-art classification results outperforming the alternatives by incorporating the high-level ensemble feature descriptor.

II. THE EMPLOYED HIGH-LEVEL FEATURE DESCRIPTORS

In this section, we briefly introduce the three pre-trained DCNNs that will be used as the high-level feature descriptors in the proposed approach. It has to be stressed that the pre-trained DCNN models are used directly without tuning.
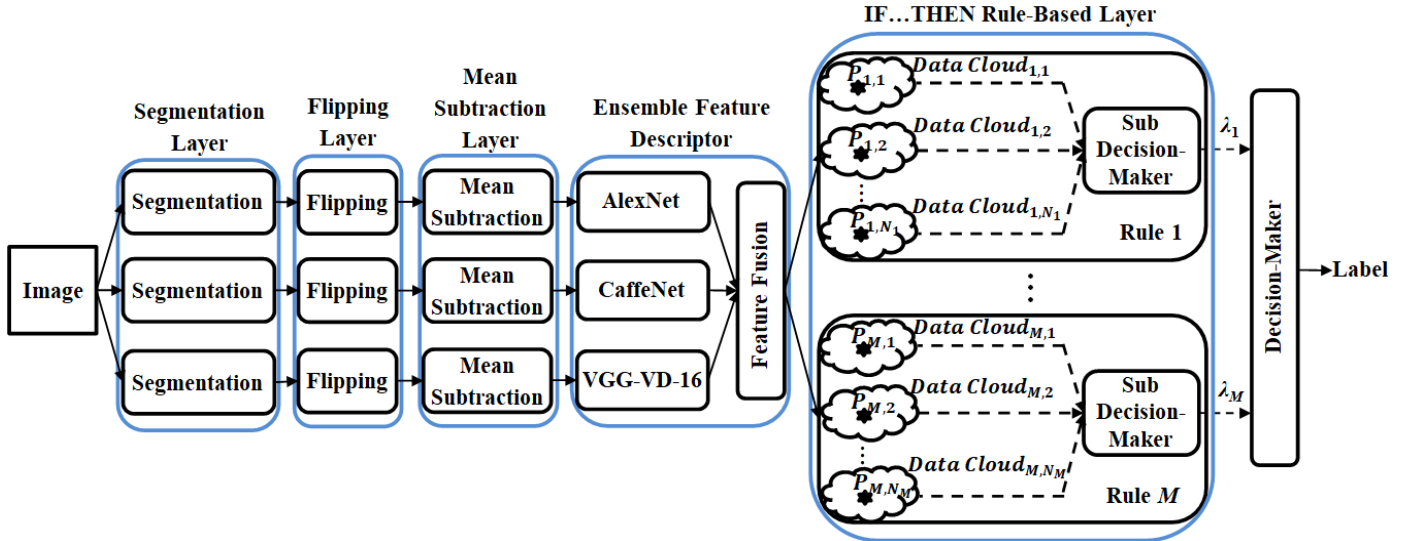
Fig. 1. The general architecture of the proposed DRB approach

A. AlexNet

AlexNet [18] was the winning DCNN model of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012. It largely popularized the applications of DCNNs and has become a baseline model of DCNNs. AlexNet was trained on ImageNet dataset, which contains 1.3 million images. It has eight layers with weights. The first five are convolutional layers, the first and second of which are followed by the normalization layers. The two normalization layers and the fifth convolutional layer are also followed by one max-pooling layer, respectively. The remaining three layers with weights are fully-connected [18]. The last fully-connected layer is linked to a softmax layer which produces the output of the network. To reduce overfitting, AlexNet involves data augmentation by cropping smaller-size segments and horizontally flipping these segments from original images. This operation artificially creates more training images. The size of input images required by AlexNet is 227×227 pixels. In this paper, we use the 1×4096 dimensional activations from the first fully connected layer as the feature vectors of the input images.

B. CaffeNet

CaffeNet [16] has a similar architecture to AlexNet and is also trained on the image set of ILSVRC 2012. Nonetheless, there are two differences between CaffeNet and AlexNet [3]: 1) the order of max-pooling and normalization layers are exchanged; 2) data augmentation is not used. The size of input images required by CaffeNet is 227×227 pixels. Similarly, the 1×4096 dimensional activations from the first fully connected layer are used as the feature vector of the input images [2].

C. VGG-VD-16 Model

VGG-VD-16 was introduced in [17] and is one of the best-performing pre-trained DCNN models. This model has 16 layers with weights. The first 13 layers are convolutional and the last three are fully-connected. The second, fourth, seventh,

tenth, thirteenth convolutional layers are followed by a max-pooling layer. There is no normalization layer used in the VGG-VD-16 model. This model is also trained on the image set of ILSVRC 2012 [17]. VGG-VD-16 model requires the input images with the size of 224×224 pixels. We also extract the 1×4096 dimensional activations from the first fully connected layer as the feature vectors of the input images [2].

It has to be stressed that, practically, one can use any types of high-level feature descriptors, i.e. GoogLeNet [21], ResNet [22], PlacesNet [23], etc., and any number of them to create an ensemble for feature extraction. The main purpose of this paper, however, is to introduce the general concept and principles of the DRB classifier using ensemble feature descriptor. Therefore, we only use the most representative three DCNNs to create the ensemble descriptor. Nonetheless, one can try different combinations as well.

III. THE PROPOSED DEEP RULE-BASED APPROACH

The general architecture of the proposed DRB approach is depicted in Fig. 1. As one can see that, the DRB classifier is composed of the following layers:

1) Segmentation layer;

2) Flipping layer;

3) Mean subtraction layer;

4) Ensemble feature descriptor layer;

5) IF...THEN rule-based layer;

6) Decision-maker.

A. Segmentation Layer

This layer crops five sub-images of the required sizes (224×224 or 227×227 pixels depending on the DCNN models connected) from the central area and four corners of each image for data augmentation [2], [18]. This type of segmentation enables the DRB classifier to grasp more local

semantic information from the images and improve the generalization ability.

B. Flipping Layer

This layer flips each segment of the images horizontally, vertically, and in both direction. The flipping operation further creates three new segments from each segment [2], [18].

The segmentation and flipping layers, in total, produce $K_o = 20$ segments from each input image, which will be used for feature extraction. An example of the data augmentation is given in Fig. 2 for illustration.

C. Mean Subtraction Layer

This layer subtracts from each segment its mean, and centralizes the three channels of the segment around the zero mean. This pre-processing technique helps the pre-trained DCNN models to perform faster because gradients act uniformly for each channel.

D. Ensemble Feature Descriptor Layer

The ensemble feature descriptor, as described in Section II, consists of three different pre-trained DCNN models: 1) AlexNet, 2) CaffeNet and 3) VGG-VD-16, and a feature fusion sub-layer.

For each segment, denoted by $\mathbf{s}$, each model will produce a 1×4096 dimensional feature vector from the activations of the first fully connected layer. The feature fusion sublayer will combine the three feature vectors into a 1×12288 dimensional semantic representation by the following equation:

$$x \leftarrow \left[\frac{\mathbf{AN(s)}}{\|\mathbf{AN(s)}\|}, \frac{\mathbf{CN(s)}}{\|\mathbf{CN(s)}\|}, \frac{\mathbf{VV(s)}}{\|\mathbf{VV(s)}\|} \right]^T \quad (1)$$

where $\mathbf{AN(s)}$, $\mathbf{CN(s)}$, $\mathbf{VV(s)}$ represent the feature vectors extracted by AlexNet, CaffeNet and VGG-VD-16 models, respectively. In equation (1), L_2-normalization is used to guarantee that the feature vectors from the three models contribute equally in the semantic representation.

E. IF…THEN Rule-Based Layer

The IF…THEN rule base in this layer is the "core" of the DRB classifier. Assuming the datasets has M categories, the DRB classifier will self-organize and self-update M massively parallel IF…THEN rules from prototypes that are identified from the segments of the images of each category (one rule per category) in a nonparametric, transparent and human-interpretable manner. Each IF…THEN rule has the following form ($m = 1, 2, ..., M$) [11]–[13]:

$$IF\left(\mathbf{s} \sim \mathbf{P}_{m,1}\right) OR \left(\mathbf{s} \sim \mathbf{P}_{m,2}\right) OR...OR\left(\mathbf{s} \sim \mathbf{P}_{m,N_m}\right)$$
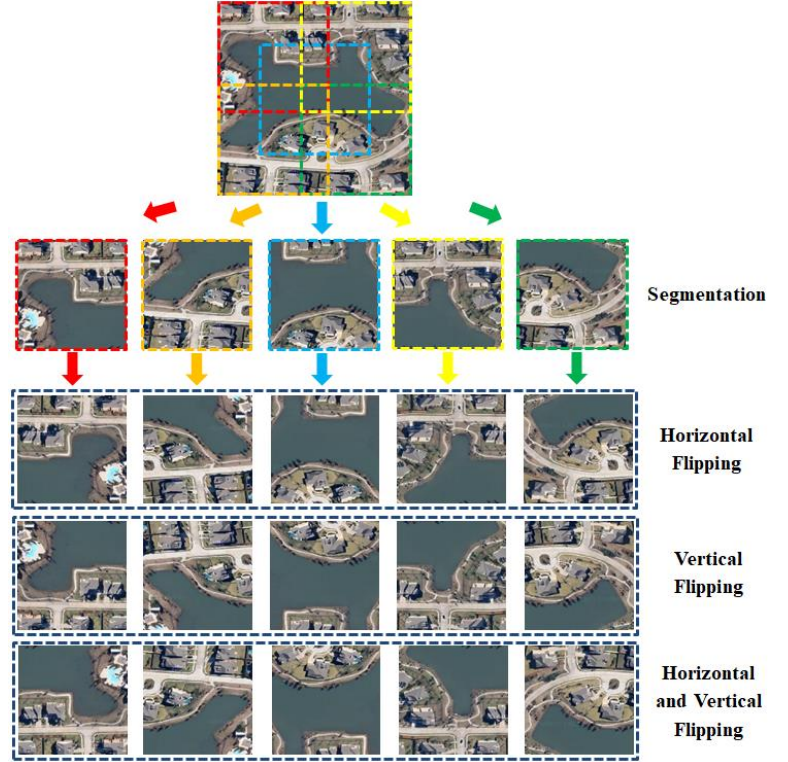$$THEN\left(category\ m\right) \quad (2)$$

Fig. 2. Illustrative example of data augmentation

where " ~ " denotes similarity, which can be seen as a fuzzy degree of membership; $\mathbf{s}$ is a particular segment with $\mathbf{x}$ as its feature vector; $\mathbf{P}_{m,i}$ denotes the ith prototype of the mth category with $\boldsymbol{p}_{m,i}$ as the corresponding feature vector; N_m is the number of identified prototypes of the mth category.

Each IF…THEN rule contains a number of prototypes that are connected by a sub-decision maker using the "winner-takes-all" principle. Therefore, each IF…THEN rule is a massively parallel series of singleton fuzzy rules of AnYa type [24] connected by logical "OR" operators .

The detailed identification process of the IF…THEN rules have been given in [11], [13]. One can also download from [25] the open source software implemented in Matlab with detailed instructions provided in [11]. To make this paper self-contained, the identification process of the rule base is summarized by the following pseudo-code. It has to be noticed that because the IF…THEN rules are identified in parallel, we present the identification process of the mth rule as an example. The same principles can be applied to the other IF…THEN rules within the same rule base.

INPUT: streaming images of the mth category
ALGORITHM BEGINS

While a new segment, $\mathbf{s}_{m,k}$ is available:
i. Extract the semantic representation, $\boldsymbol{x}_{m,k}$ from $\mathbf{s}_{m,k}$;
ii. Normalize $\boldsymbol{x}_{m,k}$ by its L_2 norm:

$$x_{m,k} \leftarrow \frac{x_{m,k}}{\left\| x_{m,k} \right\|} \tag{2}$$

iii. **If** ($k=1$) **Then**
1. Initialize the global meta-parameters:

$$N_m \leftarrow 1; \quad \boldsymbol{\mu}_m \leftarrow x_{m,k} \tag{3}$$

where, N_m is the number of prototypes; $\boldsymbol{\mu}_m$ is the global mean of the feature vectors of the images of the mth category.

2. Initialize the meta-parameters of the first data cloud, $\mathbf{C}_{m,N_m}$:

$$\mathbf{C}_{m,N_m} \leftarrow \left\{ \mathbf{s}_{m,k} \right\} \tag{4a}$$

$$\mathbf{P}_{m,N_m} \leftarrow \mathbf{s}_{m,k} \tag{4b}$$

$$\boldsymbol{p}_{m,N_m} \leftarrow x_{m,k} \tag{4c}$$

$$S_{m,N_m} \leftarrow 1 \tag{4d}$$

$$r_{m,N_m} \leftarrow r_o \tag{4e}$$

where S_{m,N_m} is the support (number of members) of $\mathbf{C}_{m,N_m}$; r_{m,N_m} is the corresponding radius of influential area; r_o is a constant to stabilize the new data cloud and $r_o = \sqrt{2\left(1-\cos\left(30^o\right)\right)}$ [11], [13].

3. Initialize the IF…THEN rule:

$$\mathbf{R}_m: \quad IF\left(\mathbf{s} \sim \mathbf{P}_{m,N_m}\right) \quad THEN\left(category\ m\right) \tag{5}$$

iv. **Else**
1. Update global mean:

$$\boldsymbol{\mu}_m \leftarrow \frac{k-1}{k}\boldsymbol{\mu}_m + \frac{1}{k}x_{m,k} \tag{6}$$

2. Calculate the data density at $\mathbf{s}_{m,k}$ and prototypes $\mathbf{P}_{m,j}$ ($j=1,...,N_m$) [26], [27]:

$$D(\mathbf{z}) = \frac{1}{1 + \dfrac{\left\| z - \boldsymbol{\mu}_m \right\|^2}{1 - \left\| z \right\|^2}} \tag{7}$$

where $\mathbf{z} = \mathbf{s}_{m,k}, \mathbf{P}_{m,1}, \mathbf{P}_{m,2},...,\mathbf{P}_{m,N_m}$; $z = x_{m,k}, \boldsymbol{p}_{m,1}, \boldsymbol{p}_{m,2},...,\boldsymbol{p}_{m,N_m}$.

3. Find the nearest data cloud, $\mathbf{C}_{m,n^*}$:

$$n^* \leftarrow \underset{j=1,2,...,N_m}{\arg\min}\left(\left\| x_{m,k} - \boldsymbol{p}_{m,j} \right\|\right) \tag{8}$$

4. **If** ($D\left(\mathbf{s}_{m,k}\right) > \underset{j=1,2,...,N_m}{\max}\left(D\left(\mathbf{P}_{m,j}\right)\right)$)

Or ($D\left(\mathbf{s}_{m,k}\right) < \underset{j=1,2,...,N_m}{\min}\left(D\left(\mathbf{P}_{m,j}\right)\right)$)

Or ($\left\| x_{m,k} - \boldsymbol{p}_{m,n^*} \right\| > r_{m,n^*}$) **Then:**
- Add a new data cloud:

$$N_m \leftarrow N_m + 1 \tag{9a}$$

$$\mathbf{C}_{m,N_m} \leftarrow \left\{ \mathbf{s}_{m,k} \right\} \tag{9b}$$

$$\mathbf{P}_{m,N_m} \leftarrow \mathbf{s}_{m,k} \tag{9c}$$

$$\boldsymbol{p}_{m,N_m} \leftarrow x_{m,k} \tag{9d}$$

$$S_{m,N_m} \leftarrow 1 \tag{9e}$$

$$r_{m,N_m} \leftarrow r_o \tag{9f}$$

5. **Else**:
- Update the meta-parameters of $\mathbf{C}_{m,n^*}$:

$$\mathbf{C}_{m,n^*} \leftarrow \mathbf{C}_{m,n^*} + \left\{ \mathbf{s}_{m,k} \right\} \tag{10a}$$

$$\boldsymbol{p}_{m,n^*} \leftarrow \frac{S_{m,n^*}}{S_{m,n^*}+1}\boldsymbol{p}_{m,n^*} + \frac{1}{S_{m,n^*}+1}x_{m,k} \tag{10b}$$

$$S_{m,n^*} \leftarrow S_{m,n^*} + 1 \tag{10c}$$

$$r_{m,n^*} \leftarrow \sqrt{\frac{r_{m,n^*}^2 + \left(1 - \left\| \boldsymbol{p}_{m,n^*} \right\|^2\right)}{2}} \tag{10d}$$

6. **End If**
7. Update the IF…THEN rule:

$$\mathbf{R}_m: \quad \begin{array}{c} IF\left(\mathbf{s} \sim \mathbf{P}_{m,1}\right) OR\ ...\ OR\left(\mathbf{s} \sim \mathbf{P}_{m,N_m}\right) \\ THEN\left(category\ m\right) \end{array} \tag{11}$$

v. **End If**
End While

ALGORITHM ENDS

OUTPUT: the massively parallel IF…THEN rule $\mathbf{R}_m$

F. Decision-Maker

During the validation process, for a particular segment, $\mathbf{s}_i$ ($i=1,2,...,20$) from an unlabelled image, $\mathbf{I}$, one can obtain M scores of confidence with the corresponding M massively parallel IF…THEN rules (one score per rule). Each score of confidence is formulated as follows ($m=1,2,...,M$):

$$\lambda_m\left(\mathbf{s}_i\right) = \underset{j=1,2,...,N_m}{\max}\left(e^{-\left\| x_i - \boldsymbol{p}_{m,j} \right\|^2}\right) \tag{12}$$

where x_i is the corresponding 12288×1 dimensional semantic representation of $\mathbf{s}_i$.

The label of $\mathbf{I}$ is given using the "winner takes all" principle by combing the scores of confidence calculated with all the segments of $\mathbf{I}$:

$$Label\left(\mathbf{I}\right) \leftarrow category\ m^*; \quad m^* = \underset{m=1,2,...,M}{\arg\max}\left(\frac{1}{K_o}\sum_{i=1}^{K_o} \lambda_m\left(\mathbf{s}_i\right)\right) \tag{13}$$

IV. NUMERICAL EXAMPLES AND DISCUSSIONS

In this section, numerical examples on well-known benchmark image sets are presented to demonstrate the performance of the proposed approach.

A. Experimental Setup

In this paper, the following three aerial image sets are used for numerical examples. The example images of the three benchmark image sets are given in Fig. 3.

1) UCMerced dataset [7]

UCMerced dataset consist of land-use images of 21 categories selected from aerial orthoimagery. This dataset has, in total, 2100 images of a size of 256×256 pixels. These images are uniformly labelled into the following 21 categories: *i)* agricultural; *ii)* airplane; *iii)* baseball diamond; *iv)* beach; *v)* buildings; *vi)* chaparral; *vii)* dense residential; *viii)* forest; *ix)* freeway; *x)* golf course; *xi)* harbour; *xii)* intersection; *xiii)* medium residential; *xiv)* mobile home park; *xv)* overpass; *xvi)* parking lot; *xvii)* river; *xviii)* runway; *xix)* sparse residential; *xx)* storage tanks; and *xxi)* tennis courts. UCMerced dataset has a variety of categories, some of which are highly overlapping. Therefore, it is widely used as a benchmark.

2) WHU-RS dataset [28]

WHU-RS dataset is a popular benchmark dataset collected from Google Earth (Google Inc.). It consists of 950 images with a size of 600×600 pixels. This dataset has 19 categories, which include *i)* airport; *ii)* beach; *iii)* bridge; *iv)* commercial, *v)* desert; *vi)* farmland; *vii)* football field; *viii)* forest; *ix)* industrial; *x)* meadow; *xi)* mountain; *xii)* park; *xiii)* parking lot; *xiv)* pond; *xv)* port; *xvi)* railway; *xvii)* residential; *xviii)* river; and *xix)* viaduct, with 50 images in each. WHU-RS dataset contains aerial images with high variations in terms of illumination, scale resolution, etc., and, thus, is a difficult problem.

3) RSSCN7 dataset [9]

RSSCN7 dataset is collected from Google Earth (Google Inc.) as well. It has seven categories, and each one contains 400 images with the size of 400×400 pixels. The seven categories include: *i)* grassland; *ii)* forest; *iii)* farmland; *iv)* parking lot; *v)* resident; *vi)* industry and *vii)* river and lake. The images of each category are sampled as four different scales (100 images per scale) with different angles, which make this problem a challenging one.

In this paper, we rescale the images of the WHU-RS dataset into the same size of the images of the RSSCN7 dataset, namely, 400×400 pixels, to avoid the loss of information during the segmentation operation.

For the training and validation sets separation, we follow the common practice by adopting two different sets [1], [3]. For UCMerced dataset, the ratios of the images for training per category are set to be 50% and 80%. For WHU-RS dataset, the ratios are set to be 40% and 60%. For RSSCN7 dataset, the ratios of the training images are set to be 20% and 50% per category.

The experimental results by the proposed approach are reported in the form of:

$$overall\ accuracy \pm standard\ deviation \tag{14}$$

Fig. 3. Illustrative example of the three benchmark problesm

All the results are the average after 10 times Monte Carlo experiments. A variety of the state-of-the-art approaches are selected for comparison purposes.

B. Experimental Results and Comparisons

The experimental results on the UCMerced dataset obtained by the proposed approach as well as the selected state-of-the-art approaches are reported in Table I.

TABLE I. NUMERICAL RESULTS ON UCMERCED DATASET

Algorithm	Percentage of Training Images per Category	
	50%	*80%*
The proposed	0.9402±0.0042	0.9736±0.0086
salM³LBP-CLM [1]	**0.9421±0.0075**	0.9575±0.0080
salM³LBP [1]	0.8997±0.0085	0.9314±0.0100
salCLM (eSIFT) [1]	0.9293±0.0092	0.9452±0.0079
Combing Scenarios I and II [2]		**0.9849**
Fine-tuning GoogleNet [29]		0.9710
CaffeNet [3]	0.9398±0.0067	0.9502±0.0081
GoogLeNet [3]	0.9270±0.0060	0.9431±0.0089
VGG-VD-16 [3]	0.9414±0.0069	0.9521±0.0120
BoVW(SIFT) [3]	0.7190±0.0079	0.7412±0.0330
VLAD(SIFT) [3]	0.7323±0.0102	0.7819±0.0166
MS-CLBP+FV [30]	0.8876±0.0079	0.9300±0.0120

The experimental results obtained by the proposed approach on the WHU-RS dataset are reported in Table II. Comparison with the state-of-the-art is reported in the same table as well.

TABLE II. NUMERICAL RESULTS ON WHU-RS DATASET

Algorithm	Percentage of Training Images per Category	
	40%	*60%*
The proposed	**0.9579±0.0066**	0.9623±0.0070
salM³LBP-CLM [1]	0.9535±0.0076	0.9638±0.0082
salM³LBP [1]	0.8974±0.0184	0.9258±0.0089
salCLM (eSIFT) [1]	0.9381±0.0091	0.9592±0.0095
Combing Scenarios I and II [2]		**0.9889**
CaffeNet [3]	0.9511±0.0120	0.9624±0.0056
GoogLeNet [3]	0.9312±0.0082	0.9471±0.0133
VGG-VD-16 [3]	0.9544±0.0060	0.9605±0.0091
BoVW(SIFT) [3]	0.7526±0.0139	0.8013±0.0201
VLAD(SIFT) [3]	0.7637±0.0201	0.8082±0.0215
MS-CLBP+FV [30]		0.9453±0.0102

The experimental results obtained by the proposed approach on the RSSCN7 dataset are reported in Table III, and are compared with the state-of-the-art in the same table.

TABLE III. NUMERICAL RESULTS ON RSSCN7 DATASET

Algorithm	Percentage of Training Images per Category	
	20%	*50%*
The proposed	**0.8826±0.0056**	**0.9175±0.0045**
CaffeNet [3]	0.8557±0.0095	0.8885±0.0062
GoogLeNet [3]	0.8398±0.0087	0.8718±0.0094
VGG-VD-16 [3]	0.8255±0.0111	0.8584±0.0092
BoVW(SIFT) [3]	0.7633±0.0088	0.8134±0.0055
VLAD(SIFT) [3]	0.7727±0.0058	0.8082±0.0215
DBNFS [9]	0.7119	0.7581

In Tables I, II and III, the best results reported are highlighted.

C. Discussions

Tables I, II and III demonstrate that the proposed approach is able to produce the state-of-the-art results in all three benchmark image sets. In particular, the proposed DRB approach outperforms all other comparative approaches on the RSSCN7 dataset. Therefore, one may conclude that the proposed approach is a strong alternative to other approaches for aerial image classification.

V. CONCLUSION AND FUTURE WORK

In this paper, a new deep rule-based (DRB) approach using an ensemble of high-level feature descriptors for aerial scene classification is proposed. With the discriminative semantic representations from the sub-regions of the aerial images extracted by the ensemble feature descriptor, the DRB approach is able to produce highly accurate classification results after a nonparametric, self-organizing and human-interpretable learning process outperforming the alternatives. Numerical examples on benchmark datasets verify the proposed concept and principles.

As future work, we will investigate the performance of the DRB approach with different combinations of the high-level feature descriptors as well as different feature fusion strategies.

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