Reducing feature dimensionality for cloud image classification using local binary patterns descriptor

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ABSTRACT

Clouds play a crucial role in precipitation and weather prediction. Identifying and differentiating clouds accurately poses a significant challenge. In this paper, we present a novel approach that utilizes the local binary patterns (LBP) feature descriptor to extract color cloud images. We employ feature fusion to combine LBP features from the independent channels of the RGB color space. Furthermore, we apply five well-known feature selection methods, namely ReliefF, Ilfs, correlation-based feature selection (CFS), Fisher, and Lasso, to select relevant and useful features. These selected features are then fed into a support vector machine (SVM) classifier. Experimental results demonstrate that our proposed approach achieves superior performance by significantly reducing the number of features while maintaining prediction accuracy.

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1. INTRODUCTION

Clouds have a direct impact on the weather anywhere in the world. Clouds are the root cause of all rain. By observing and differentiating the clouds, we can predict weather using a worldwide norm and it is a challenging task. Nowadays, weather forecasting has evolved with significant technological advancements, including aviation, agriculture, remote sensing, computer vision [1]. The number of photographs of the sky and clouds taken from the ground is rising as a result of the absence of radio waves and satellite observations in space. This procedure has produced a large amount of cloud/sky image data over a long period of time. Cameras have opened up new opportunities for monitoring the Earth’s atmosphere. This adds value to satellite imaging by giving geologists access to less expensive, quicker, and more precise data.

The successful recognition of cloud patterns in sky/cloud photographs is the most basic issue with cloud photography. Because clouds lack any particular structure, boundaries, shape, or size, it is a difficult problem to solve [2]. Cloud photography, as a naturally striated structure, often displays significant intrinsic variances due to variations inillumination, environment, and distortion. In recent years, numerous approaches have been proposed to effectively extract discriminative information from cloud images. These techniques aim to enhance our understanding of cloud formations, improve weather forecasting, and aid in various other applications [3], [4].

Several studies have been developed to recognize and classified cloud images according to their bulk, form, thickness, height, and coverage. Among them, the classification of the sky and clouds has made heavy use of color. To address this issue, numerous methods based on various color patterns and spectrum wavelengths have been developed [5]. Because of the wide differences in illumination, climate, and distortion, cloud imaging is a type of naturally textured structure and has a very great intrinsic diversity. Cloud identification [6] is a topic that can be applied to many practical applications such as weather forecasting, rain and sun prediction for internet of things (IoT) devices. It has been suggested that the local binary patterns (LBP) [7] and its variations be used as the feature extraction method for categorizing natural texture photographs. Low complexity and resilience to monotonic brightness variations are two properties of LBP features. However, because the LBP is dependent on differences in intensity, it is particularly sensitive to noise and does not perform well on portions of "flat" textured images. In order to remove irrelevant feature of the extraction process, feature selection (FS) is widely applied for many task related to pattern recognition [8]–[10]. Despite deep learning (DL) methods are demonstrated its effectiveness, some works are combined FS and DL in order to enhance the pattern recognition [11]–[13].

In this paper, we propose to study the efficacy of a FS approach for classifying cloud images. We utilize the support vector machine (SVM) classifier and LBP descriptor to classify the cloud images, and evaluate our proposed approach on two different datasets. The remaining sections of this paper are organized as follows: section 2 introduces the feature extraction and selection methods that rely on local image descriptors. Section 3 presents our proposed approach and the experimental results. Lastly, in section 4, we discuss the conclusion of our study.

2. THE FEATURE EXTRACTION AND SELECTION METHODS

This section reviews cloud feature extraction by using LBP method, and FS methods which compose of Lasso, ReliefF, correlation-based feature selection (CFS), Fisher, and Ilfs. These methods were applied to the experiments. Brief reviewings for these techniques are explained below.

2.1. Local binary patterns

The $LBP_{\mathrm{P,R}}(x_{c,}y_c)$ code of each pixel $(x_{c,}y_c)$ is determined by comparing the gray value g_c of the central pixel with the gray values $\{g_i\}_{i=0}^{P-1}$ of its P neighbors, as (1) [7]:

$$LBP_{\mathrm{P,R}} = \sum_{p=0}^{P-1} \Phi(g_p - g_c)\, 2^p \tag{1}$$

where g_c is the gray value of the central, g_p is the gray value of P, R is the radius of the circle and $\Phi(g_p - g_c)$ is calculated by:

$$\Phi(g_p - g_c) = \begin{cases} 1 \text{ if } (g_p - g_c) \geq 0, \\ \quad 0 \text{ otherwise.} \end{cases} \tag{2}$$

2.2. Feature selection

FS is a method to reduce redundant attributes from given set of features, so it allows to decrease the storage and increase the time processing. In some cases, it achieves better performance and has a compact representation. We present here the common feature selection approach considered in this paper. Lasso enables FS by assuming a linear dependence between input features and output values. When the sum of absolute values of regression coefficients is below a certain constant, Lasso minimizes the sum of squares of residuals, resulting in certain regression coefficients being precisely set to zero [14], [15].

ReliefF [16] is an extension of the Relief algorithm [17] to assist with the multiclass issue. ReliefF appears to be a potential heuristic function that could help current inductive learning algorithms overcome their myopia. Prior to learning, Kira and Rendell used ReliefF as a preprocessor to remove pointless attributes from the data description. ReliefF is comprehensive, comparatively effective, and trustworthy enough to direct search during the learning process [18].

CFS mostly uses heuristic approaches to determine the impact of each group's unique feature to produce the best possible subset of attributes. Fisher [19] aims to discover a set of features that maximize the inter-class distances between samples while minimizing the intra-class distances. Fisher chooses the top features based on its scores. Ilfs [20] involves three steps, which include feature weighting using a fully connected network within each node that connects all features, as well as preprocessing. To assess the correspondence between the path length and the feature, energy scores of the path length are calculated, enabling the ranking of their significance.

3. PROPOSED APPROACH AND EXPERIMENTAL RESULTS

In this section, the experiment and the results are explained. Dataset are prepared for training and testing stage. Afterthat, the experimental results are shown and discussed.

3.1. Experimental setup

To conduct the experiment, the Singapore whole-sky imaging categories (SWIMCAT) dataset [5], [21], [22] is considered to evaluate the proposed approach. This dataset consists of 784 images (Figure 1) of the sky and clouds that have been divided into 5 categories: a clear-blue sky, pattern, thick-dack, thick-white, and cover. Additionally, a new dataset was developed using the concept of the SWIMCAT dataset's cloud/sky segmentation, but with a higher number of photos and more cloud/sky categories, namely Cloud-ImVN 1.0 [23]-[25]. This dataset has 2,100 images (Figure 2) of the sky and clouds categorized into 6 categories.

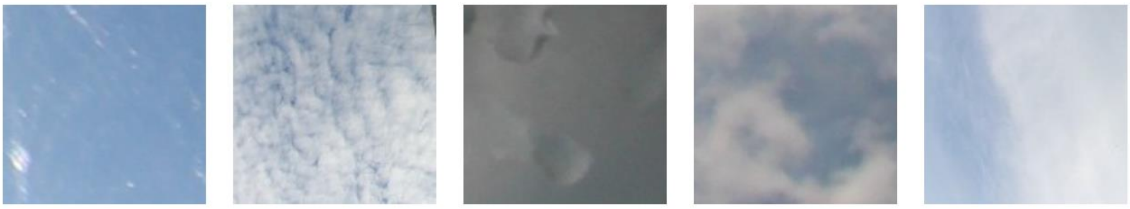


Figure 1. Several selected images from SWIMCAT dataset

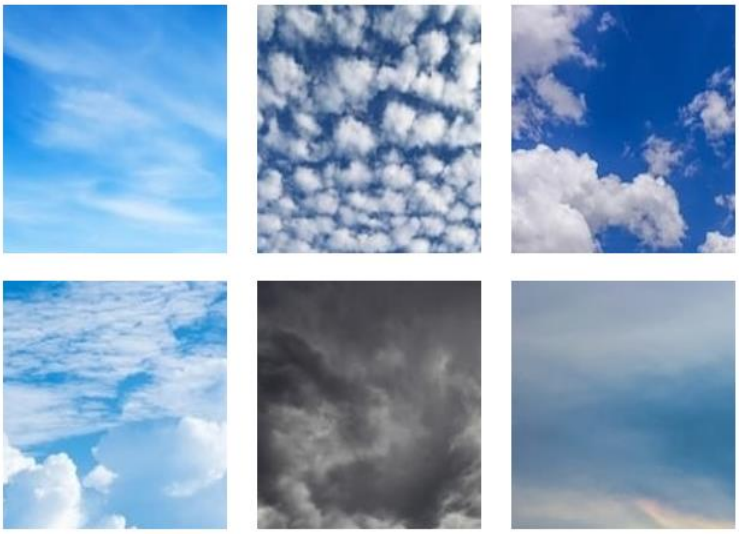


Figure 2. Several selected images from Cloud-ImVN 1.0 dataset

We extract LBP features from 3 components of RGB color space, with different values of parameters r=1, 2, 3, 4 and p=8, 12. The SVM classifier is applied after FS process. Each dataset is divided into the training testing set by using K-fold method (with k=5). The experiment is conducted and simulated by MATLAB 2020a and under a PC with CPU 2.26 GHz, 48 GB of RAM.

3.2. Results

Table 1, Figures 3 and 4 show the accuracy obtained by LBP with *r* and *p* parameter by incorporating FS methods. We observe that the FS methods clearly achieve better performance, not only improving the accuracy but also reducing the dimension space. Although with DL might achieve better results, however it requires more resources than traditional methods. In this case, FS is a good candidate for this kind of task since we obtain good results with less storage. This model can be embedded into tiny machine and used for IoT systems for weather forecasting.

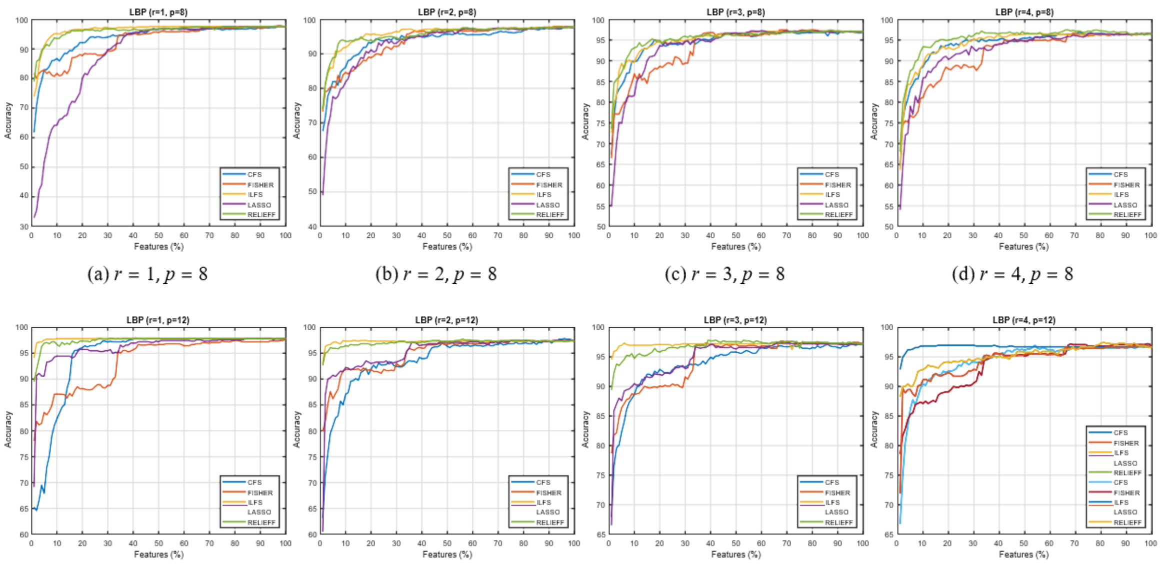
After FS, the SWIMCAT dataset had the maximum accuracy of 97.96% (Table 1) with only 92.00% of the feature are used. The result is already 100% greater than the number of features (97.82%)

when using LBP (*r*=2, *p*=8) and Fisher, and the number of features is further reduced by 8%. However, there is a potential LBP (r=1, p=12) alternative that uses CFS and yields a result of 97.94% (still higher by 0.12%) while using only 41% of the initial characteristic number. Although the accuracy is only 0.02% lower than the highest accuracy (97.96%), the memory usage has not decreased by half (41%), which makes it ideal for machines with less storage memory. Similar to the Cloud-ImVN 1.0 dataset, the achieved accuracy is 95.43% (*r*=1, *p*=8, CFS) when using only 20% of the original features. This reduction in features corresponds to an 80% decrease, yet the accuracy remains significantly higher than the original 4.43% accuracy.

Table 1. LBP features-results achieved with different FS methods

(%)	SWIMCAT						Cloud-ImVN 1.0					
	r, *p*	FS					*r*, *p*	FS				
	FAcc	CFS	Fisher	Ilfs	Lasso	Relieff	FAcc	CFS	Fisher	Ilfs	Lasso	Relieff
Acc	1, 8	97.69	97.82	97.57	97.57	97.57	1, 8	95	94.81	95.43	95.14	94.43
Std	97.57	0.41	0.43	0.55	0.55	0.55	91.00	0.87	0.97	1.08	0.82	0.96
Dim		97	97	47	76	86		56	86	20	48	77
Acc	1, 12	97.94	97.81	97.81	97.83	97.82	1, 12	94.71	94.71	94.86	94.71	94.71
Std	97.81	0.87	1.30	1.30	0.94	1.76	91.14	1.00	1.25	1.12	1.82	1.13
Dim		41	100	10	85	27		24	72	2	98	6
Acc	2, 8	97.82	97.96	97.69	97.69	97.82	2, 8	94.14	94.52	94.29	94.33	93.57
Std	97.69	0.98	0.68	1.46	1.46	1.25	97.69	0.36	0.81	1.68	2.15	1.60
Dim		96	92	88	97	98		52	93	15	38	42
Acc	2, 12	97.82	97.44	97.44	97.44	97.69	2, 12	94.81	95.14	94.19	94.91	94.71
Std	97.32	0.88	0.68	0.78	1.09	1.07	91.29	1.50	1.70	2.00	1.57	1.44
Dim		96	92	9	75	56		4.3	85	24	51	86
Acc	3, 8	97.08	97.46	97.21	97.21	97.46	3, 8	94	93.62	93.33	94.19	93.48
Std	97.08	0.64	0.96	0.90	1.10	1.14	92.24	1.76	1.77	1.53	0.82	1.60
Dim		93	67	60	56	87		53	86	22	31	44
Acc	3, 12	97.21	97.69	97.33	97.33	97.83	3, 12	94.29	94.76	94.05	94.57	93.86
Std	97.21	1.26	1.32	1.40	1.33	0.70	92.52	1.97	1.17	0.94	1.60	1.43
Dim		100	68	6	66	39		52	82	4	66	19
Acc	4, 8	96.83	96.69	96.57	96.69	97.46	4, 8	94.05	93.91	93.71	94.05	94
Std	96.44	1.12	1.46	0.99	0.98	0.96	93.38	1.59	1.83	1.53	1.66	0.87
Dim		71	69	56	76	66		69	86	96	60	49
Acc	4, 12	97.07	96.94	96.94	97.04	97.44	4, 12	94.52	94.62	94.29	94.29	94.19
Std	96.69	1.56	1.18	1.18	1.12	0.78	93.95	1.43	0.99	1.23	1.33	0.78
Dim		98	16	16	95	81		59	99	13	94	90

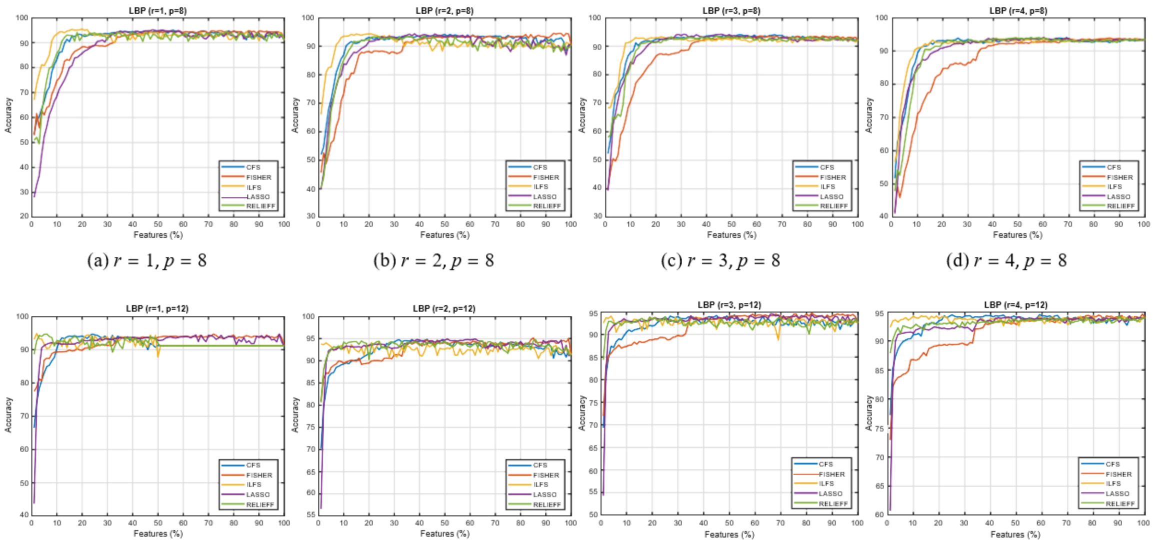
*Acc: max accuracy; r, p FAcc: r and p of LBP descriptor, accuracy with full feature; dim: percentage of selected features



(a) $r = 1, p = 8$ (b) $r = 2, p = 8$ (c) $r = 3, p = 8$ (d) $r = 4, p = 8$

(e) $r = 1, p = 12$ (f) $r = 2, p = 12$ (g) $r = 3, p = 12$ (h) $r = 4, p = 12$

Figure 3. SVM classifier on LBP features (SWIMCAT)



(a) $r = 1, p = 8$ (b) $r = 2, p = 8$ (c) $r = 3, p = 8$ (d) $r = 4, p = 8$

(e) $r = 1, p = 12$ (f) $r = 2, p = 12$ (g) $r = 3, p = 12$ (h) $r = 4, p = 12$

Figure 4. SVM classifier on LBP features (Cloud-ImVN 1.0)

4. CONCLUSION

Despite limited resources for training, FS approaches can still be highly relevant in this study, providing several benefits that are well-suited for the actual situation. FS remains advantageous as it reduces data dimensionality, enhances accuracy, reduces processing time, and can be integrated into IoT systems. The future path for improving performance in this work is through the combined use of FS and DL approaches, leveraging the strengths of both techniques to achieve optimal results.

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