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Deep Feature Fusion Method for Images Classification

Najwan Waisi

[1] Department of Computer Engineering, Northern Technical University Mosul, Iraq

***Correspondence:** najwan.tuhafi@ntu.edu.iq

Abstract: In this paper, a new method for extracting features from images is proposed based on fusion technology to recognize and classify image contents. To obtain the best features, the most important techniques used for extraction were combined, which include convolutional neural network (CNN), histogram of oriented gradient (HOG), and local binary pattern (LBP). This technique enables the model to fit features from the following aspects: integrating the features of shape, texture, scale, rotation, and translation. Homogeneous descriptors were also employed to feed the classification process, relying on a support vector machine (SVM) classifier. We applied this method to the oxford_flowers102 data set, due to the importance of flowers in the food chain of living organisms. Through experiments, we obtained results showing the superiority of the proposed method in terms of performance and accuracy over competing methods.

Keywords: CNN; HOG; LBP; SVM; Feature Fusion.

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1. Introduction

Nowadays, deep learning techniques, in particular, convolutional neural networks, are considered one of the most prominent tools for extracting features from images. This is achieved by exploiting the power of multiple max-pooling and convolutional layers [1]. In this way, a very complicated patterns in image features are efficiently identified, resulting a meticulous image classification method. Additionally, the deep learning resilience makes it perfect to adjust its structure and optimize the performance for particular classifications. In image classification, deep learning is excellent in decreasing false positives [2,3]. In the proposed work, CNN, histogram of oriented gradients (HOG), and histogram of local binary patterns (LBP) is employed for image feature extraction. Also, the SVM classifier approach is used to classify the extracted features. Flowers are very important in human live; for that reason, researchers made distinguished efforts in this field. Texture, shape, and color are characteristics used in conventional flower classification. Nevertheless, in such ways, human intervention is required in the feature selection process which might lead to less accurate classification [4] this makes the first challenge in image classification.

The second challenge the same type of flower takes different shapes depending on the environments and the time of year. Furthermore, the accuracy of data sets plays a crucial role in image classification which makes it difficult in some environments like forests [5]. There are types of flowers that looks alike even in leaf shape and length which makes it challenging to the classification process [6]. Thus, detailed examination is crucial for the classification accuracy. The detailed examination must include stem form, shape of the leaf, the way that the branches are attached, and color because those details remarkably affect the process of classification. Recently, flower identification is achieved by flower species recognition. Image normalization and resizing are preprocessing techniques applied to flower data sets [7]. This approach successfully improves the classification of the flower species. CNN has been proved to show excellent outcomes regarding feature extraction [8].

Nonetheless, deep CNN models demand a high computational resource, and might produce overfitting or local optimization issues. To overcome the aforementioned reasons, fusion feature extraction model is implemented in this study. Thus, various fusion approaches are combined together, and detailed results analysis took place in the experiment. The proposed model outcomes showed distinctive accuracy in flower recognition in comparison with other models. Furthermore, the propose model showed generalization capabilities and robustness, resulting a more accurate classification.

2. Related Work

Recently, there are many studies in the field of flower recognition and classification. The authors in [9] utilizes a combination of multicore frames as features. They applied SVM to classify the flowers in the Oxford-102 dataset. The achieved accuracy was 88.33%. In [10], a novel technique is used by firstly applying segmentation, then the HOG and the locality constrained linear coding (LLC) methods is used to extract features. The researchers in [11] employed a fine-grained classifier in which, 93.14%, and 79.1% accuracies was achieved in the Oxforf-17 and Oxford-102 datasets respectively. In [12], the authors implemented a combination of SVM and fusion descriptors, they achieved 86.17% accuracy on the Oxford-17 dataset.

In terms of deep learning and computer vision including classification of images, CNN recently became the ruling model. In image classification, significant features are extracted and then classified in to predefined classes. CNN models take the lead into identification of objects in images and specify them to known classes. The authors in [13] used CNN in flower classification accuracy enhancement. Thus, they took advantage of the powerful classification CNN ability in comparison with the other traditional techniques that depends on the manual crafting of visual features. In this way, they achieved 84.02% accuracy on the Oxford-102 flowers dataset.

Nevertheless, extracting manually selected features has its own limitations, because that the target characteristics might not completely captured. As a result, the performance is not optimal. Also, overfitting problem may occur in flower recognition using deep CNN, leading to lower accuracy. In [14], the authors employed a pre-trained CNN model designed by Google, which known as GoogLe-Net in addition to the inception-v3 module to classify the flowers. The experiments conducted in the study involved the use of two datasets, namely the Oxford 17-Flowers and Oxford-102 Flowers, which were also utilized in previous studies as well as in their own research. Despite the datasets not being of significant size, the authors achieved remarkably high accuracy rates of 95% and 94% for the Oxford 17-Flowers and Oxford-102 Flowers datasets, respectively. [15] employed two datasets and utilized the Alex-Net model in addition to VGG-16 to extract the features of images. The resulted features by these two models were combined, and a feature selection process was performed using the minimum redundancy maximum relevancy (MRMR) algorithm. The selected features were then classified using support vector machines (SVM). [16] conducted a comparative study between YOLOv7 and YOLOv4, which are state-of-the-art object detection models, for the classification of apple flower buds. The datasets used in the study were artificially manipulated to vary the quality of image annotations, ranging from 100% to 5%. Notably, across all growth stages and at all levels of training image annotation quality, YOLOv7 consistently outperformed YOLOv4. The results clearly demonstrated the superior performance of YOLOv7 in apple flower bud classification.

3. Dataset

The 102-Flowers dataset is used in this work, which is a dataset provided by the Oxford Visual Geometry Group and; it is a set of different flower species found in England. Each flower category in the dataset is comprised of 40 to 200 images. Also, each image in the data set has a different setting of lighting and exposure conditions. Moreover, there are classes in the dataset that explains the significant differences, and classes share similar characteristics with others. Figure 1 shows a 20 different kind of flowers from the Oxford-102 Flowers dataset [17].

Figure 1: Examples of 20 flower species from the Oxford 102-Flower Dataset [17].

4. Proposed Methodology

Multiple phases are considered in this work, starting with noise detection and removal for quality enhancement purposes. Next, the system defines where the regio of interest (ROI) is, so that to concentrate on the distinctive image characteristics. Convolutional Neural Network (CNN), Histogram of Oriented Gradient (HOG), and Local Binary Pattern (LBP) are techniques used together to extract the different features from the ROI like shifting, contrast, pattern, and scale. Finally, the Support Vector Machine (SVM), which is a multi-class classifier, is used to classify the 102 classes in the Oxfor-102 dataset.

4.1 Pre-Processing

To decrease the computations complexity and resource requirements in the preprocessing phase, the images in the dataset are downscaled to reduce their sizes in all dimensions. By doing this, the data is processed in efficient way, while the processing time is reduced. Thus, the preprocessing phase makes sure that the images are optimized for the upcoming phases.

4.2 CNN as Feature Descriptor

The CNN architecture is comprised of multiple layers that extracts the desired features [18]. The first one is the convolutional layer with a filter size of 32, where the input image is applied to a set of filters to extract local patterns and features. The next layer is pooling, its job is to reduce the spatial dimensions of the feature maps and at the same time, preserve the most relevant information. To down-sample the feature maps, the pooling layer uses a pooling window of size 2 * 2 and a stride of 1. To aid in capturing different levels of features from the input data, the pooling and the convolutional layers are repeated alternately for the first six layers of the network. The ReLU (rectified linear unit) activation function is the following layer in the network. ReLU presents non linearity to the network, which allows modeling complex relationships between the input and the extracted features. To capture a higher-level representation, another convolutional layer is added with a filter size of 128. The softmax activation is the final layer, which normalizes the outputs of the previous layer into a probability distribution over the possible output classes. To ensure consistent and accurate calculations, it is important to keep the weights of the convolutional layers and the values of variables in the max-pooling layers constant int the network. The input images used in the network are grayscale with a size of 224 * 224 * 1, where the last dimension represents the number of channels. Finally, to enable the network to learn and classify the input images effectively, the images are propagated through all the layers during the forward propagation process.

4.3 HOG as Feature Descriptor

One method to extract the important information from images is transforming the image to a sequence of blocks and split them into smaller cells that connected to each other. After that, the direction of the cell is determined using the technique of histogram the gradient directions within each cell, and by analyzing the color gradient of the pixels inside the cell, they are classified based on their directions [19]. The final step represents by the normalization of the concatenated histogram outcome from all the cells inside a larger spatial region, which is named by a block, to obtain a superior performance.

4.5 LBP as Feature Descriptor

The main Local binary pattern (LBP) factor is a robust means of texture description. it represents an effective method for gray-scale and rotation invariant texture classification. it is used to extract features that is not affected by possibility of mean illumination, the aim of LBP is to detect the feature which is invariant against gray-scale shifts.

4.6 Feature Selection

The Minimum Maximum Relevance (MR-MR) technique has been utilized in this paper, to select the most important characteristics of subject categories. This method is aim to improve feature-category relevance and minimize redundancy, enhance the flow of information. The MR-MR, is used to select the information-rich features that enhance the classification process, boosting the model's efficiency and accuracy [20, 21]. The MR-MR algorithm, based on mutual information, is described in the following formula.

$$\max\ [\ \frac{1}{|s|}\sum_{x_i\in s} I(x_i;C) - \frac{1}{|s|^2}\sum_{x_i\in s}\sum_{x_j\in s}(I(x_i;x_{j)})\ ] \qquad \ldots\ldots (1)$$

where x_i is the nth feature in subset S.

5. Classification

After finishing the feature extraction and selection stages, significant stages represent by classification of the selected features is started. In the proposed work, the trained model has the selected features as input and classifies the images into classes. For classifier training, 80% of the dataset is used for training, and the remaining 20% for testing. For classification, SVM is implemented in this work, which is a supervised learning algorithm [22, 23]. The implementation of SVM enables the system to grasp the characteristics and patterns of the features and construct the predictions depending on the learned knowledge [24-27]. Figure 2 shows the proposed architecture.

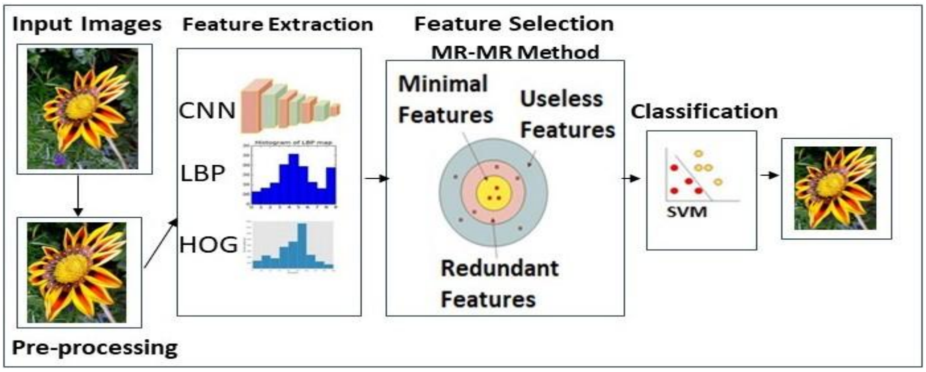

Figure 2. The proposed model architecture.

6. Experimental Evaluation

A detailed overview of the conducted experiments and the achieved results are presented in this section. The proposed system efficiency is evaluated by using a large and diverse dataset, and various metrics are used to measure the system's performance. Also, a cross-validation experiments are conducted to ensure the robustness of the proposed system. A combination of CNN, HOG, and LBP algorithms are used for feature extraction during the training phase. The CNN architecture consisted of multiple convolutional and pooling layers, which were alternately stacked to capture important visual patterns. The Softmax function was used for classification at the final layer, and the ReLU activation function was utilized to enhance the learning process. After 100 iterations, an accuracy of 95% was achieved.

For image classification, the SVM algorithm is incorporated, which is effective supervised learning method that works with datasets that is rich in features. To acquire the best configuration, the SVM is trained on multiple combinations of feature descriptors. Table 1 shows the summary of the combination's performance for every classifier. The obtained results distinguish the proposed model in comparison with other flower classification models.

Table 1. Proposed models performance evaluation.

Method	Precision (%)	Recall (%)	Accuracy (%)	F1 Score (%)
SVM_CNN	93	93.88	93.5	93.46
SVM_HOG_LBP	85.1	84.89	85	85.82
SVM_CNN_HOG_LBP	95.1	94.71	95	94.82

7. Comparative Analysis

For performance evaluation purposes, multiple experiments have been conducted to compare the proposed model against other models. The experiments took place on the Oxford-102 dataset. Table 2 shows that the proposed model achieved better accuracy than the other models. The higher accuracy achieved by our method showcases its potential for practical applications and its contribution to the advancement of flower recognition techniques.

Table 2. The proposed model Vs. Another research works on the Oxford-102 dataset.

Method	Performance
[8]	79.1%
[15]	84.02 %
[11]	88.33 %
[17]	91.9%
Proposed method	95%

8. Conclusions

This research work presents classification of images of flowers by utilizing the methods of multiple feature descriptor. The Oxford-102 Flowers dataset is used in the training and testing phases of the proposed model. The flower dataset includes several species with multiple characteristics, which is beneficious in performance evaluation. The process of classification took place in multiple steps including feature extraction and classifier training. The first step is the images preprocessing, where the image quality is enhanced and the noise is removed. The next step is to incorporate the proposed multiple feature descriptor including CNN, HOG, and LBP. The aforementioned techniques allow to catch different flower features like texture, spatial relationships and shape. To remove the redundant information, the Minimum Redundancy-Maximum Relevance (MR-MR) method is used in this work. In this way, the most relevant features are selected while the redundancy is minimized. As a final step, the support vector machine (SVM) is used to classify the flowers images. The SVM training took place on the previously extracted features. Thus, the proposed work utilized a combination of multiple feature extraction methods and a robust classifier, resulting an improvement in the accuracy and the robustness in the flower classification. Finally, different datasets are need to be tested in the future to further evaluate the system.

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