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Original Article

An Efficient Flower Classification System using Feature Fusion

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Abstract - *Automatic classification of flowers is essential in research on flowers, medicinal use of flowers, flower patent analysis etc. Traditionally, flower classification is done using low-level features like color, shape, texture and geometry. There exist large intra-class variation and interclass similarity among flower classes. Search engine-based flower identification and classification system are not efficient and robust because they are based on visual search. The accuracy and robustness of flower classification depend highly on the feature descriptor. Deep features have shown excellent performance in the last few years on high-resolution images, but they cannot extract accurate global features from low-resolution images. Hence, an efficient flower classification system using a fusion of handcrafted features and deep features is proposed in this paper. Low-level features are extracted using Color Coherent Vector (CCV), Centre Symmetric Local Binary Pattern (CSLBP) and Edge Histogram Descriptor (EHD). Deep features are extracted from pre-trained networks: ResNet-50 and AlexNet. Further, a Multiclass Support Vector Machine (SVM) is used to yield high classification accuracy. Experiments are carried out on Oxford Flower 17, Flower102, Kaggle flower dataset and Corel-1K dataset. Classification accuracy of 100, 95.3, 94 and 92% is obtained on the Corel dataset, Oxford Flower 17, Kaggle flower dataset and flower 102 dataset, respectively, which is better than existing approaches. A remarkable achievement in classification accuracy of 86.4% is observed on the pooled dataset.*

Keywords - *Deep Learning, Image descriptor, Convolutional Neural Networks, Image classification, Pooled dataset.*

1. Introduction

Flowers are an integral part of our ecosystem. They are mainly used in floriculture, the cosmetic industry and herbal medicine. Given several flower images, it is very time-consuming to identify flower species manually. Automated flower classification is challenging due to a large number of similarities among classes, the complex structure of flowers and the unpredictable variety of flower classes in nature. Flower image classification is a vibrant research area in image processing and computer vision. Plenty of classifiers have been proposed in the recent past for different applications. Most traditional classifiers use local, global or both types of image features. Low classification accuracy due to inadequate feature descriptors is the major limitation of these methods. Ala et al. [1] used RGB color moments, HSV color histogram, Gray level Co-occurrence Matrix (GLCM) texture features, Scale Invariant Feature Transform (SIFT) key points, and Histogram of Oriented Gradients (HOG) features for flower classification. The authors observed a success rate of 83.5 % for the Flower 17 dataset with the SGD classifier.

Most of the traditional methods require various pre-processing techniques. This is very challenging. Therefore many researchers have automatically done feature extraction instead of using manual methods. Deep learning has provided excellent results in the applications of computer vision like object detection, image segmentation, image classification etc. Different neural layers process an enormous amount of data in deep CNNs, like the human brain. Deep features are very much valuable for image classification.

Tian et al. [2] classified images from Flower 17 dataset using the data augmentation method with their CNN model. The classification was done using the Softmax function. The authors reported a classification accuracy of 92%. M. Ghazi et al. [3] employed pre-trained AlexNet, GoogleNet and VGG-16 CNNs for the flower classification. They used the image augmentation technique to obtain the new augmented image dataset and observed an accuracy of 80%. However, due to low resolution, interclass similarity and intra-class variety among flower classes, it is very challenging to classify the images correctly.

It is observed that no single feature extraction method is sufficient for flower image classification. To tackle this issue, a new method using the fusion of handcrafted features and deep features to improve the classification accuracy of flower images is proposed in this paper. Handcrafted features are extracted using CCV[4], CSLBP[5] and EHD [6] and deep features are extracted using ResNet-50 [7], and AlexNet [8] and the final feature descriptor is obtained by fusion of handcrafted features and deep features in this research. Classification is done using a multiclass SVM classifier [9].

The classification success is tested on the Oxford flower dataset [10], Corel 1K dataset [11] and pooled dataset. The sections in this study are as follows: the related work is presented in Section II, the proposed work is explained in section III, a description of datasets is provided in section IV, experimental results are described in section V, and the conclusion is provided in VI.

2. Related Work

Conventional flower classification techniques, i.e. non-deep learning-based methods, use a blend of features extracted from the flower images to improve classification accuracy [12-14]. Different flower species are identified using colour, texture, shape and statistical information [15]. In 2006, authors proposed a Visual Vocabulary for representing the color, shape and texture of flower images from the Oxford flower 17 dataset and achieved an accuracy of 75.3% for shape, 56.0% for texture and 49.0% for colour [16] for flower identification. The best performance (81.3%) was obtained by combining shape and colour.

Automatic classification of flower images using the K-nearest neighbour classifier was done in [17]. Image texture features were extracted using Gray Level Co-occurrence Matrix (GLCM) and Gabor responses. Then classification was performed by using a k-nearest neighbour. However, the classification accuracy in this approach was moderate. In [18], authors extracted texture features using GLCM and color features using Color moment. The classification was done using a neural network classifier. Experiments were performed on a small dataset having only five flower classes containing 200 images. In [19], experiments were performed on the Oxford Flower-102 dataset. The authors used the HSV color descriptor, GLCM texture descriptor and Invariant Moments (IM) as shape descriptors for flower feature extraction. The classification was done using a Back-Propagation Artificial Neural Network (ANN), which provided a classification accuracy of 81.19%, which is relatively low.

In the recent past, Deep CNN has been used popularly for solving complex problems with a massive amount of data [20]. For example, authors obtained good classification accuracy using the ImageNet dataset [8] consisting of 1000 categories. The motivation for using deep features was to eliminate the difficulty in feature extraction. Nowadays, deep learning technology is considered a promising research topic in machine learning, artificial intelligence, data science and analytics because of its learning capabilities from the given data [22].

In [23], AlexNet, GoogleNet, ResNet-50, and VGG-16 CNN models were used for feature extraction. Efficient features were selected and classified by SVM. Excellent classification success on the Kaggle flower dataset demonstrated the importance of deep features. However, four deep networks were used by authors. In [24], authors have explained advancements in image classification using different Convolutional Neural Networks.

The base Vgg-16 model was fine-tuned in [25] to classify flowers into five categories. The authors reported a classification accuracy of 95%. However, this approach could classify only five types of flowers. It was reported in [26] that deep features outperform handcrafted features. The authors analysed classification accuracies using OverFeat, Inception-v3 and Xception architectures on Flower 102 dataset, and it was reported that Inception-V3 yields the highest accuracy among the three architectures. In [27], an analysis of the performance of VGG-16, VGG-19 and Resnet-50 on the ImageNet dataset was presented. The arbitrary set of annotated images was given as input to these three networks for classification. It was reported by the authors that the performance of ResNet-50 was better compared to VGG-16 and VGG-19.

There exist numerous flower species in nature. The flower classification model designed for a particular dataset may not be applicable if the dataset is changed or expanded. Also, there exists scope for improvement in the classification accuracy of existing models. From the review of the literature, it is revealed that deep features alone are not sufficient to extract all the important information from the image. Neither handcrafted features nor deep features alone can be considered efficient image feature descriptors for image classification. Hence, the fusion of handcrafted and deep features for flower image classification is proposed in this paper. Handcrafted features are extracted using CCV, CSLBP and EHD. Deep features are extracted from pre-trained networks: ResNet-50 and AlexNet. Further, Multiclass SVM is used to yield high classification accuracy. Experiments are conducted on five different publicly available datasets. In addition, we have created a pooled dataset by combining these datasets to check the robustness of the proposed method.

3. Proposed Work

The proposed method involves three steps for flower image classification. In the first step, handcrafted features and deep features from flower images are extracted. The fusion of deep and handcrafted features is done in the second step. Classification is done using a multiclass SVM classifier in the last step. Fig. 1 shows the framework of the proposed method.

3.1. Handcrafted Features

The most important block of the image classification model is the feature extraction block. A feature is used to capture the visual properties of an image. Color, texture, shape, etc., are the most widely used features in most image classification systems. It is observed that no single feature is sufficient to describe the visual content of the image completely. Hence, after performing a series of experiments following features were found to represent image content effectively.

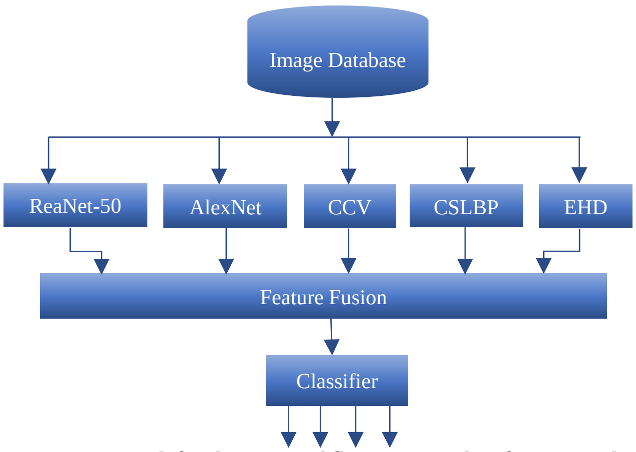

Fig. 1 Framework for the proposed flower image classification method

3.1.1. Color Coherent Vector

Color is the most popular feature on account of invariance to scaling, translation and rotation of an image [4]. Color histogram is widely used in many applications. However, spatial information of pixels is neglected in the color histogram, which may result in an identical histogram for dissimilar images. Color-coherent vector solves this problem [28]. Authors of [4] compared the performance of color histograms, color moments and color coherent vectors for the Content-Based Image Retrieval (CBIR) problem using 14500 images and reported that CCV is the best color feature descriptor. Hence, we have chosen CCV as the color feature extraction method in the proposed work.

In CCV, each histogram bin is divided into two types: coherent and incoherent. CCV represents all colors in the image. The pixel groups are determined by finding the connected components.

Let the number of coherent pixels of the j'th discretized color j as α_j and the number of incoherent pixels β_j. The color coherence vector for the image is given by

$$(\alpha_1,\beta_1), (\alpha_2,\beta_2),\ldots\ldots.(\alpha_n,\beta_n)$$

By default, the number of colors in the Color Coherence Vector is 27, as provided in [28]. Hence, the size of CCV is 1x54.

3.1.2. Center Symmetric Local Binary Pattern

Texture features are crucial in image classification problems. Commonly used texture features are obtained using Local Binary Pattern (LBP) [5]. The histogram of LBP is calculated for the given picture or patch where the histogram length is 2N. The LBP histogram is extended and cannot be used efficiently for area descriptors. Due to this, we have used a histogram of CSLBP for texture feature extraction from flower images. The CS-LBP [5] is used to describe the relationship of the pixel intensity between the point and its local region. The CSLBP operator [29] compares the pixel value pairs in the neighborhood with the center pixel. If it is greater than or equal to the center pixel, it is 1; otherwise, it is 0. An ordered binary string is thus obtained, which is then converted into a decimal number as the code of the center pixel. Fig. 2 shows the circle neighborhood for the CSLBP operator

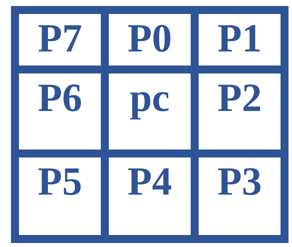

Fig. 2 Circle neighborhood for CSLBP

The binary pattern for the CS-LBP feature of pc is given by

$$\text{CSLBP pc}= S(p^0\text{-}p^4)\,2^0 + S(p^1\text{-}p^5)\,2^1 + S(p^2\text{-}p^6)\,2^2 + S(p^3\text{-}p^7) \quad (1)$$

Tolerance to lighting changes and blurs is the most advantageous property of this feature. The numerical calculations involved in this feature are less, and it has good anti-noise ability.

The CSLBP operator is a quantized LBP operator which is given by

$$CSLBP_{N,r,T}\,(p) = \sum_{i=1}^{N/2} s(|ni| - \left|ni + \tfrac{N}{2}\right|)\ 2^{i-1}$$

$$s(j) = \begin{cases} 1, & j \geq 0 \\ 0, & otherwise \end{cases} \quad (2)$$

Where ni and ni+N/2 signify the normalized gray values of centre-symmetric pairs of pixels on a circle with a radius of r, and j represents the threshold of normalized gray value. In this research, R = 1, N = 8 and j = 0.01 is used.

Based on eight neighbouring textures, Equation (2) uses 16 specific patterns, these patterns are represented by decimal numbers from 0-15, and the CSLBP feature vector of these 16 patterns for all pixels is calculated for the given patch P. Size of CSLBP feature vector is 1x16.

3.1.3. Edge Histogram Descriptor

The Edge Histogram Descriptor (EHD) [6] is used for shape detection, which signifies the relative frequency of occurrence of 5 types of edges sub-image. The histogram for each sub-image characterizes the relative distribution of the 5 types of edges, as shown in Fig. 3.

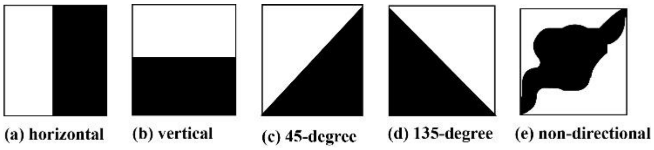

Fig. 3 Five types of edges in EHD

An edge histogram is obtained by applying digital filters in the spatial domain. The filter coefficients for edge detection are shown in Fig. 4. In addition to the local histogram, the global histogram is also needed. Bin values for all global histograms can be obtained from the local histogram. For the five edge types, there are five bins for the global edge histogram. As a result of this, there are 80 bins (local) + 5 bins (global) = 85 bins. Hence, EHD has a size of 1x85.

$$\begin{array}{ccccc}
\begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix} &
\begin{bmatrix} 1 & 1 \\ -1 & -1 \end{bmatrix} &
\begin{bmatrix} \sqrt{2} & 0 \\ 0 & -\sqrt{2} \end{bmatrix} &
\begin{bmatrix} 0 & \sqrt{2} \\ -\sqrt{2} & 0 \end{bmatrix} &
\begin{bmatrix} 2 & -2 \\ -2 & 2 \end{bmatrix} \\
\text{a) Vertical edge Filter} & \text{b) Horizontal Edge Filter} & \text{c) Dia 45 Edge Filter} & \text{d) Dia 135 Edge Filter} & \text{e) Non Edge Filter}
\end{array}$$

Fig. 4 Filters for edge detection

3.2. Deep Feature Extraction

We have used two different pre-trained networks for deep feature extraction in the proposed work. Fig.5. shows a general framework for deep CNN-based feature representation using the pre-trained network. Image features are obtained from the fully connected layer in the deep neural network.

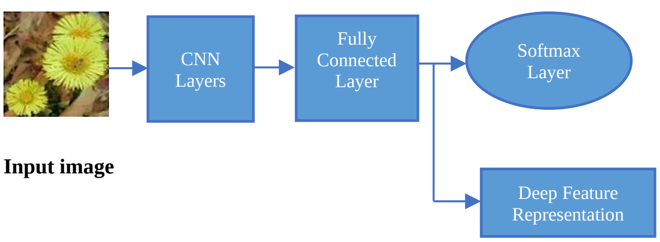

Fig. 5 Deep CNN-based feature representation

3.2.1. ResNet-50 Deep features

The accuracy and performance of the deep neural network can be increased by stacking additional layers in the network. More complex features are learnt using these layers. However, the network's performance degrades if the number of layers is increased beyond a certain threshold. To solve this problem, He et al. [7] proposed a residual network named ResNet-50 by avoiding connections on two to three layers containing Rectified Linear Unit RELU and batch normalization among the architectures. It was demonstrated that image features were extracted well by ResNet.

The residual block on ResNet is defined as follows

$$y = F(x, W+x) \tag{3}$$

Where x is the input layer, y is the output layer, and the residual map represents the F function. High-level features extracted from the deep layer are well-matched for recognition tasks because they combine all primitive features into a richer representation. The activation method can extract features from any of the deeper layers. The deep residual neural network ResNet-50 is used in the proposed work. It has 50 layers. Database flower images are resized to 224x224 and given as input to ResNet- 50 pre-trained network. Features are extracted from the layer right before the classification layer i. e. FC-1000 layer of ResNet-50.

3.2.2. AlexNet Deep Features

AlexNet [8] is an eight-layer network with five convolutional layers (Conv1 - Conv5) and three fully connected layers (fc6, fc7 and fc8). Features are extracted in convolution layers. The initial layers in the network learn low-level features and subsequent layers learn high-level features. In the proposed work, features are extracted from the fc8 layer of the network. The Alex-Net model is chosen in this work because of its superior performance, fewer training parameters and strong robustness.

The output of the first convolutional layer captures the presence or absence of edge at a particular orientation and location in the image; the second layer detects corners and other colours/edge conjunction; the third layer mainly captures motifs and textures; the fourth layer is more class-specific and starts detecting parts of objects; the last convolutional layer detects entire objects—features extracted by the fully connected layers, capture characteristics of flower images.

In the second step, a fusion of handcrafted features and deep features is done. The fused feature vector is then given as input to the SVM classifier.

Feature Fusion: To differentiate between images using handcrafted features has some limitations. Also, deep features alone are not capable of image classification for different types of datasets. Therefore, the proposed work uses the fusion of shallow and deep features to improve classification accuracy.

The fused feature vector is obtained as
FFV= {F1 F2 F3 F4 F5}
Where F1, F2, F3, F4 and F5 are mentioned in Table 1.

Table 1. Notations used for different features

Feature	Notation
ResNet-50	F1
AlexNet	F2
CCV	F3
CSLBP	F4
EHD	F5

3.3. SVM Classifier

A support vector machine is a standard tool used for supervised learning [9]. It constructs hyperplanes from a set of labelled training datasets. In the proposed work, multiple flower classes make generating support vectors difficult. We initially trained the model to solve this problem by generating support vectors for all "n" classes. These vectors separate one class from all other classes, which are then used for predicting the class labels.
Let $C_1, C_2, \ldots, C_n$ be n number of flower classes.
Let $S_1, S_2, \ldots, S_m$ are the support vectors of the above classes.
In general,

$$C_i = \sum_{k=1}^{n-1} \sum_{j=1}^{m} c_k S_j \tag{4}$$

Where C_i consists of a set of support vectors Sj, which separates the n^{th} class from all other classes.

The features obtained by the fusion of handcrafted and deep features assist SVM in classifying flower images.

4. Datasets Used

Six publicly available datasets are used to evaluate the proposed method's performance. A brief explanation of each of the datasets is given below:

4.1. Oxford Flower 17 Dataset

This dataset consists of 17 categories of flowers, with 80 images of each [10]. Some categories of flowers have very different features, whereas some categories are very similar to each other. Class diversity and slight differences between categories make it challenging to classify them correctly. Sample images from this dataset are shown in Fig.6.

4.2. Oxford Flower 102 Dataset

This dataset consists of 8189 images divided into 102 flower categories [10]. This dataset is more challenging than Flower 17 dataset since it has more images and categories. Sample images from each category are shown in Fig.7.

4.3. Corel 1K

Corel 1K database contains 1,000 natural images divided into 10 diverse classes [11].

4.4. Open access Flower Dataset: Kaggle dataset

This dataset contains 4323 images of flowers from Kaggle [30]. It includes 5 types of flower images with different resolutions. This dataset consists of consists of 769 daisies, 1052 dandelions, 784 roses, 734 sunflowers, and 984 tulip images.

Fig. 6 Sample images from Oxford Flower 17 dataset

Fig. 7 Sample images from Oxford Flower 102 dataset

4.5. KLU Flower dataset

Authors of [39] created this dataset. It consists of 30 flower classes with 100 images in each class.

4.6. Pooled dataset-1 and Pooled dataset-2

We have obtained these datasets by combining flower 17, flower 102, Kaggle flower dataset and Corel-1000 dataset. Pooled dataset-1 consists of 8309 flower images with 124 classes, and Pooled dataset-2 consists of 14821 flower images with 154 classes.

Table 2 shows the dataset name and the corresponding number of images in it.

Table 2. Datasets used

Dataset	Number of classes	Number of images
Oxford Flower-17	17	1360
Oxford Flower-102	102	8189
Corel- 1K	10	1000
Kaggle dataset	5	4323
KLU Flower Dataset	30	3000
Pool Dataset-1	124	8309
Pool Dataset-2	154	14821

5. Experimental Results

This section presents the experimental results of the proposed feature fusion-based flower classification system. Experiments are conducted on the datasets mentioned above. The success of classification is evaluated using classification accuracy. Handcrafted features are extracted using CCV, CSLBP and EHD. Deep feature extraction is done using pre-trained networks ResNet-50 and AlexNet. The notations used for various feature combinations are as given in Table 3.

In the first experiment, we extracted CCV, CSLBP and EHD features of all images in the Flower-17 and Flower-102 datasets. These features were concatenated to obtain a combined feature vector of size 1x155. The SVM classifier classified these features. The classification accuracies of 60% and 57.2 % were obtained for the flower-17 and flower-102 datasets, respectively.

In the second experiment, we trained the deep CNN model ResNet-50 with the flower-17 and flower-102 datasets. Deep features were extracted from the FC-1000 layer of ResNet-50. These features were classified with an SVM classifier. Classification accuracy of 87.6 % and 84.2 % were observed for the flower-17 and flower-102 datasets, respectively.

In the third experiment, we trained the deep CNN AlexNet with both datasets mentioned above. Deep features were extracted using FC-8 of AlexNet. These features were classified by the SVM classifier giving classification accuracy of 90 % and 78.6 % for the flower -17 and flower-102 datasets, respectively.

We obtained a fusion of handcrafted and deep features in the fourth experiment to get a new feature set. Classification accuracy for various combinations of features is given in Table 4. Experimental results reveal that fusion of ResNet-50 deep features and handcrafted features provides better classification accuracy compared with AlexNet deep features and handcrafted feature fusion. The network depth of the ResNet-50 is more extensive, so it achieves better accuracy and is computationally more efficient than AlexNet. ResNet-50 overcomes the vanishing gradient problem or degradation problem and hence provides better accuracy compared with AlexNet.

The classification accuracy for combination (F1+F2) and (F1+F3+F4+F5) for the flower 17 dataset is the same, i.e. 95.3 %; there is a difference in the number of features used. The total number of features in (F1+F2) is 2000. Hence, more computations are needed resulting in more time complexity. The number of features in the combination (F1+F3+F4+F5) is 1155, which requires comparatively fewer computations and hence less time for providing classification results. For the flower 102 dataset, classification accuracy for the combination (F1+F2) is less compared with the (F1+F3+F4+F5) combination. However, for other datasets, it is higher even though the number of features is less. It is an important observation in the proposed work.

The classification accuracy on all datasets used in this work is better when the fusion of Handcrafted features and ResNet-50 deep features are done. It is comparatively less when handcrafted features and AlexNet deep features are combined. Oxford flower 102 datasets is more challenging than the Flower17 dataset; therefore, comparatively less classification accuracy is obtained. The proposed method gives a classification accuracy of 100 % on the Corel-1K dataset. Both the pooled datasets used in this work are challenging. 88.7 % and 86.4 % are classification accuracies obtained on pooled dataset-1 and pooled dataset-2, respectively. The accuracy for the KLUF dataset was 96.9 %.

The size of the handcrafted feature vector (CCV, CSLBP, and EHD) is 1x155. The deep feature vector has a size of 1x1000. Hence, the fused feature vector has a size of 1x 1155. It is important to note that the proposed method achieved promising accuracies on different datasets using the minimum number of features, which obviously saves memory space and training time. Fig. 8 shows classification accuracy for various feature combinations.

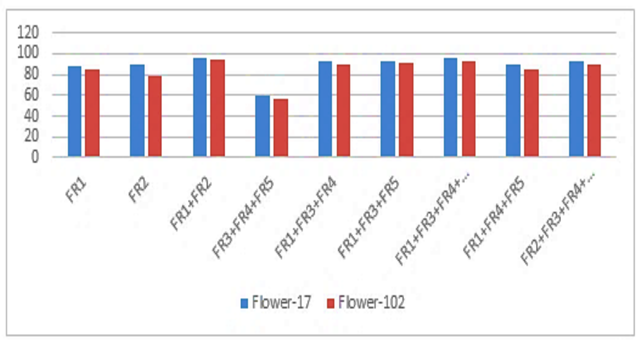

Fig. 8 Classification accuracy for various feature combinations

Table 3. Notations used

Feature Combination	Notation
F1	F1
F2	F2
F1+F2	FC1
F3+F4+F5	FC2
F1+F3+F4	FC3
F1+F3+F5	FC4
F1+F3+F4+F5	FC5
F1+F4+F5	FC6
F2+F3+F4+F5	FC7

Table 4. Classification Accuracy for various feature combinations

Features	Dataset	Classification Accuracy %
F1	Flower 17	**87.6**
F2		90.0
FC1		95.3
FC2		60
FC3		92.9
FC4		93.2
FC5		**95.3**
FC6		89.5
FC7		93.5
F1	Flower 102	84.2
F2		78.6
FC1		94.3
FC2		57.2
FC3		90.1
FC4		90.8
FC5		**92.0**
FC6		85.1
FC7		89.5
F1	Corel 1K	90.2
F2		92.0
FC1		96.3
FC2		80.2
FC3		93.4
FC4		94.3
FC5		**100**
FC6		89.5
FC7		98.0
F1	Kaggle dataset	86.2
F2		80.6
FC1		93.3
FC2		62.2
FC3		92.1
FC4		91.5
FC5		**94.0**
FC6		88.4
FC7		92.1
F1	Pooled dataset-1	77.6
F2		79.3
FC1		82.3
FC2		60
FC3		65.9
FC4		82.2
FC5		**88.7**
FC6		80.5
FC7		88.3
F1	Pooled dataset-1	75.3
F2		77.2
FC1		88.5
FC2		58.2
FC3		65.9
FC4		82.2
FC5		**86.4**
FC6		78.4
FC7		85.1

Fig 9 (a) and (b) show the confusion matrix and ROC, respectively, for Corel 1K dataset

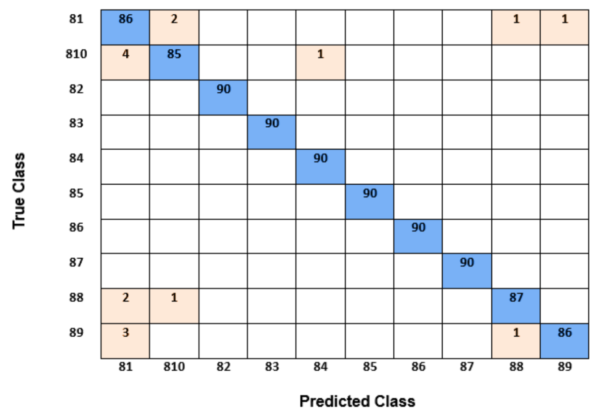

Fig. 9 (a)Confusion Matrix for dataset Corel-1K

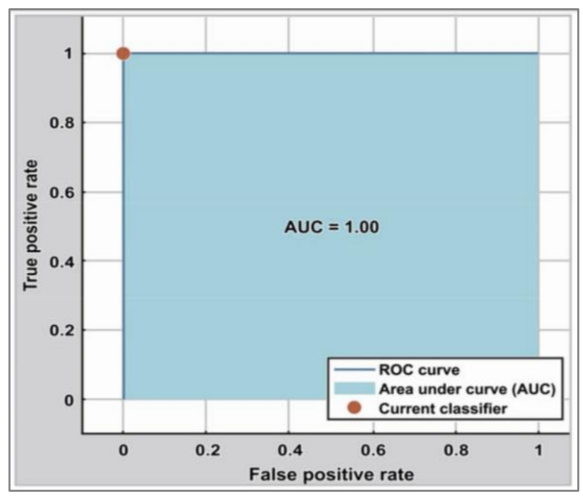

Fig. 9 (b) ROC for dataset Corel-1K

Fig. 10 and 11 show the confusion matrix for the Kaggle flower dataset and Flower 17 dataset, respectively

Fig. 10 Confusion matrix for Kaggle flower dataset

In the fifth experiment, category-wise average precision for the Corel-1K dataset was studied, given in Table 5.

It is observed that precision for Bus, Dinosaurs and Elephant images is 100 % and that for African people images, it is less (83.35 %).

Table 5. Category wise Avg. Precision for Corel 1K dataset

Category	Average Precision %
African People	85.35
Beach	97.2
Building	94.3
Bus	100
Dinosaurs	100
Elephant	100
Flower	99
Horse	98.25
Mountain	98.95
Food	96.5

5.1. Comparison of Proposed Method and Existing Methods

In the sixth experiment, the proposed method is compared with existing methods regarding classification accuracy. The analytical comparison based on technique and accuracy achieved is presented in Table 6. which indicates that the proposed approach is better than existing approaches. Three datasets out of six datasets used in the proposed work are used for comparison purposes, depending on the availability of literature for image classification.

In [32], authors combined a saliency map with the gray-scale map to select a flower region which was then given as input to train the PCANet. The classification was done using a 102-way softmax layer. The authors achieved 84.12% accuracy on Oxford Flowers 17 dataset. The reason for less accuracy in [32] is the simple network in feature learning. In [33], the authors segmented the input image by applying the active contour segmentation method. LBP and SURF features were then extracted and concatenated. The SVM classifier was used for classification. A success rate of 87.2 % was achieved on Oxford Flower 17 dataset. The accuracy was moderate due to the use of handcrafted features alone.

Authors in [34] combined saliency detection and VGG-16 convolutional neural network and adopted a stochastic gradient descent algorithm. Use of CNN improved the classification accuracy (91.9 %) on the flower-102 dataset. Flower image features were extracted using HSV color descriptor, GLCM texture descriptor and Invariant Moment shape descriptor in [20]. The classification was done using an artificial neural network. Low classification accuracy was due to the use of handcrafted features alone.

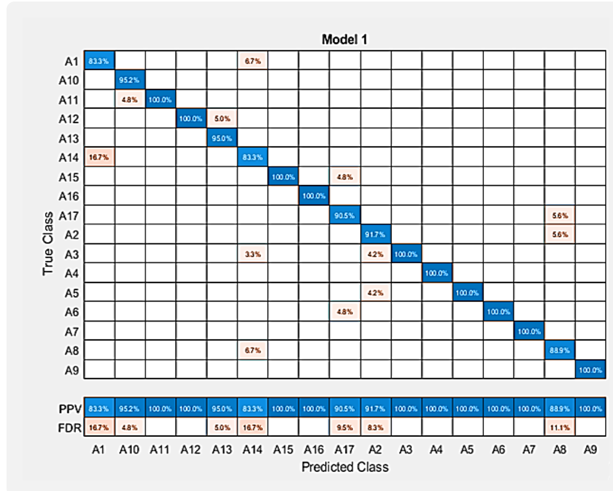

Fig. 11 Confusion matrix for Flower 17 dataset

Table 6. Comparison of the proposed method with existing methods

Method	Author and Year	Dataset	Classification Accuracy %
PCANet	Yan Yangyang 2019	Flower 17	84.12
LBP and SURF features	P. Dhar 2019		87.2
ResNet50+ handmade features	Proposed method		**95.3**
VGG- 16	RongxinLv 2021	Flower 102	91.9
Image processing and ANN	H. Almogdady 2018		81.19
ResNet50+ handmade features	Proposed method		**92.1**
VGGNet	Gadkari 2019	Kaggle dataset	91.73
VGGNet	Chen 2019		89.0
Inception ResNetV2	F. Bozkurt 2021		92.25
ResNet50+ handmade features	Proposed method		**94.0**

Chen et al. [36] used machine learning and deep learning methods (Custom CNN, VGG, ResNet and DenseNet) and observed that the deep learning method works much better. A classification accuracy of 90 % was observed on the Kaggle flower dataset. Gadkari et al. [37] used transfer learning methods for flower classification. They obtained the best validation accuracy of 91.73% with the VGGNet model on the Kaggle flower dataset. Various pre-trained models were used for the classification of flowers [38]. Using the InceptionResNetV2 model, an accuracy of 92.25% was obtained on the Kaggle flower dataset. None of the approaches mentioned above has used pooled datasets. In the proposed work, we have done extensive experimentation on publicly available datasets as well as pooled datasets. As inferred from Table 5, it is seen that the classification accuracy of the proposed method is better than existing methods.

Table 7. Effect of Number of Features on Classification accuracy (Dataset: Flower 17)

ResNet 50 Features	Handmade features	Total number of features	Classification Accuracy %
1000	155	1155	95.3
1000	70 (CCV+CSLBP)	1070	93.2
1000	139 (CCV+EHD)	1139	92.9
1000	0	1000	87.6
800	155	955	93.0
600	155	755	80.0
400	155	555	76.2
0	155	155	60.0

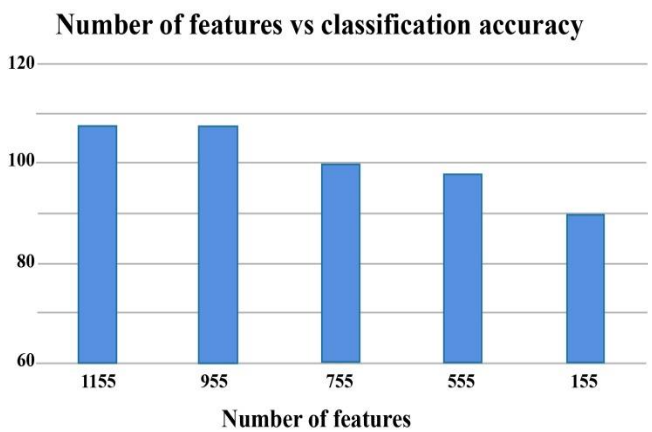

Fig. 12 Number of deep features vs Classification accuracy (Dataset: Flower 17)

The optimum size of the feature vector is essential to ensure efficient use of memory. Hence, in the last experiment, we observed the effect of the number of ResNet-50 deep features on classification accuracy, which is given in Table 7. The number of handcrafted features was kept constant. It was observed that classification accuracy reduces as the number of deep features decreases.

If deep features alone are used, the accuracy was found to be 87.6% on the flower 17 dataset. At the same time, handmade features alone yielded an accuracy of only 60 %. This observation indicates that the fusion of deep features and handcrafted features is essential for improving classification accuracy. Also, it was observed that the combination of CCV and CSLBP improves accuracy by 0.3 as compared to CCV and EHD combination along with deep features. This indicates that CSLBP features are slightly more important than EHD in the flower classification problem. Fig. 12 shows the effect of the number of deep features on Classification accuracy for the Flower 17 dataset.

6. Conclusion

This paper proposes an efficient flower classification system using a fusion of handcrafted and deep features. CCV, CSLBP and EHD were first concatenated to form the handcrafted feature vector. Pre-trained models ResNet-50 and AlexNet were used for deep feature extraction. A fusion of handcrafted and deep features was then done to obtain the final feature vector. Multiclass SVM was used for classification. Publicly available datasets and pooled datasets were used for experimentation. The datasets were partitioned into 75 % training and 25 % testing samples. Seven types of experiments were performed in the proposed work. It was found that the fusion of handcrafted features and deep features yields better classification results than traditional machine learning methods in multi-class classification problems. The proposed flower classification system will help researchers to discover other combined approaches for image classification using different deep-learning models. We have demonstrated high performance on imbalanced databases using the optimum number of features.

The proposed feature fusion-based approach provides high classification accuracy with the optimum number of features. A trade-off between accuracy and the number of features is achieved. The approach is sensitive to intra-class similarity and interclass variety. Classification Accuracy of 87.6 % and 60 % is obtained when Deep features and handcrafted features alone are used, respectively. The fusion of deep features from ResNet-50 and handcrafted features is effective in the flower classification problem. Classification accuracy of 95.3% and 92.0 % on Oxford flower 17 and Flower 102 datasets is obtained, respectively, which is better than existing approaches. The proposed feature fusion method is useful in applications like flower patent analysis, research on flowers for medicinal use, plant identification etc.

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