Plant species classification based on leaves using CNN model

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Abstract: For plant ecologists and botanists, plant leaf shapes are very essential as they can aid to differentiate plant species. A large range of plant species are eligible and the estimate grows year after year. Species awareness is must for various classes of the community such as foresters, farmers, environmentalists, educators for various fields of work. That makes a detection of species multidisciplinary concern. Therefore, leaf image classification is an important and tough task in the present scenario. So, the aim of this paper is to propose a classification of plant species based on leaves using the model of two-layer convolutional neural network (2L-CNN). This is accompanied by pre-processing where images values are re-scaled for each pixel and then divided the data into training and testing databases and after that, a 2L-CNN model is created in which re-scaled images are given and features have been extracted. Obtained classification accuracy is good using training of a neural network for 10 epochs. The proposed algorithm obtained a classification accuracy of 99.09% using Swedish image database. Obtained results and their comparison with existing algorithms on same image database are better which confirmed that the proposed algorithm outperformed and superior to other kinds of related works.

**Abstract:** Leaf. Plant species. Two-layer convolutional neural network. Classification

1. Introduction

Trees are important as they provide us oxygen to live, keep carbon, sustain the soil and support wildlife of the world. Trees are significant for life as well as being the longest living species on earth; they are an association between our past, present, and future. There are a variety of ways through which plants can be identified like leaf, flowers, stem, fruit, flowers, root, shape, size etc. Leaf identification for the detection of species of the plant is an important area of interest for the image processing and computer vision fields. Although many approaches have been introduced till present, some problematic concerns are to be addressed by the predominant computational models for leaf detection. Some of these issues are the recognition of the characteristics of the plant leaf and its description to better classify the plant species. One of the key characteristics for distinguishing various species of plants is the shape of plant leaves. Several models of plant identification are proposed, primarily based on leaf shapes [1-2].

Söderkvist et al. [3] implemented a computer based methods for leaves classification on Swedish Leaf Database (SLDB) [4] created by himself. Fifteen tree species images were used in the dataset, including seventy-five leaves for each kind. Belongie et al. [5] suggested a shape matching algorithm (SMA) and deep-learning (DP) from SLDB. Adamek et al. [6] proposed multiscale representation method (MSRM) with a single closed out line for leaves classification using SLDB. Fu et al. [7] proposed an approach to extract leaf veins in which a thresholding technique was combined with an artificial neural network (ANN). An initial segmentation that followed the intensity histogram leaf image is initially implemented for the vein regions to be verified. After that, a fine segmentation followed by the use of trained ANN classifier including ten extracted features as its inputs from a window centred on the object pixels. Felzenszwalb et al. [8] the author combines shape and vein, colour and texture, and for classification probabilistic neural network (PNN) is used. To represent form features they used Fourier-descriptors, leanness-ratio, roundness-ratio and dispersion. Colour moments were used to reflect colour which hold mean, skewness and variance. Finally, lacunarity was used to extract twelve various features of textures. Alajlan et al. [9] proposed an application of triangle-area representation (TAR) and dynamic space warping (DSW) for shape recovery for the classification of leaves. Ling et al. [10] proposed a method for classification of the shape of the leaves by using inner-distance shape classification (IDSC). Liu et al. [11] proposed a classification of the plant by wavelet transforms (WT) and support vector machine (SVM). Bai et al. [12] proposed an IDSC, learned distance (LD) and contour only (CO) based method for classification of leaves using neural network (NN). Zhang et al. [13] proposed a classification of plant leaf by using rough set (PLCRS). A Plant leaf classification method has been used focused on neighbourhood rough set. The conventional rough set system was commonly for use in the feature extraction and attribute-reduction applications. Nonetheless, the model can manage the minimal data only. They introduced and attribute-reduction in the work dependent on rough neighbourhood sets and enforced that for leaf plant classification. Approximately 30 classes were effectively-identified for realistic plant leaves. Wu et al. [14] proposed a visual descriptor for scene categorization (VDSC) using gray scale image (GSI), spatial principal component analysis of census transform histograms (sPCACH) and SVM. Kadir et al. [15] proposed a classification of the leaves by using shape, colour, and texture features (SCTF). Hu et al. [16] used multiscale distance matrix (MDM) for the classification of leave.

In 2013 Mouine et al. [17] suggested a multiscale triangular representation (MSTR) based on shape approach for leaf classification. In 2014 Elhariri et al. [18] proposed a method for classifying plants focusing on features of leaves. A relative study has been suggested by the author among two classifiers, random forests (RF) and linear discriminant analysis (LDA) to rectify the issue of categorization of plants. Charters et al. [19] proposed an Edge Angle descriptor (popularly known as EAGLE) along with bag-of-visual-words model (BoVWM). EAGLE descriptor (ED) is used to recognize the relation of angle between vein lines.

In 2015 Eid et al. [20] it provided an appropriate and computational way of identifying plant-species through digital leaf images. The proposed identification mechanism integrates the biometric features of the leaf, where the characteristics of venation and shape were used to characterize images of the leaf. Ten combined features of biometric leaf were retrieved and transferred to classifier hidden Naive bays for categorization. Many experiments were performed and illustrated on 32 distinctive plant species having 1907 leaves sample from the flavia dataset. Wang et al. [21] proposed a multi-scale arc height descriptor (MSAHD). It evaluated the height of the arch of palmate shaped & lobe shaped leaves but it was undesirable for overlapping leaves. A local standardization scheme was implemented for rotation and scaling. Zhao et al. [22] proposed pattern counting approach (PCA) based method for plants detection with leaf shapes.

After 2016, Cao et al. [23] suggested multi-scale R-angle descriptor (MSRAD) based method for leaf image retrieval. Yang et al. [24] suggested multi-scale triangular centroid distance (MSTCD) technique for plant-leaves recognition using leaf shapes. Grinblat et al. [25] proposed a vein morphological patterns (VMP) based deep learning (DL) for plant leaf classification. Uçar et al. [26] proposed an object recognition and detection using DL. Sun et al. [27] used exact height function feature descriptor (EHFFD) for fast shape retrieval. Adinugroho et al. [28] extracted ensemble features (EE) and used for leaves classification using NN. First 31 characteristics of the leaves were derived from 13 species representing leaf colour, leaf shape and its texture. Then, the characteristics were selected in keeping with their correlation to the class label. The data with pruned features of 25.8 per cent was then used to train a neural feed forward network. The network was trained and tested by implementing a 10-fold process using 975 images. Liu et al. [29] a unique plant leaf classification method was proposed by the author because of its powerful feature extraction and classification capabilities, and it was based on a CNN. A ten-layer CNN was designed to grade the leaves of the plant. Test augment for leaf was added to the images to expand the database for effective classification. Some methods such as horizontal flip, vertical flip, vibration, colour jittering, and rotation had been used for data enhancement. Swedish leaf database (SLDB) of images, containing 1,125 images of 15 distinct species, had been used in [3] then after pre-processing was done by using Gaussian filtering technique, and then extracting colour and texture characteristics. Hu et al. [30] proposed a model classifying plant leaves through multi-scale fusion and CNN (MSF+CNN).

In 2018, Zhang et al. [31] proposed a plant species identification using modified local discriminant projection (MLDP). The reported accuracy was 94.06% from SLDB. In 2019 Xu et al. [32] proposed a geometric parameter (GP) based unified multi-scale method UMSM) for leaf classification. Kaur et al. [33] used machine learning (ML) techniques like multi-class SVM (MC-SVM) for plant species classification. Bao et al. [34] used histogram of oriented gradients feature (HOGF) and CNN for plant species recognition by pattern of the leaf. In 2020 Wang et al. [35] proposed EHG (elliptical half Gabor) and MGLLDP (maximum gap local line direction pattern) based novel leaf recognition method using SVM.

In this paper, we suggested an approach for creating a 2L-CNN that can differentiate between 15 species of plants. Section-2 explains the data used for the results. Section-3 introduces the proposed methodology while Section-4 displays experimental results along with discussion. Finally the conclusion is given in Section-5.

1. ****Image database****

The Swedish Leaf Database (SLDB) [4] is composed of 1,125 images of 15 types. There are 75 images of each type of leaf. Every leaf is an RGB image, with a white background. The image resolution is 300-DPI. One image for each type of leaf from the (SLDB) is shown in Fig.1.

dwtH1.jpg dwtH2.jpg dwtH3.jpg emdH1.jpg emdH2.jpg emdH3.jpg ewtH1.jpg ewtH2.jpg ewtH3.jpg vmdH1.jpg vmdH2.jpg vmdH3.jpg vmdH1.jpg vmdH2.jpg vmdH3.jpg

**Fig. 1** One image for each type of leaf from the Swedish leaf database [4]

1. ****Proposed methodology****

In this work, a 2L-CNN model is proposed for plant species classification based on leaves. 32 filters of a 33 size are taken and pushed it over the image from the upper left to the lower right and the size of images are 64643. A value is determined using a convolution method for every point on the image, based on the filter. For every filter, a feature maps are created when the filters moved over the image. This is taken by the activation function ReLU which are applied on each pixel and replaced each negative-value in feature map with 0. A 22 matrix in the pooling layers are taken to pick up the biggest values on the feature maps and used them as input for corresponding layers. After that, to convert all the pooled images through Flattening into a continuous vector, a function called Flatten is used. The last layer, a fully connected layer used an activation function called softmax. The convolutional and pooling layers output’s reflects high-level features of input image. These features are used by fully connected layer to divide the input images in different classes depending on the training set. The obtained results are validated using SLDB.The block diagram of the methodology is depicted in Fig. 2. And method is explained in the following steps:

Image Acquisition

Pre-processing

CNN Architecture

Train Model

Classification

Results

Apply Test Set

Fig. 2 Block diagram of proposed methodology

* 1. **Image acquisition**

The presented method is evaluated on publically available 1,125 images of 15 types of (SLDB) [4]. Swedish leaves used in this research work contain 3 maps: red, green, and blue. The input image used is 64×64×3, where 64×64 is the size of the images and 3 stands for RGB, which is a colour image.

* 1. **Pre-processing**

All original images are an RGB image within range 0 to 255, the maximum value is since 255 but these values would be too large for the proposed model to process. Therefore, values are targeted in between 0 and 1. Each pixel value is rescaled from the [0,255] to [0, 1] range by 1. /255.

* 1. **CNN architecture**

CNNs are feed-forward neural networks and a group of neural networks that have been shown to be very effective in the recognition and classification of images and are made up of several layers. CNNs comprise kernels, neurons, and filters that have learnable weights, parameters, and biases. This filter receives inputs, transforms them and optionally continues them with nonlinearity [26]. Figure 3 demonstrates CNN architecture. It comprises the Convolutional, Pooling, Fully Connected, and Rectified Linear Unit (ReLU) layers.



**Fig. 3** CNN architecture

**3.3.1 Convolutional layer**

The convolutional layer is a main building block for a convolutional network and performs several computational tasks. The primary purpose is, get characteristics from the input data of the image form. By learning image attributes, it manages and maintains the spatial connection among pixels. It uses small squares of the given image. The provided input image is convoluted by the use of group of detectable neurons. This generates an activation or feature map in the output frame, and subsequently, the feature maps are inserted into the next convolution layer as input data.

**3.3.2 Pooling layer**

It decreases the dimensionality of every activation map. Nevertheless, the most relevant data remains available. The image input is slitted into a group of rectangles which are not overlapping. Non-linear operation like average/maximum wills down-sample each region. A pooling or a sub-sampling layer in CNN layers is added after a convolution layer once getting the function maps. This is to reduce the computing power needed for the data processing by reducing the dimensionality. Pooling shortens training time and prevents over-controls.

**3.3.3 ReLU layer**

It is wise non-linear element procedure that comprises of rectifier-employing units. It is applied per pixel, and all negative values are reconstituted by zero in the feature map.

**3.3.4 Fully connected layer**

When each filter of the preceding layer is linked in the next layer of each filter then it is called fully connected layer (FCL). The results of all the layers like pooling, convolutional, & ReLU are instances of the high-level input image features. The purpose of using the FCL is by using all the features to identify the input image depending on the training set into different classes. FCL is known as final pooling layer which uses Softmax, an activation function to feed the features to a classifier. The summation of performance probabilities on the FCL is 3. This is accomplished with the use of Softmax. This will accept a vector of real-valued arbitrary scores and press them into a value vector among 0 and that added up to 1.

**3.3.5 Optimization**

For DL models, the right option for optimization algorithm could significantly improve both declines in training time and progress in precision. ADAM was first reported in 2014, as an optimization algorithm to train deep neural networks (DNN) with adaptive learning. ADAM optimizer is gaining enormous popularity in DL applications such as computer vision. This algorithm is an improved and updated version of traditional stochastic gradient descent algorithm. ADAM optimizer shows finer results and performance as compared to classical stochastic gradient descent.

In this paper, a convolution layer has been introduced using Conv2D function with 4 parameters. (1) The number of filters = 32, (2) the size of each filter = 33, (3) input shape and image type of each image whether it is RGB or Black image. The input image used by proposed model is 64**×**64×3, where 64×64 is the size of the images and 3 stands for colour image. (4) Activation function (AF), relu AF has been used that stands for a rectifier function. To perform pooling operation on the resultant feature maps getting after the convolution operation is done on an image. A 22 matrix has been taken to minimize the size of the images to the limit.

The above two steps have been repeated to built a 2L-CNN architecture. After that, to convert all the pooled images through flattening into a continuous vector a Flatten function has been used. In this additional parameters are not required as Kerascan understand that the object classifier already holds pooled image pixels so they need to be flattened.

In the next step, two dense functions have been used which area FCL, in first dense layer, Keras used the vector as the input for the NN which has been obtained above and provided the output of 128 classes by using relu AF. In the next dense layer, a softmax AF has been used to determine specific target output result. After completing the building the 2L-CNN model, it has been compiled. Further, ADAM optimizer has been used for better results.

* 1. **Training and testing of model**

*Keras* is a great high level library that allows everyone to build strong ML models. Keras has the ImageDataGenerator class and has three methods for reading pictures from image containing directories such as flow(), flow\_from\_directory(), flow\_from\_dataframe().

A directory has been set to the path where 15 training dataset classes are accessible and in the same directory, target\_size, batch\_size, class\_mode, and subset have been initialized. The target\_size is the size of input images; every image is resized to this size which is (64, 64) in the proposed model. Batch\_size is the no. of images to be yielded from the generator per batch here batch size is 32. Class\_mode is set to *categorical*. A subset represented statistically the correct mix of dataset. To read training dataset, 70% of whole dataset have been applied for training subset and 30% of total dataset has been used to load the testing dataset subset for validation.

The data have been fitted in within the proposed model by using steps\_per\_epoch, training\_set, test\_set, validation\_steps, and epochs. *Steps\_per\_epoch* includes number of training images, i.e. the totalnumber of images contained in training set folder, which are 260 here. *Validation\_steps* are only significant when steps\_per\_epoch is described and it is the total number of validation phases before the stoppage. Validation steps are 260 here. And *epochs*, a single epoch is a single stage in the training of a NN; that is, when a NN is trained only in one pass on each training sample, and said an epoch is over. Therefore, the phase of training will consist of more than one epoch. Here 10 epochs has been specified for this scenario to get the good classification accuracy.

* 1. **Classification results**

Classification results are obtained with reference to Precision, Recall, F1score, and Accuracy of each class, and over all accuracy [36-38].

*Precision* It gives the information about how the precise the model is out of those positive assumptions and how many are false and it is calculated as:

(1)

*Recall* It measures if any of the actual positives our model catches by marking them as positive and it is calculated as:

(2)

*F1score* It is a representation of the accuracy of a test. F1 score is the harmonic mean (HM) of the precision and recall, and achieves its highest value at 1. F1 score is calculated as:

(3)

*Accuracy* It may be represented as the ratio of correctly predicted images to a total images count. Accuracy is calculated as:

(4)

Here,: True positive,: True negative,:False negative, and : False positive.

1. Experimental results and discussion

In this paper, plant species classification based on leaves using 2L-CNN model has been proposed. After re-scaling images a 2L-CNN model has been developed which includes 2 convolutional layers, 2 pooling layers, 1 flatten layer and 2 dense layers.

Obtained confusion matrix of the proposed model has been presented in Table 1. In the Table 1 CS has been used to represents the class from 1 to 15. It is a 15×15 confusion matrix, in which the column signifies the true values of each class and the row signifies the predicted values of each class. A confusion matrix is a chart that is used to explain the performance of a model’s classification on a set of test data for which the true values are identified. It consists of, , , and .

Table 1 Confusion matrix of the proposed model for classification of Swedish leaf database [4]

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Classes | CS1 | CS2 | CS3 | CS4 | CS5 | CS6 | CS7 | CS8 | CS9 | CS10 | CS11 | CS12 | CS13 | CS14 | CS15 |
| CS1 | 21 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| CS2 | 0 | 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| CS3 | 0 | 0 | 21 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| CS4 | 0 | 0 | 0 | 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| CS5 | 0 | 0 | 0 | 0 | 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| CS6 | 0 | 0 | 0 | 0 | 0 | 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| CS7 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| CS8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| CS9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 0 | 0 | 0 | 0 | 0 | 0 |
| CS10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 0 | 0 | 0 | 0 | 0 |
| CS11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 0 | 0 | 0 | 0 |
| CS12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 0 | 0 | 0 |
| CS13 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 0 | 0 |
| CS14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 0 |
| CS15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 |

The proposed approach has been implemented on SLDB. Firstly, these images have been categorized into 2 sets. Set 1 Contains 70% data and mainly used to train the model while the remaining 30% data have been kept in set 2 and used for model testing. There are 75 images of each species of plant. For training and testing purposes, a total of 53 and 22 images have been used, respectively. In this way 795 and 330 images have been used for training and testing purpose, respectively.

The obtained results using the proposed model have been represented in Table 2. Proposed work obtained 100% training accuracy and 99.09% testing accuracy, after training model for 10 epochs using SLDB [4]. The average accuracy obtained by the proposed method is 99.09%.

Table 2 Precision, Recall, F1 score, and Accuracy of individual class using Swedish leaf database [4]

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1 Score | Accuracy (%) |
| CS1 | 1 | 0.95 | 0.98 | 95.45 |
| CS2 | 1 | 1 | 1 | 100 |
| CS3 | 1 | 0.95 | 0.98 | 95.45 |
| CS4 | 0.96 | 1 | 0.98 | 100 |
| CS5 | 0.96 | 1 | 0.98 | 100 |
| CS6 | 1 | 1 | 1 | 100 |
| CS7 | 1 | 1 | 1 | 100 |
| CS8 | 1 | 1 | 1 | 100 |
| CS9 | 0.96 | 1 | 0.98 | 100 |
| CS10 | 1 | 1 | 1 | 100 |
| CS11 | 1 | 1 | 1 | 100 |
| CS12 | 1 | 1 | 1 | 100 |
| CS13 | 1 | 0.95 | 0.98 | 95.45 |
| CS14 | 1 | 1 | 1 | 100 |
| CS15 | 1 | 1 | 1 | 100 |

The existing work in this field showed that there is still a need to increase the accuracy. Söderkvist et al. [3] reported an accuracy of 82.40% using BI and MLP from Swedish leaf database [4]. Charters et al. [19] used ED and BoVWM to obtain an accuracy of 94.9%. In 2015 Eid et al. [20] proposed a model of plant classification frequently showed an average identification results accuracy of 97 %. In 2007, Alajlan et al. [9] proposed a shape retrieval using TAR and DSW for the classification of leaves. The reported accuracy was 95.97%. Ling et al. [10] reported an accuracy of 94.13 using IDSC method. Liu et al. [11] used WT and SVM to obtain an accuracy of 91.33%.

Authors of the following papers [6, 9, 10-12, 16, 19, 23, 25, 27, 31, and 33] have reported accuracy less than 96% using the same image database. But the following papers [14, 17, 21, 22, 24, 30, and 32] reported an accuracy value more than 96% but less than 98% using the same image database. In 2019, Bao et al. [34] HOGF and CNN for plant species classification. The reported accuracy was 98% from SLDB. In 2020 Wang et al. [35] proposed a method using EHG and MGLLDP. The reported accuracy was 98.4%.

A graphical comparison for last five years of leaf classification methods on Swedish Leave Database [4] has been shown in Fig. 4. Figure 4 also demonstrated that plant species classification based on leaves using 2L-CNN model achieves best result.



**Fig. 4** Comparison of proposed and last five years methods

A comprehensive comparison of proposed and existing leaves classification methods on Swedish Leave Database [4] has been given in Table 3. Table 3 demonstrated that plant species classification based on leaves using 2L-CNN model achieves best result.

Table 3 A comprehensive comparisons of leaves classification methods on Swedish Leaf Database [4]

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Author/Ref. | Year | Database/no. of images | Methods | Accuracy (in %) |
| Söderkvist et al./[3] | 2001 | Swedish/1125 | BI+MLP | 82.4 |
| Belongie et al./[5] | 2002 | Swedish/1125 | SMA+DP | 88.12 |
| Adamek et al./[6] | 2004 | Swedish/1125 | MSRM | 94.75 |
| Alajlan et al./[9] | 2007 | Swedish/1125 | TAR+DSW | 95.97 |
| Ling et al./[10] | 2007 | Swedish/1125 | IDSC | 94.13 |
| Liu et al./[11] | 2009 | Swedish/1125 | WT+SVM | 91.33 |
| Bai et al./[12] | 2010 | Swedish/1125 | IDSC + LD+CO+NN | 93.8 |
| Wu et al./[14] | 2011 | Swedish/1125 | sPCACH +GSI+SVM | 97.92 |
| Hu et al./[16] | 2012 | Swedish/1125 | MDM | 93.6 |
| Mouine et al./[17] | 2013 | Swedish/1125 | MSTR+NN | 96.53 |
| Charters et al./[19] | 2014 | Swedish/1125 | BoVWM+ ED | 94.9 |
| Wang et al./[21] | 2015 | Swedish/1125 | MSAHD+KNN | 96.21 |
| Zhao et al./[22] | 2015 | Swedish/1125 | PCA | 97.07 |
| Cao et al./[23] | 2016 | Swedish/1125 | MSRAD | 93.2 |
| Yang et al./[24] | 2016 | Swedish/1125 | MSTCD | 96.31 |
| Grinblat et al./[25] | 2016 | Swedish/1125 | VMP+DL | 92.45 |
| Sun et al./[27] | 2017 | Swedish/1125 | EHFFD | 95.07 |
| Hu et al./[30] | 2018 | Swedish/1125 | MSF+CNN | 96.78 |
| Zhang et al./[31] | 2018 | Swedish/1125 | MLDP | 94.06 |
| Xu et al./[32] | 2019 | Swedish/1125 | GP+UFMSM | 96.27 |
| Kaur et al./[33] | 2019 | Swedish/1125 | MC-SVM | 93.26 |
| Bao et al./[34] | 2019 | Swedish/1125 | HOGF+CNN | 98 |
| Wang et al./[35] | 2020 | Swedish/1125 | FHG+MGLLDP | 98.4 |
| **Proposed Method** | 2020 | Swedish/1125 | 2L-CNN | 99.09 |

1. ****Conclusion****

This paper presented a plant species classification based on leaves using 2L-CNN. A better leaf classification method is presented in this paper. The paper presents an efficient way to identify plants using their leaves images with the help of CNN and ADAM Optimizer. The obtained accuracy is higher than other sorts of associated works listed in Table 3 for the Swedish Leave Database [4]. The proposed algorithm obtained an average classification accuracy of 99.09%. Obtained results and their comparison with existing algorithms on same image database are better which confirmed that the proposed algorithm outperformed.

In the future work, further improvement in classification accuracy of the proposed model may be extended. Idea may be extended to classify real time automatic plant species classification.

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