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Deep convolutional neural network based plant species recognition through features of leaf

Dhananjay Bisen [1]

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Abstract
In present scenario, the research under image processing has been rapidly transformed from machine learning to deep learning. The deep learning algorithms are usually applied in the various areas like images to be classified or identified more accurately. One of the application areas of deep learning is the plant identification through its leaf which helps to recognize plant species. Botanists consume most of time in identifying plant species by manually scrutinizing and finding its features. This paper proposes an automated plant identification system, for identifying the plants species through their leaf. This task is accomplished using deep convolutional neural network to achieve higher accuracy. Image pre-processing, feature extraction and recognition are three main identification steps which are taken under consideration. Proposed CNN classifier learns the features of plants such as classification of leafs by using hidden layers like convolutional layer, max pooling layer, dropout layers and fully connected layers. The model acquires a knowledge related to features of Swedish leaf dataset in which 15 tree classes are available, that helps to predict the correct category of unknown plant with accuracy of 97% and minimum losses. Result is slightly better than the previous work that analyzes 93.75% of accuracy.

Keywords Deep learning · Image pre-processing · Feature extraction · Leaf recognition · CNN classifier · Swedish leaf dataset

1 Introduction

There are huge numbers of plants existing in nature and they are one of the life saving element of our planet. Traditionally botanists accord their life to study about plants so that they identify plants species present in earth. But on planet there are about 320 thousand species of plants. It is absolutely impossible task for botanist to study about all these plant species present on

✉ Dhananjay Bisen
bisen.it2007@gmail.com

[1] Rajkiya Engineering College Banda, Atarra, UP, India

planet and also to find some characteristics which helps them to differentiate the plant species. Bambil et al. [2] collected 40 different kinds of leaves of 30 trees from scanners or phone camera. They identified species using color, shape and texture. Some authors also gave systematic studies on computer vision techniques for plant species identification in terms of plant features. They included approximate 100 peer-reviewed studies, published in last 10 years. Furthermore this study is applied more on available datasets and evaluated classification accuracy [19, 4].

Secondly, Biologist faces a problem in classifying those plant species which are different but they show almost same characteristics. They also invest their huge time on identifying plant species by researching and finding their features. In 2016, Arafat et al. [1] analyzed various technique of leaf classification and compared one another in terms of accuracy for Flavia dataset and others. Wang et al. [20] represented another efficient classification framework for leaf images of complicated background which was based on pre-segmentation and morphological operation. Segmentation is a way of separating the leaf from its background using the adaptive threshold for accomplishment. Segmentation of leaf has been represented in Fig. 1. The first step in segmentation is to construct a 20-bin image intensity histogram. In the second step two major peaks are obtained, respectively, in the histogram representing the leaf and its background. In third step, bin with lowest value has to be found. Then, for separating leaf and its background the median of the bin is used as a threshold. In this process, first the leaf image is converted to grayscale image. This grascale image is than converted to binary form using adaptive thresholding. After this, some morphological operations are performed to remove leaf holes caused by previous thresholding. By using AND operation between RGB image and binary image the leaf is procured.

This was successfully classified into 20 classes of practical plant leaves with classification rate of 92.6%. This kind of work helps researcher to identify plant species but due to emergence of automated plant identification using CNN classifier saves the inestimable time of botanists. They use these time in identifying more number of species. Automated plant identification also helps common people who have no knowledge about plant, can identify and use plants for their purpose. Kumar [12] introduced 'Leafsnap' mobile application where plant species from dataset of 184 trees was identified using automatic visual recognition. Another authors Barre et al. [3] also proposed plant identification system 'LeafNet' which was based on convolutional neural networks that used images of leaves of three dataset to compute the performance of system.

In 2011, kadir et al. [9] classified leafs in which texture was regional descriptor helping in the process of retrieval. Probabilistic Neural network has been used by identification systems as a classifier and it has the capability to learn from training dataset. The feature such as colour, shape, vein and texture are extracted from the leafs in the feature extraction. There are two types of shape features mainly used as geometric features and Fourier descriptors of PET.Geometric features used for leaf identification roundness and leaf slimness.

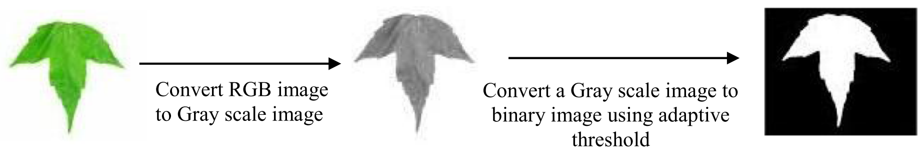

Fig. 1 Segmentation of leaf

a. Slimness is sometimes referred to as aspect ratio, it is defined in Eq. (1).

$$\mathbf{Slimness} = \mathbf{l_1} \div \mathbf{l_2} \tag{1}$$

Where l_1 is the width of the leaf and l_2 is the length of the leaf shown in Fig. 2(a).

b. The leaf's roundness is also a feature defined as in Eq. (2).

$$\mathbf{Roundness} = (\mathbf{4\pi A}) \div \mathbf{P^2} \tag{2}$$

Where A is the area of leaf image and P is the perimeter of leaf contour.

c. Using morphological operations, the vein features of a leaf can be extracted. It is performed on the leaf's gray-scale image with a flat, disk-shaped structuring element of radius and subtracted remained margin image. These 3 characteristics are calculated as follows, on the basis of $V_1 = A_1 \div A$, $V_2 = A_2 \div A$, $V_3 = A_3 \div A$.

In this case, features of veins are represented as V_1, V_2 and V_3 and A_1, A_2 and A_3 represents the total pixels of veins along with parts of leaf.

d. Another kind of feature is called Dispersion(irregularity), it deals with an object that has an irregular shape like the leaf included in the Fig. 2(b). It is represented as Eq. (3)

$$\boldsymbol{Dispersion} = \frac{\boldsymbol{max}\left(\sqrt{\left(\boldsymbol{X_i} - \boldsymbol{X'}\right)^2 + \left(\boldsymbol{Y_i} - \boldsymbol{Y'}\right)^2}\right)}{\boldsymbol{min}\left(\sqrt{\left(\boldsymbol{X_i} - \boldsymbol{X'}\right)^2 + \left(\boldsymbol{Y_i} - \boldsymbol{Y'}\right)^2}\right)} \tag{3}$$

Where (X_i, Y_i) is the coordinate of the pixel in the leaf contour and (X', Y') is the centroid of the leaf.

e. Texture can be observed through the fractal dimension of images but in case of leafs, it is not really fractals, i.e. at different scales they display different structures. However, it is measured by lacunarity, which can help to distinguish between two fractals with the same fractal dimensions. Lacunarity can be evaluated using Eqs. (4), (5) and (6).

$$L_S = \frac{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} P_{mn}^2}{\left(\frac{1}{MN}\sum_{k=1}^{M}\sum_{l=1}^{N} P_{kl}\right)^2} - 1 \tag{4}$$

$$L_a = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|\frac{P_{mn}}{\frac{1}{MN}\sum_{k=1}^{M}\sum_{l=1}^{N} P_{kl}} - 1\right| \tag{5}$$

$$L_P = \left(\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(\frac{P_{mn}}{\frac{1}{MN}\sum_{k=1}^{M}\sum_{l=1}^{N} P_{kl}} - 1\right)^P\right)^{1/P} \tag{6}$$

These formulas are applied to gray scale images where P_{mn} is a gray value at coordinates (m,n).

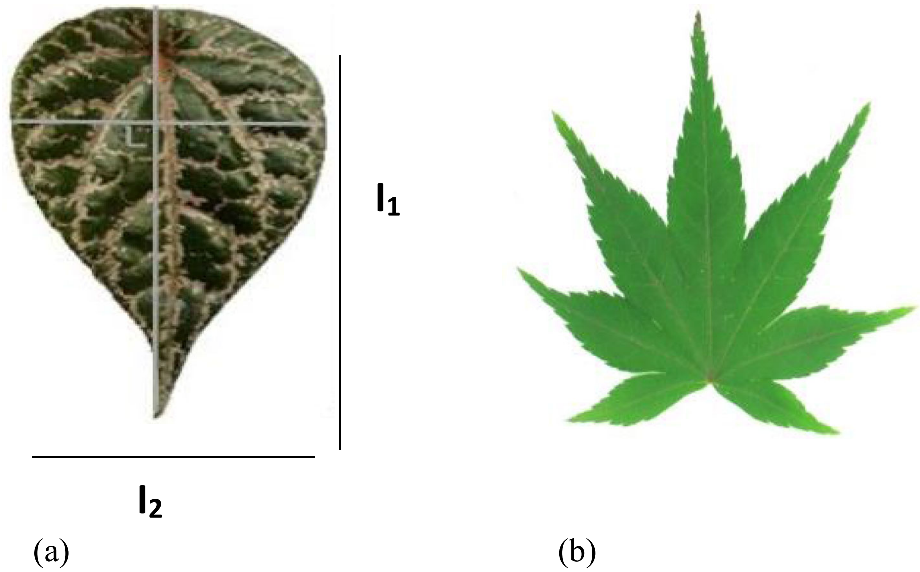

Fig. 2. **a** Leaf width and length **b** Image irregularity

Farabet et al. [8] introduced a technique for retrieving texture, shape, contextual information and system recorded accuracies on some dataset like Flow dataset, Barcelona dataset as well as Stanford background dataset. Earlier, the features extracted from the images were analyzed in terms of colors (RGB and HSV), shapes and texture in which local binary pattern (LBP) [13, 14] and gray level co-occurrence matrix [10] are widely used. Authors introduced novel texture feature named as local gray gabor pattern by combining LBP and Gabor, that was applied in soybean leaf diseases for its efficiency retrieval. Chaki et al. [5] had introduced fuzzy color, edge texture histogram and bag-of-features based collective approach to recognize fragmented images including deviation in their scale and angle. Authors considered center, top-left, top-right, bottom-left and bottom-right fragmented images from testing samples and observed accuracy with variation of percentages, which was better in case of 20% fragmentation of testing image. Saleem et al. [15] conducted valuable study for recognition and classification of plants type in which leaf shape features were automatically analyzed using different kind of classifiers such as KNN, SVM [16], decision tree and naïve Bayes, also compared with CNN [7]. They were evaluated using Flavia dataset of plant (1600 leaf images) and self collected dataset of 625 images with 96.1% (precision rate) and 97.3% (recall rate). On the motivation of above analysis, this paper proposes CNN model which can easily identify and classify plants using leaf.

Consequently, the main task is to develop a model which can automatically identify plants through its leaf using deep convolutional neural networks. It is designed for Swedish leaf dataset where total 15 tree classes are present and total number of leaves are 1125 [17]. Model collects information from available images and predicts the correct category of unknown plant, which either belongs or does not belongs to that category. This helps biologist and common people to identify plants easily through given image of plant. This model predicts the category of plant on the basis of knowledge gain through training of large plant dataset. But the major challenge it faces, is to differentiate those plant species which show huge similarity in characteristics irrespective of they belong to different categories. For solving this problem, find out the features of leaf which help to differentiate these plant species. The deep learning approaches [11] like CNN discover higher level features automatically from the data given by user. Layers of CNN model automatically extract generic and low-level features of leaf like edges, shape, texture, intensities of color etc. Other network's successive layers are tuned to the details and extract high-level data features. Likewise model trains itself and classify images.

The rest of paper is organized as follows. Section 2 includes the detailed discussion of proposed identification system. Result analysis shown in Section 3 and finally section 4 depicts the conclusion and discusses the future breadth of work.

2 Proposed methods

This section introduces the leaf dataset that is used in training and pre-processing of leaf images, as well as the deep CNN model of plant identification system that has been used for identification and classification of plant species through a given leaf image. Initially images transform into a suitable form in which feature extraction become easy, it is done using image pre-processing techniques, after that features are extracted using different layers of CNN and at last by using these features finally it classifies plant.

2.1 Dataset

Classification of plant species is based on leaf dataset that is collection of different kinds of tree leaves. Several datasets of plant leaves or self- collected real time dataset are publically available in web for example UCI plant leaf dataset, Herbarium dataset, Flavia dataset [7] and Swedish leaf dataset [17]. Every dataset has different tree classes, leaf images, features and samples of each class. Flavia dataset contains 32 plant species classes and each class have more than 50 images. In this work, CNN model has trained for Swedish leaf dataset, it is widely used dataset and it contains scanned images with a white background so that minimum pre processing is required. The dataset consist of 15 plant species with approximate 75 images in each class, so dataset mainly contains approximate 1125 images. Due to its attractive qualities, Swedish dataset is used for evaluation of plant species.

2.2 Image pre-processing

Image pre-processing is the universal phrase considered for the transformation and noise removal, which is applied to the images before feeding them into the model. Rotation, centering (sample wise and feature wise), resizing, normalization, rescaling (gray scaling) and shear are the operations which are included under pre-processing [18, 6]. Normally there are two situations when preprocessing might be performed:

a. Data Cleaning usually applies to remove artifacts using set of possible transformations for improving the learning process of model.
b. Data Augmentation applies when number of samples in dataset are very less, under this condition deep learning model cannot scheme well. In this case, available sample images can be represented in various possible ways using transformations like rotation, shearing and zooming. These augmented samples also add in dataset which increases the size of the dataset, this will help to model it for learning at the time of training.

In proposed system, data cleaning and augmentation have done in which some transformation operations have been applying into the images and more training samples have generated. It is represented in Table 1 and Fig. 3.

2.3 CNN model

Initially computer reads the images that will consist of three basic colors like Red, Green and Blue that are known as RGB colors. Each color has its own respective pixel values. For example if there is an image, it's size is B × A × 3 that means there are B rows and A columns and 3 colors. Consider an image like 24 × 24 × 3 that means 24 rows, 24 columns with 3 colors that's how computer reads the images. In case of black and white colors, only two colors are needed.

In most of previous work, fully connected networks are used in image classification. Hence consider images which have 24 × 24 × 3 and 200 × 200 × 3 pixels, when these images feed to fully connected network, the total number of weights required in the first hidden layer will be 1728 and 120,000 respectively. Therefore it deals with such a huge amount of parameters that require more number of neurons to process an entire complex image set, so that this can eventually lead to overfitting or it is not practically possible. For that reason, convolutional neural networks are used instead of fully connected network for image classification. It is like feed forward artificial neural network that consists of neurons with learnable weights and biases. These neurons learn and convert inputs like images into corresponding output label during training. In CNN, a neuron in layer will be connected to limited number of neurons (like small region) so that it needs less neurons and handle fewer amounts of weight unlike the fully connected network where single neuron will be connected to all neurons. Every neuron accepts numerous inputs one, performs a weighted sum over them. Exceed it through an activation function and responds with an output. Generally a CNN has four layers that assist in extracting information from an image such as convolution layer, ReLU layer, Pooling layer and Fully connected layer. In proposed work, CNN takes plant leaf as an input, creates some deformed images and classify them. CNN recognizes images in the form of a matrix of numbers associated with respective pixel.

Convolution layer has several feature filters that perform the convolution operation. These features are going to compare two small pieces of bigger images if it matches then image will be classified correctly. There are four steps that will require in this layer, first it needs to line up the feature filter in the image and then multiply each image pixel by the corresponding feature pixel. After that add the values and calculate sum that will divide by total number of pixels in the feature. The final observed value is placed at the center of the filtered image. Similarly,

Table 1 Data augmentation

S.No	Transformation operations	Properties
1	Rotation range	20 degrees clockwise and anti-clockwise
2	Width shift range	0.1 fraction of total width
3	Height shift range	0.1 fraction of total height
4	Zoom range	0.2% smaller or larger of original image
5	Validation split	0.3 or 30% of data was taken as validation dataset.
6	Rescale	1/255 multiplied with image channel values to normalize input
7	Resize image	300x300x3 pixels

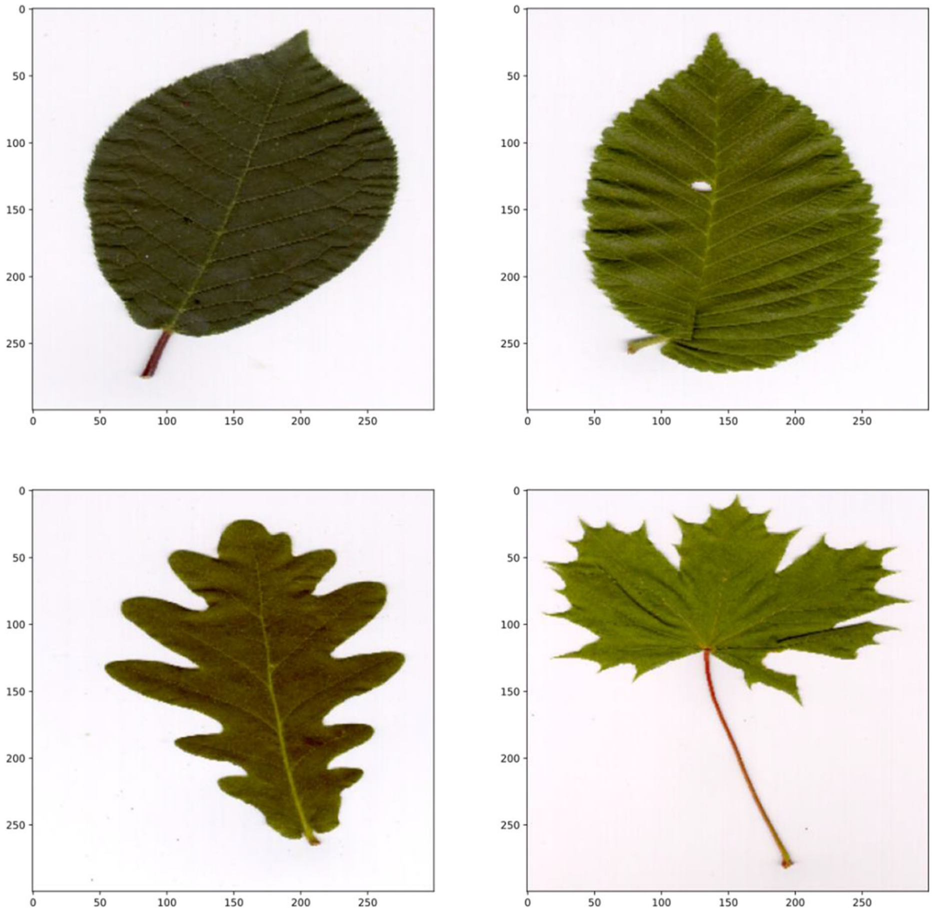

Fig. 3 Augmented leaf images (after pre-processing)

feature filter moves throughout the image, everywhere on the image and repeat same previous steps. For every feature filter, this process is repeated to get the convolution output (feature maps are extracted).

Other is rectified liner unit (ReLU layer) which is an activation function that will only activate a node, if the inputs above the certain quantity are below zero the output is also zero as shown in Fig. 4(a). When the input rises above the certain threshold it has a linear relationship with the dependent variable. That function removes all the negative values and gets convert to zero from the convolution. It is applied to all the feature images so as to generate the output (rectified feature map). Another type of activation function is sigmoid, represented as S-shape shown in Fig. 4(b). It is mainly used where output is predicted as the probability, means output exits between the range of 0 and 1.

In pooling layer, reduces the dimensionality of feature map or shrink the images. It applies in filtered images after passing through the activation layer. Some steps are usually included in Pooling. Initially select the window size (2×2 or 3×3) and this will move across the filtered image and than maximum value will be taken from each window. Finally pooled feature map is flattened and fed to fully connected layer where actual classification happens and predicts

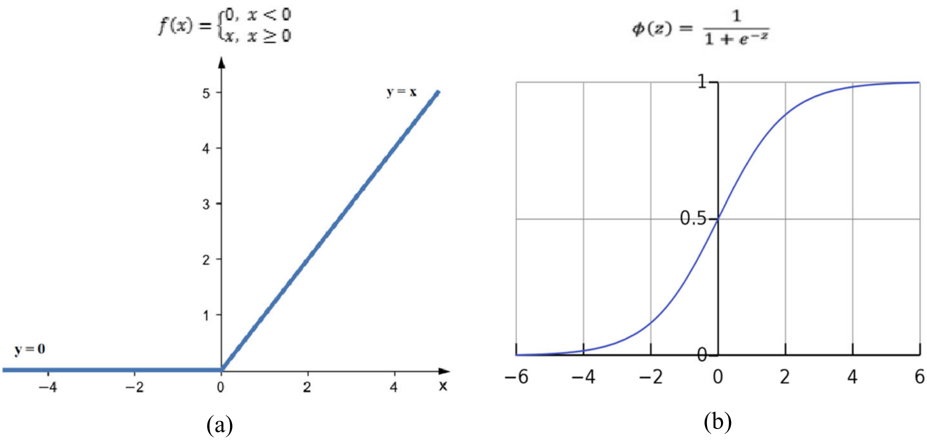

Fig. 4. a ReLU activation function **(b)**. Sigmoid function

the final output. Fully connected network uses softmax activation function (shown in Eq. (7)), it is kind of logistic regression that follows a probability distribution and normalizes an input value into vector of values. The output values are between the range [0,1]. It is also known as maximum entropy classifier.

$$p\left(y = j|\theta^{(i)}\right) = \frac{e^{\theta^{(i)}}}{\sum_{j=0}^{k} e^{\theta_k^{(i)}}}, \text{Where } \theta = W_0X_0 + W_1X_1 + - - + W_kX_k \tag{7}$$

Model uses dropout layers to overcome the overfitting problem. In machine learning, regularization reduces over-fitting by adding penalty with loss function, likewise CNN use dropout layer for regularization in which neurons are dropped randomly. This means that their contribution to the activation of downstream neurons is temporally removed on the forward pass and any weight updates are not applied to the neuron on the backward pass.

The proposed model takes a RGB image of 300 x 300 x 3 as input, after that eight 7×7 filters are passed over it with stride of 3. That converts images into 98×98 as output shape. It is followed by another set of sixteen 7×7 filters, this time with stride of 1 which gives 92×92 output shape of images. This will map to a 2×2 Max Pool layer which reduced the size from 92 to 46. Then comes 2 blocks of Convolutional and Max pool layers where convolutional layers have 5×5 filter size and 32, 64 filters respectively. Finally the layer outputs are flattened into a vector form which is followed by a 128 units fully connected layer. A 20% dropout was used here to reduce overfitting followed by a 15 units fully connected layer with softmax as activation. Implemented CNN architecture is represented in Fig. 5 and output of each layer shown in Fig. 6.

Model summary is also included in Table 2, it shown that model is sequential in which details of layers, output shape of each layer, number of parameters, filter size, receptive field, its coverage and capacity are included. Here filter capacity is analysed as the ratio of real filter size (striding or pooling of previous layer) to the receptive field. It is determined of how well a filter will able to spot complex structures in images. Next, the coverage is analysed as the ratio of receptive field to the input image size [7]. It is thus identified how much big piece of the input image the layer can observe.

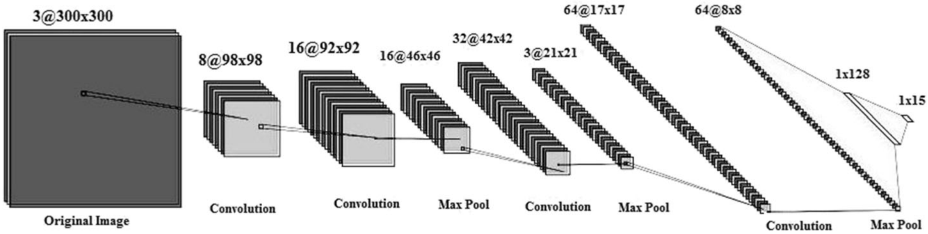

Fig. 5 CNN Architecture of automated plant identification system

3 Results and discussion

In this work, the proposed automated plant identification system has been tested on the Swedish dataset containing leaf images of 15 plant species. Cross-validation applies in dataset in which 70% of dataset from each class used as training set and remaining 30% as validation set. Training dataset is utilized to train the model and it helps the model in gaining knowledge related to leaf images. Validation dataset is used to provide unbiased evaluation of a model fitted on the training data.

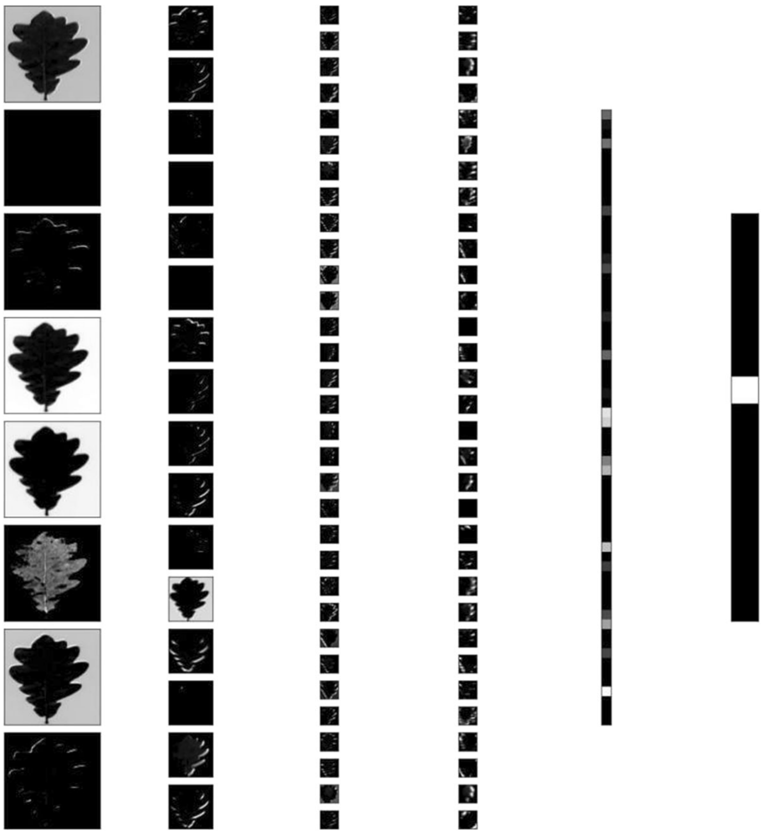

Fig. 6 Layer wise outputs of sample image

Table 2 Model summary (Model: "sequential")

S.N	Layer (type)	Output Shape	Parameter	Filter size	Receptive Field	Coverage (%)	Capacity (%)
1	conv2d_32 (Conv2D)	(None, 98, 98, 8)	1184	7	7	2.33	100
2	conv2d_33 (Conv2D)	(None, 92, 92, 16)	6288	7	25	8.33	28
3	max_pooling2d_24 (MaxPooling	(None, 46, 46, 16)	0	2	28	9.33	7.14
4	conv2d_34 (Conv2D)	(None, 42, 42, 32)	12,832	5	52	17.33	9.61
5	max_pooling2d_25 (MaxPooling	(None, 21, 21, 32)	0	2	58	19.33	3.44
6	conv2d_35 (Conv2D)	(None, 17, 17, 64)	51,264	5	106	35.33	4.71
7	max_pooling2d_26 (MaxPooling	(None, 8, 8, 64)	0	2	118	39.33	1.69
8	flatten_8 (Flatten)	(None, 4096)	0				
9	dense_15 (Dense)	(None, 128)	524,416				
10	dropout_26 (Dropout)	(None, 128)	0				
11	dense_16 (Dense)	(None, 15)	1935				
	Total Parameters:	**597,919**					
	Trainable Parameters:	**597,919**					
	Non-trainable Parameters:	**0**					

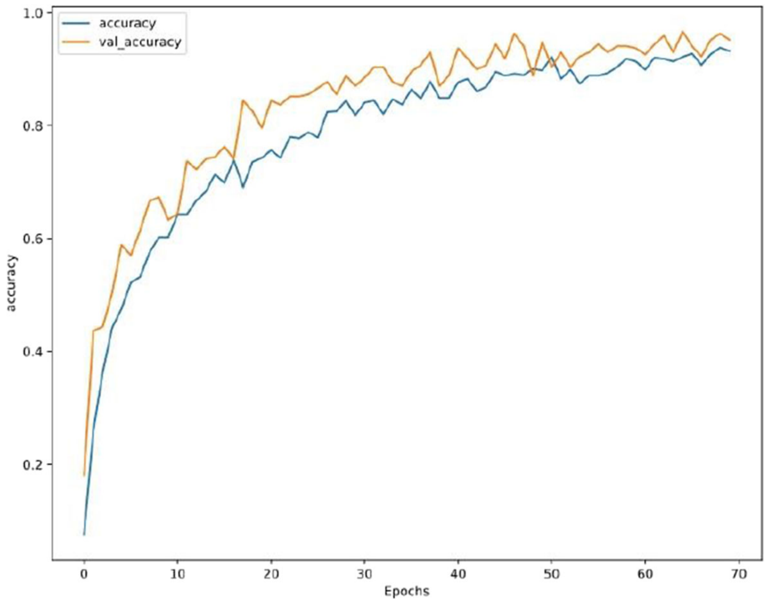

Fig. 7 Model accuracy vs epoch

Figures 7 and 8 shows the accuracy and loss according to each epoch of the training and validation. The accuracy of a model varies with number of epochs and also due to regularization done by dropout method. When the number of epochs increases accordingly, accuracy increases and thus loss percent decreases. The model gets the highest accuracy achievable without over-fitting, the training has stopped after 70 epochs and under this point the measured

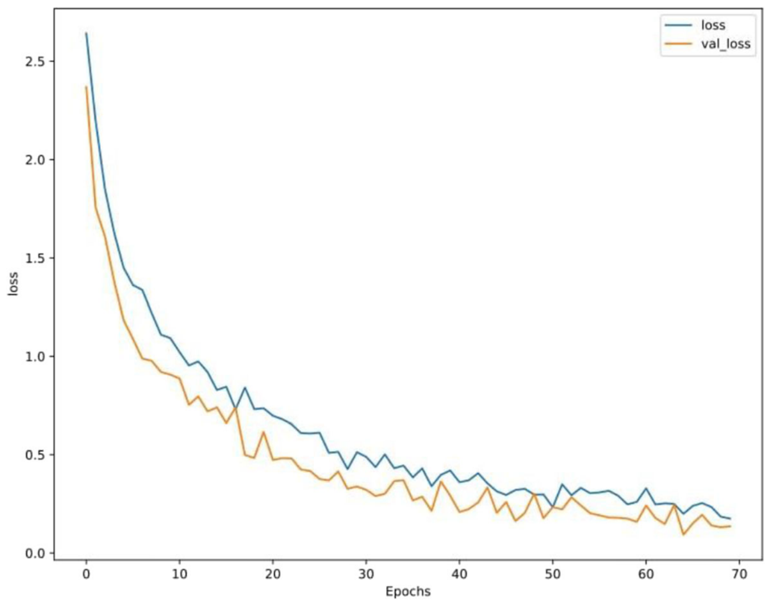

Fig. 8 Model loss vs epoch

True Label \ Predicted Label	Ulmus carpinifolia	Acer	Salix aurita	Quercus	Alnus incana	Betula pubescens	Salix alba 'Sericea'	Populus tremula	Ulmus glabra	Sorbus aucuparia	Salix sinerea	Populus	Tilia	Sorbus intermedia	Fagus silvatica
Ulmus carpinifolia	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Acer	0	0.91	0	0	0	0.05	0	0	0	0	0	0	0.05	0	0
Salix aurita	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Quercus	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Alnus incana	0	0	0	0	0.95	0.05	0	0	0	0	0	0	0	0	0
Betula pubescens	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Salix alba 'Sericea'	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Populus tremula	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Ulmus glabra	0	0	0	0	0	0	0	0	0.82	0	0	0	0	0	0.18
Sorbus aucuparia	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Salix sinerea	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Populus	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Tilia	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Sorbus intermedia	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0.95	0
Fagus silvatica	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0	0.95

Fig. 9 Confusion matrix for the prediction of 15 species

classification accuracy is 97%. After that, the validation and training loss starts to flatten and loss gap increases between them.

Table 3 Confusion matrix report

Tree Name	precision	recall	f1-score	support
Ulmus carpinifolia	1	1	1	22
Acer	1	0.91	0.95	22
Salix aurita	1	1	1	22
Quercus	1	1	1	22
Alnus incana	1	0.95	0.98	22
Betula pubescens	0.92	1	0.96	22
Salix alba ‘Sericea’	1	1	1	22
Populus tremula	1	1	1	22
Ulmus glabra	0.9	0.82	0.86	22
Sorbus aucuparia	1	1	1	22
Salix sinerea	1	1	1	22
Populus	1	1	1	22
Tilia	0.96	1	0.98	22
Sorbus intermedia	1	0.95	0.98	22
Fagus silvatica	0.84	0.95	0.89	22
accuracy			**0.97**	**330**
macro average	**0.97**	**0.97**	**0.97**	**330**
weighted average	**0.97**	**0.97**	**0.97**	**330**

Table 4 Comparison of proposed model with existing methods

Methods	Accuracy
Probabilistic Neural network (PNN) [8] (%)	93.75
SVM-BDT PNN [15] (%)	90.31
Proposed CNN model (an automated plant identification system) (%)	97

Figure 9 shows the confusion matrix for the prediction of 15 species in which diagonal numbers indicates the percentage of correct classification for each class. It represents fraction of misclassification for 15 plant species. Hear it is observed that some categories like *Ulmus carpinifolia*, *Salix aurita*, Quercus, *Betula pubescens*, *Salix alba* 'Sericea', *Populus tremula*, *Sorbus aucuparia*, Salix sinerea and Populus are correctly classifying with the accuracy of 100%. Whereas Acer, *Alnus incana*, *Ulmus glabra*, *Sorbus intermedia* and Fagus silvatica species are misclassified in some cases. These are correctly classifying with only 91%, 95%, 82%, 95% and 95% respectively. This is due to low number of training samples for these species. Overall, it shows most of species are classifying with higher accuracy.

On the basis of confusion matrix, calculate the precision, recall and f1-score for each class of leaf. It is represented in Table 3 as confusion matrix report.

Table 4 shows the results obtained from proposed model and compared with previously classification methods. It provides classification accuracy of existing methods and proposed model, this gives clear result how the proposed model performs compare to others in terms of accuracy.

4 Conclusion

In this paper, an automated identification techniques of plant species has been introduced which belongs to Swedish leaf dataset. Under this, a convolutional neural network has been constructed for classifying and identifying images of leaf. The task under consideration has 15 categories of plant species, each with 75 images. Model uses 70% images as training and remaining 30% as validation. This model learns features of given species of plant images which helps it to predict the correct category of unknown plant species. As a result it shows the classification accuracy ranged from 10% up to 100% with an average accuracy of 97%. Especially some categories are classified correctly with accuracy of 100%. Although the developed system is not intended to replace human taxonomists, it may provide a rapid and easily accessible technique to identify plants and its acceptable accuracy. Taxonomists are those who can identify plant samples correctly, are in great shortage affecting research in applied sciences like biotechnology and genetics. In future, proposed method can be applied in other leaf datasets and worked on improving the segmentation and recognition of leaves from foliage photos.

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