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International Journal of Performability Engineering

vol. 18, no. 10, October 2022, pp. 702-709
DOI: 10.23940/ijpe.22.10.p3.702-709

Deep Learning based Aquatic and Semi Aquatic Plants Morphological Features Extraction and Classification

Jibi G. Thanikkal[a], Ashwani Kumar Dubey[a,*], and Thomas M. T.[b]

[a]*Amity School of Engineering and Technology, Amity University Uttar Pradesh, Noida, Uttar Pradesh, 201303, India*
[b]*Department of Botany, St. Thomas College, Thrissur, Kerala, 680001, India*

Abstract

In Ayurveda, the ancient medicinal plant identification system is based on the morphological comparison of leaf, fruit, flower, root, stem etc. Botanists use morphometrics for aquatic and semi-aquatic medicinal plants classification. However, deep learning networks provide the highest image classification result in digital image processing. Existing deep learning algorithms generate feature maps for pixel-wise image classification. In the feature map of deep learning output, most of the morphological features are missing. This issue leads to the Catastrophic forgetting issue of deep learning. To generate a traditional morphological feature-based medicinal plant identification system, we are introducing morphometrics and morphological feature-based deep learning networks for aquatic and semi-aquatic plant classification. This article contains: (a) A detailed morphological features database of aquatic and semi-aquatic medicinal plants, (b) a summary of the importance of the morphological features-based leaf classification, (c) a morphological features extraction algorithm and (d) the morphological features-based deep learning approach for aquatic and semi-aquatic plant classification. This human brain-like procedure achieved 97% classification accuracy and reduced the Catastrophic forgetting issue of continual learning.

Keywords: image processing; medicinal plants; aquatic plants; deep learning; morphometric

(Submitted on June 26, 2022; Revised on July 20, 2022; Accepted on September 6, 2022)

1. Introduction

Plants with an impact on individual comfort and protection are called medicinal plants [1]. Medicinal plants show a beneficial pharmacological effect on the human body [2]. A medicinal plant that grows in water or is rooted in the mud or floating in water is called an aquatic medicinal plant. Aquatic plants balance oxygen level, act as a food chain foundation, and provide to beauty to the aquatic environments. Aquatic medicinal plants play a vital role in human healing [3]. The aquatic and semi-aquatic plants have stunning medicinal importance and unique biological features. The morphological characteristics of the aquatic and semi-aquatic plants are identical to standard land plants [4]. The main morphological features used for identifying aquatic medicinal plants are arrangement of leaves and stem, shape of leaf blade, leave edge and leaf venation etc. [5]. The leaves are the most available part of the plant. So, leaf blade, edge and venation are used in the image processing based on aquatic and semi-aquatic medicinal plant identification [6-8].

In this article, Section 1 includes the introduction of aquatic medicinal plants. In Section 2, the morphometrics of aquatic and semi aquatic plants are presented. Section 3 contains morphological features extraction from morphometrics of aquatic and semi aquatic plants. Section 4 contains the morphological features based deep learning network for the classification of aquatic and semi aquatic plants.

Section 5 comprises of the results of this proposed model. Section 6 explains the accuracy of this system and comparison to benchmarked deep learning models. Section 7 contains the discussion on morphometrics, and morphological features based deep learning and future studies. The final Section 8 consists of the conclusion.

* Corresponding author.
E-mail address: dubey1ak@gmail.com

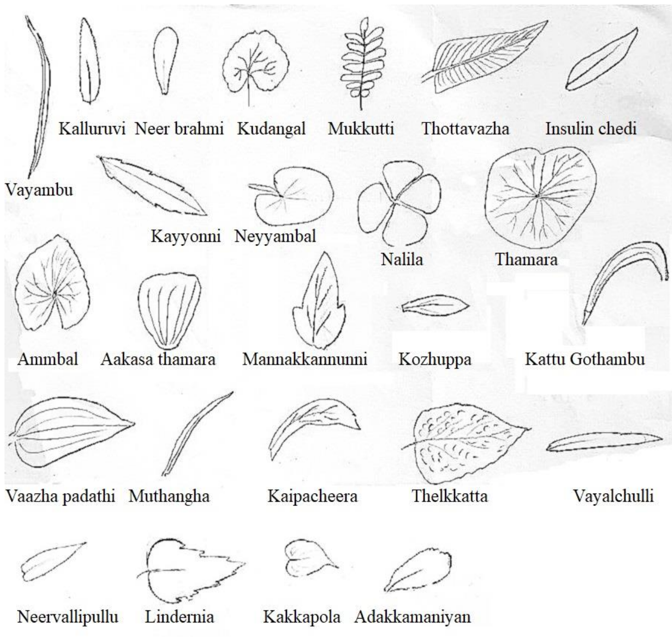

Figure 1. Morphometrics of aquatic and semi aquatic plant leaves and leaf petals

Table 1. Indian aquatic and semi-aquatic plant's morphological properties.

Si No	Botanical Name	Shape	Vein	Apex	Base
1	Acorus calamus [16]	Linear	Parallel	Acute	Attenuate
2	Ammannia baccifera [17]	Oblong	Single	Subacute	Attenuate
3	Bacopa monnieri [18]	Oval	Parallel	Obtuse	Cuneate
4	Centella asiatica [19]	Reniform	Palmate	Rounded	Auriculate
5	Biophytum sensitivum[20]	Oblong	Parallel	Acute	Truncate
6	Canna indica[21]	Elliptic	Parallel Convergent	Apiculate	Aequilateral
7	Costus igneus[22]	Oblong	Single	Aristate	Attenuate
8	Eclipta prostrate[23]	Lobed	Single	Acute	Cuneate
9	Limnanthemum indicum[24]	Orbicular	Parallel Divergent	Obtuse	Cordate
10	Marsilea quadrifolia [25]	Spatulate	Parallel	Obtuse	Cuneate
11	Nelumbo nucifera Gaertn [26]	Orbicular	Parallel Divergent	Obtuse	Cordate
12	Nymphaea pubescens Willd [27]	Ovate	Parallel Divergent	Subacute	Sagittate
13	Pistia stratioites [28]	Oblanceolate	Parallel	Obcordate	Attenuate
14	Sphagneticola Calendulacea [29]	Reniform	Reticulate Pinnate	Acute	Cuneate
15	Alternanthera sessilis [30]	Entire	Reticulate Pinnate	Subacute	Cuneate
16	Coix lacryma-jobi [31]	Ensiform	Parallel Convergent	Aristulate	Rounded
17	Commelina benghalensis Linn [32]	Ciliate	Parallel Convergent	Acute	Cuneate
18	Cyperus iria Linn. [33]	Acerose	Single	Acute	Attenuate
19	Glinus oppositifoilus [34]	Oblong	Parallel	Apiculate	Acute
20	Heliotropium indicum [35]	Dentate	Reticulate Pinnate	Acute	Rounded
21	Hygrophila schulli [36]	Lanceolate	Single	Apiculate	Attenuate
22	Hygroryza ristate [37]	Cordate	Parallel Divergent	Subacute	Cordate
23	Lindernia crustacean [38]	Deltoid	Reticulate Pinnate	Apiculate	Aequilateral
24	Monochoria hastate [39]	Cordate	Parallel Convergent	Acute	Cordate
25	Sphaeranthus indicus [40]	Ovate	Reticulate Pinnate	Subacute	Attenuate

2. Leaf Morphometrics

Aquatic plant identification is diverse from existing image processing-based plant identification [7]. Reaching a live plant with a camera directly to capture images in water is a challenging task. So, in the remote data collection and identification, drones, underwater cameras, etc. are commonly used. Geometric and statistical features set are totally depending on the image acquisition hardware details. Botanists collect samples of whole plants or plant parts and save them in archives in Herbarium

[9]. Herbarium is used as reference to those plants in the future. Leaf Morphometrics in botany deals with the description and relation of size and shape of leaf morphological features [9]. Morphometrics is useful for the morphological features-based studies. Leaf Morphometrics is a quantitative research method that deals with the description, analysis, and interpretation of leaves shape in botany. Morphometric data-based leaf image identification is novel in the image processing field. Advanced edge detection algorithm for morphological features extraction is explained in [10]. Digital shape descriptor generation using morphological features is explained in [11]. The basis of morphological evolution and importance of leaves and leaf morphology in plant identification is explained in [12,13]. Leaf shape variation-based leaf classification and morphological patterns based comparison is illustrated in [14]. Morphological leaf pattern relation to their leaf shape determination is given in [15]. Table 1 contains the Indian aquatic and semi-aquatic plant's Morphological properties. The Morphometrics database created for Indian aquatic and semi-aquatic plants are shown in Figure 1.

3. Morphological Features Extraction

Selection and extracting of relevant morphological features from an image is the toughest process in image processing. Normally, geometrical and statistical features are used in the image classification. This process depends upon the pixel rate, focus, angle, etc. of the camera and image acquisition method. In the morphological features-based image processing, image acquisition details and hardware details are hidden. Morphological features are extracted directly from the extracted image edge details. Four main features-shape, vein, apex, and base-are considered in the morphological feature-based identification. Leaf shape is the main morphological property in the leaf-based plant identification. Leaf shape is totally dependent on the sun light and shade receiving on that plant [41]. The shape of leaves helps in photosynthesis by receiving enough sunlight and carbon dioxide with balanced heat absorption and without water loss. Large-shaped leaves absorb more sun light but needle-shaped leaves absorb less sun light [42]. Leaves apexes and base parts are also different for each plant and helpful in the identification. Edge detection is mainly used in the feature set generation. In the training phase, all the leaves are rotated according to petiole of the leaf. In the next step, edge pixels are extracted using the Advanced Canny edge detection explained in [10]. The outer portion of the leaf edge pixel set representing the leaf shape and the pixel set provides the vein details of the leaf. Finally, the leaf base and leaf apex are extracted from the leaf shape image. The algorithm for leaf morphological features extraction is given in Figure 2.

4. Morphological Features based Deep Learning

Deep learning has arrived with the help of artificial intelligence and machine learning. In a deep learning architecture, each neuron connection has a set of inputs, weights, and biases. Deep learning includes an enormous set of related learning algorithms. Typical separations between these algorithms are made with layers of hidden neurons learned [43]. In [44], authors explain the back propagation based Convolutional Neural Network for learning handwritten digits.

In a Convolutional Neural Network, each neuron retrieves the output of previous layer and provides details into the next layer. A feed forward neural network with convolution, ReLU, pooling layers and fully connected layers are called Convolutional Neural Network (CNN). The convolution is a mathematical operation that calculates the relationship between pixels and helps to extract the feature map from the input image. The ReLU, or rectified linear unit, is the piecewise linear activation function mostly used in the convolutional neural network which does not activate all the neurons at the same time. The pooling layers provide the down sampling operation which help to reduce the features present in a particular image region. The fully connected layer is feed forward neural networks that perform the classification process of the Convolutional Neural Network. The fully connected neural network compiles the result of pooling layer and provides the final output.

The main advantage of a Deep learning network is, deep learning does not require a separate feature set for classification. In deep learning, a feature set is self-calculated through convolution, ReLu, and pooling operations. However, in the leaf classification procedure, most of the leaves are like one another. The feature map result of convolution is calculated by comparing the neighboring pixels using the kernel matrix. This feature map completely depends upon the shape, texture, and color details of the pixel image.

However, in the leaf identification and classification algorithms, all the input leaf images are very much like each other. So, in this proposed method, leaf shape, leaf vein, leaf apex, and leaf base features are trained in the system. The morphological features of a trained deep learning network generate the most relevant properties using the convolution network.

In this proposed method, leaf shape, leaf vein, leaf apex, and leaf base features extracted from leaf morphometrics are used to train the system. As a result, the system can understand the important morphological features required for identifying the leaf image. Each morphological feature, which details in different angles, is created and trained to the system. For the shape images, 250 x 46 = 10,500 images are used in training phase. Similarly, vein, apex, and base details are trained. In the testing phase, the leaf morphological features are extracted from the input image and compared with the previously trained knowledge set. Learning accuracy of leaf morphological features training procedure is shown in Figure 3. The morphological deep leaning training phase trained the system to understand the important features from the leaf image. Here, the system is trained using the morphological features. So, the first procedure in the testing phase is the extraction of morphological features from the leaf image. Then, each morphological feature is separately sent into the deep leaning network to compare with the trained database. The system returns the maximum matching morphological properties as output. Leaf morphological features based deep leaning architecture is shown in Figure 4. The outcome of the deep learning part is a set of comparison to the trained data set. So, most matching leaves are identified by checking the features all together. In this proposed system, four morphological properties are compared before the final decision.

Algorithm : Feature Extraction

```
G ← Gray_Scale( image)
E← Extract_Edge(G)
for i←1 to Width(E)
  for j←1 to Height(E)
    if E(i,j)<=127
      E1(i,j) ←0
    else
      E1(i,j) ←1
    end
  end
end
for i←1 to Width(E1)
  for j← 1 to Height(E1)
    if E1(i,j)==1
      SP ← E1(i-1,j-1)+ E1(i-1,j) + E1(i-1,j+1) + E1(i,j-1)+ E1(i,j+1)+ E1(i+1,j-1) + E1(i+1,j) +
      E1(i+1,j+1)
      if SP ==8
            Shape(i,j) ←0
            Vein(i,j) ←1
      else
            Shape(i,j) ←1
            Vein(i,j) ←0
      end
    else
      Shape(i,j) ←0
      Vein(i,j) ←1
  end
end
end
for i←1 to Width(Shape)
   for j←1 to Height(Shape)
      if j <= (Height(Shape) /2)
            Apex(i,j) ← Shape(i,j)
      else
            Base(i,j) ← Shape(i,j)
      end
   end
end
```

Figure 2. Leaf morphological features extraction algorithm.

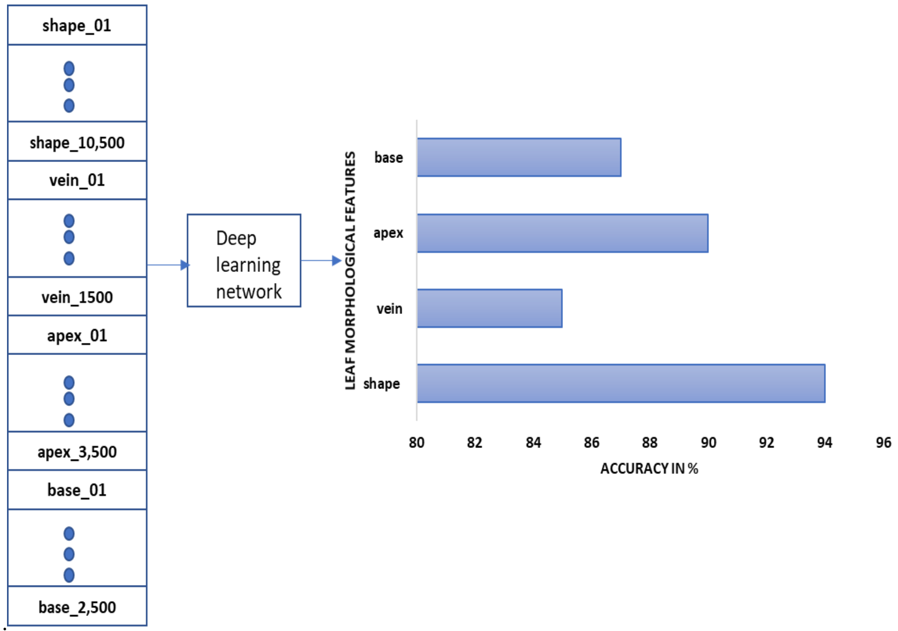

Figure 3. Learning accuracy of leaf morphological features training procedure

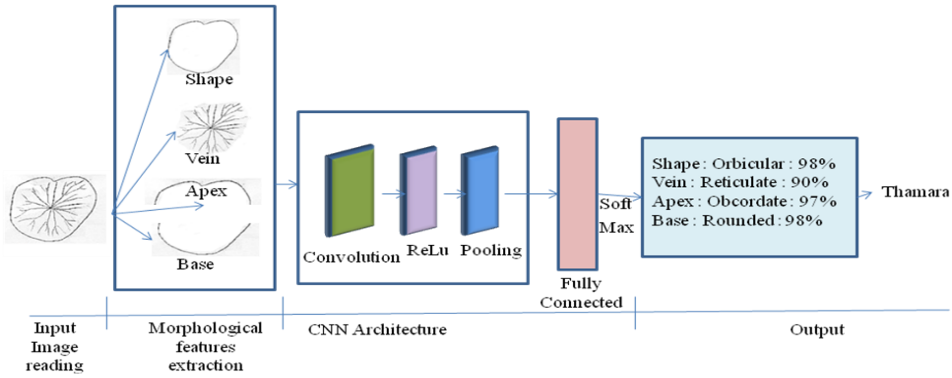

Figure 4. Leaf morphological features based deep leaning architecture

5. Result, Discussion and Future Studies of Proposed Model

To understand the result of the proposed morphological features based Deep learning network model, morphological feature extraction and leaf identification of Thamara leaf (Botanical name is *Nelumbo nucifera Gaertn* [26]) is given in Figure 5. This Deep learning network detected that the input leaf has a 98% similarity with Orbicular shape, 90% similarity with Parallel Divergent vein structure, 97% similarity with Obtuse apex shape, and 98% similarity with Cordate base structure. By comparing the similarity result of deep network result with the Table 1, the final result provided was *Nelumbo nucifera Gaertn*.

In this article, morphometrics of aquatic and semi aquatic plants is used to classify the aquatic and semi-aquatic plants. The evaluation of morphometrics vs. morphological features is conducted to analyze the accuracy of morphological feature based deep learning model over the accuracy on each morphological feature dataset. To evaluate the performance of proposed morphological features based Deep learning network model, benchmarked deep learning models [45] accuracy is compared. Efficient Net [46] is a Convolutional neural network architecture designed by Mingxing Tan and Quoc V in 2019. In Efficient Net architecture, a compound coefficient is used to scale all modules uniformly. Mobile Net [47] is a lighter and streamlined CNN architecture that uses depth-wise separable convolutions for real world applications. ResNet-18 [48] is an 18 layered Convolutional neural network designed for easy training of networks. VGG19 is a 19 [49] layered deep learning network which contains 16 convolution layers, 3 fully connected layer, 5 MaxPool layers, and 1 SoftMax layer. Accuracy of these benchmarked deep learning models and proposed morphological features based Deep learning network model is given in Table 2. Graph representation of accuracy comparison is given in Figure 6.

In the Deep learning model, convolution processes help to generate the feature for the desired conclusion and automatic learning. These features are worked and tuned for the desired conclusion. However, it is difficult for the model to settle on where the false positives exist. This proposed morphological feature-based method specifies the exact feature format, which helps to avoid the false positive detection of leaf feature. The detailed features set explained in this article help to improve the feature understanding capacity of the deep learning method. So, this morphological feature-based method optimally tunes the classification result for desired outcome. This deep learning architecture is flexible and can be adapted to new image processing problems in the future.

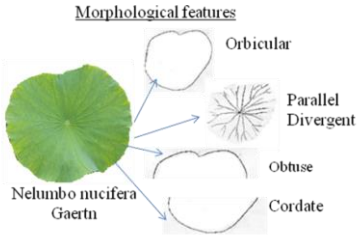

Figure 5. Leaf morphological features extracted from morphometrics of a leaf image

Table 2. Accuracy comparison of benchmarked deep learning models vs. morphological features based deep learning network model.

Deep learning model	Training Accuracy	Testing Accuracy	Average Accuracy
Efficient NetB0	92.12	91.30	91.71
Mobile Net	91.64	91.78	91.71
ResNet18	92.06	90.50	91.28
VGG19	91.97	89.80	90.89
Proposed model	98.76	95.12	96.94

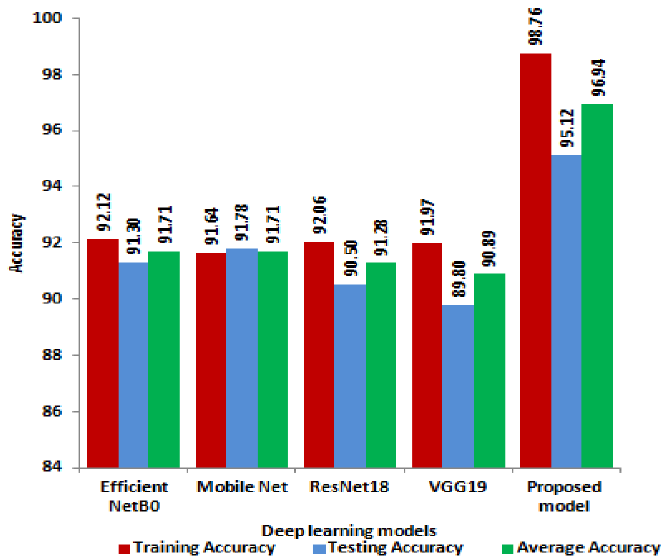

Figure 6. Comparison of accuracy of benchmarked deep learning models and proposed morphological features based Deep learning network model

6. Conclusion

In this article, we introduced the morphometrics for Aquatic and Semi Aquatic Plants. This is the first leaf morphometrics based deep learning system for plant leaf classification. Existing leaf morphological features contains color, texture, and shape of leaf. Here we introduced the extraction steps for leaf shape, apex, base, and vein morphological features. This article also discussed about the importance of morphological features-based leaf classification. This proposed method is trained to assist the deep learning system to concentrate on the morphological features of the input image. This architecture behaved equivalent to the human brain. A novel deep learning-based aquatic and semi aquatic plant's morphological features extraction and classification algorithm explained in this article achieved 97% accuracy. This morphological feature based deep learning network helped to overcome the catastrophic interference of continual learning. This robust and flexible morphometrics and morphological features based deep learning approach can be applied to many different image processing applications in future.

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Jibi G Thanikkal is a PhD scholar at Amity School of Engineering and Technology, Amity University Uttar Pradesh, Noida, India. Her research interests include computer vision, digital image processing and deep learning.

Ashwani Kumar Dubey is a Professor at Amity School of Engineering and Technology, Amity University Uttar Pradesh, Noida, India. His research interests include computer vision, image processing, deep learning, smart sensors, IoT and wireless sensor networks.

Thomas M T is an Assistant Professor of St. Thomas' College, Thrissur, Kerala, India. His research interests include medicinal plant identification, and plant species identification.