Applied Computer Science, vol. 17, no. 1, pp. 81–89
doi:10.23743/acs-2021-08

Submitted: 2021-03-22 | Revised: 2021-03-24 | Accepted: 2021-03-27

classification, leaf edges, leaf veins morphological, wavelet convolutional neural network

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PLANT CLASSIFICATION BASED ON LEAF EDGES AND LEAF MORPHOLOGICAL VEINS USING WAVELET CONVOLUTIONAL NEURAL NETWORK

Abstract

The leaf is one of the plant organs, contains chlorophyll, and functions as a catcher of energy from sunlight which is used for photosynthesis. Perfect leaves are composed of three parts, namely midrib, stalk, and leaf blade. The way to identify the type of plant is to look at the shape of the leaf edges. The shape, color, and texture of a plant's leaf margins may influence its leaf veins, which in this vein morphology carry information useful for plant classification when shape, color, and texture are not noticeable. Humans, on the other hand, may fail to recognize this feature because they prefer to see plants solely based on leaf form rather than leaf margins and veins. This research uses the Wavelet method to denoise existing images in the dataset and the Convolutional Neural Network classifies through images. The results obtained using the Wavelet Convolutional Neural Network method are equal to 97.13%.

1. INTRODUCTION

Leaves are an important component in plants. The way to identify the type of plant is to look at the shape of the leaf edges. These leaf edges can affect the shape of veins in plants. In this vein of plants, there is a clear correlation between vein characteristics and some leaf traits, such as damage and drought tolerance (Scoffoni et al., 2011). Botany, agriculture, and horticulture all rely heavily on computer identification and classification of plants. Not only for non-experts, but also for botanists and ecologists, to enhance identification and classification. Plant classification can be used to learn more about a plant's genus or family (Heredia, 2017). Veins can be used to classify plants because they carry information relevant to plant classification when shape, color, or texture cannot be observed. However, because humans only see leaves based on their shape, this feature frequently goes unnoticed.

Machine learning advancements, especially in computer vision, have made classification less difficult. Convolutional Neural Network is an architecture constructed by a typical visual sense system of living things, consisting of several layers of convolution where each layer performs functions that are mediated by cells in the visual cortex (Gu et al., 2018; Zhang, Wang & Liu, 2018). Convolutional Neural Networks are intended to process data in the form of multiple arrays. Numerous information modalities are as various exhibits: 1D convolution

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for signs and groupings, including language; 2D convolution for picture or sound spectrograms; and 3D convolution for video or volumetric images (Lecun, Bengio & Hinton, 2015). Convolutional Neural Networks have evolved over time, from 5 layers to 50 layers. Based on its development, there are 10 common Convolutional Neural Network architectures, namely LeNet-5 (Choi et al., 2005), AlexNet (Krizhevsky, Sutskever & Hinton, 2012), VGG-16 (Simonyan & Zisserman, 2015), Inception-v1 (Szegedy et al., 2015), Inception-v3 (Szegedy et al., 2016), ResNet-50 (He, Zhang, Ren & Sun, 2016), Xception (Chollet, 2017), Inception-v4 (Szegedy, Ioffe, Vanhoucke & Alemi, 2017), Inception-RestNets (Szegedy et al., 2017), and ResNeXt-50 (Xie, Girshick & Doll, 2017). Because of its high accuracy, this Convolutional Neural Network architecture is a machine learning approach that is often used for image recognition or classification.

Images that are used as a dataset for image recognition or classification will be mixed with a certain amount of noise. Noise will deteriorate the image quality (Hongqiao & Shengqian, 2009). Wavelet transform is often used for image denoising because it has low entropy, high multi-resolution, flexibility, etc. (Song, Ma, Cao & Han, 2016).

Wavelet Convolutional Neural Networks have begun to be widely used, especially in the medical field. In the medical field Wavelet Convolutional Neural Network is used to reconstruct MRI images (Ramanarayanan, Murugesan, Ram & Sivaprakasam, 2020), heart rate classification (Bouny, Khalil & Adib, 2020), and image restoration to repair degraded or degraded images (Liu, Zhang, Zhang, Lin & Zuo, 2018).

In this study, a classification based on the shape of the leaf edges and veins was performed using the Wavelet Convolutional Neural Network technique, where the wavelet serves to denoise the image.

2. RELATED WORK

2.1. Convolutional Neural Network

Previous research used a Convolutional Neural Network as image processing for plant identification (Lee, Chan, Wilkin & Remagnino, 2015; Grinblat, Uzal, Larese & Granitto, 2016), classification (Yalcin & Razavi, 2016; Dyrmann, Karstoft & Midtiby, 2016; Liu, Yang, Cheng & Song, 2019; Alimboyong & Hernandez, 2019), and classification based on leaf features (Lee, Chan, Mayo & Remagnino, 2017).

2.2. Wavelet

There are many types of Wavelet Transform, one of which is Discrete Wavelet Transform. Discrete Wavelet Transform has the advantage of temporal resolution, which can capture frequency and location information.

Discrete Wavelet Transformer is widely used for image denoising (Mohideen, Perumal, & Sathik, 2008; Kimlyk & Umnyashkin, 2018), because it produces a non-redundant image representation that gives better spatial and spectral location than image formation.

2.3. Wavelet Convolutional Neural Network

The Wavelet Convolutional Network architecture in Figure 1 illustrates the image processing flow. The Convolutional Neural Network wavelet processes the image fed through a convolution layer with a 3×3 kernel and 1×1 padding. Figures after Conv. Indicates the number of output channels. A 3×3 convolutional kernel with stride 2 and 1×1 padding is used to reduce the size of feature maps. The inserted images are decomposed through multi-resolution analysis, then the images are combined. Projection shortcut is performed with 1×1 convolution. The output of the convolutional layer is the vectorization of the combined global mean which is then followed by the fully connected layer (Fujieda, Takayama & Hachisuka, 2018).

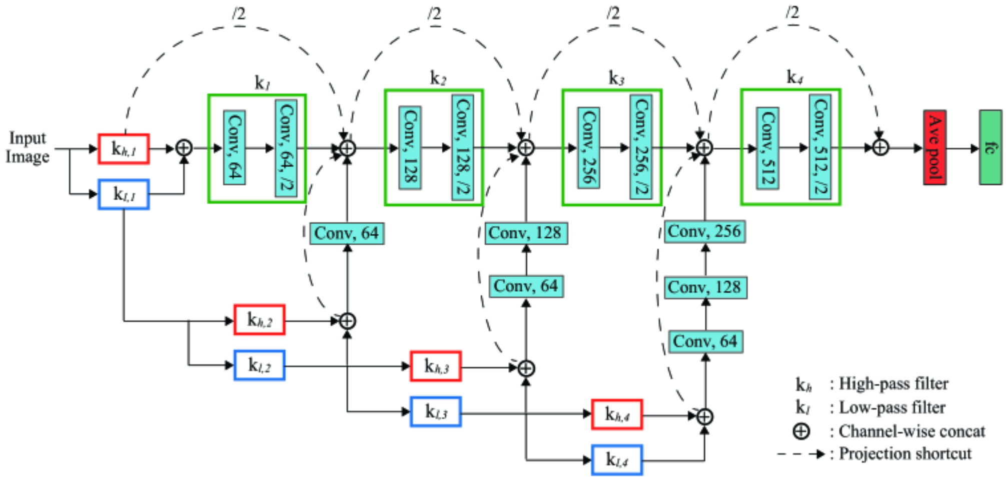

Fig. 1. Convolutional Neural Network Wavelet Architecture (Fujieda et al., 2018)

3. METHODOLOGY

There are several steps taken in this research. Table 1 will show details of the steps taken during the study.

Tab. 1. Research Implementation Phase

No.	Research Stage	Description
1.	Literature review.	The literature review is done by looking for references from journals, books, or the internet regarding previous research related to the research to be carried out, judging by the methods and objects used.
2.	Data collection.	The data was collected by taking pictures of plant leaves from the internet that matched the type of leaf edge shape and combining them with data from the Swedish dataset.
3.	Preprocessing and processing data.	The data that has been collected are then grouped according to the shape of the leaf edges and leaf veins. After that it is divided into training data and test data.
4.	WCNN modeling.	The making of this model is based on the Wavelet Convolutional Neural Network concept.
5.	Analysis and evaluation of results.	At this stage, the results of the plant classification are then analyzed, which affects the results of the classification of these plants. After that, an evaluation is carried out to whether there is anything that needs to be improved or developed so that the results obtained are as desired.
6.	Conclusions.	Based on the analysis and evaluation of the results, a conclusion is made on what affects the results of the classification of these plants.

3.1. Wavelet Convolutional Neural Network

Convolutional Neural Network is a spatial approach to image processing, such as image classification and identification. The spectral approach is also a good image processing, which is found in Wavelets. The spatial and spectral approaches have different characteristics. However, if these two approaches are combined, it will complement the weaknesses of the spatial approach, where this approach has limitations in multi-resolution analysis.

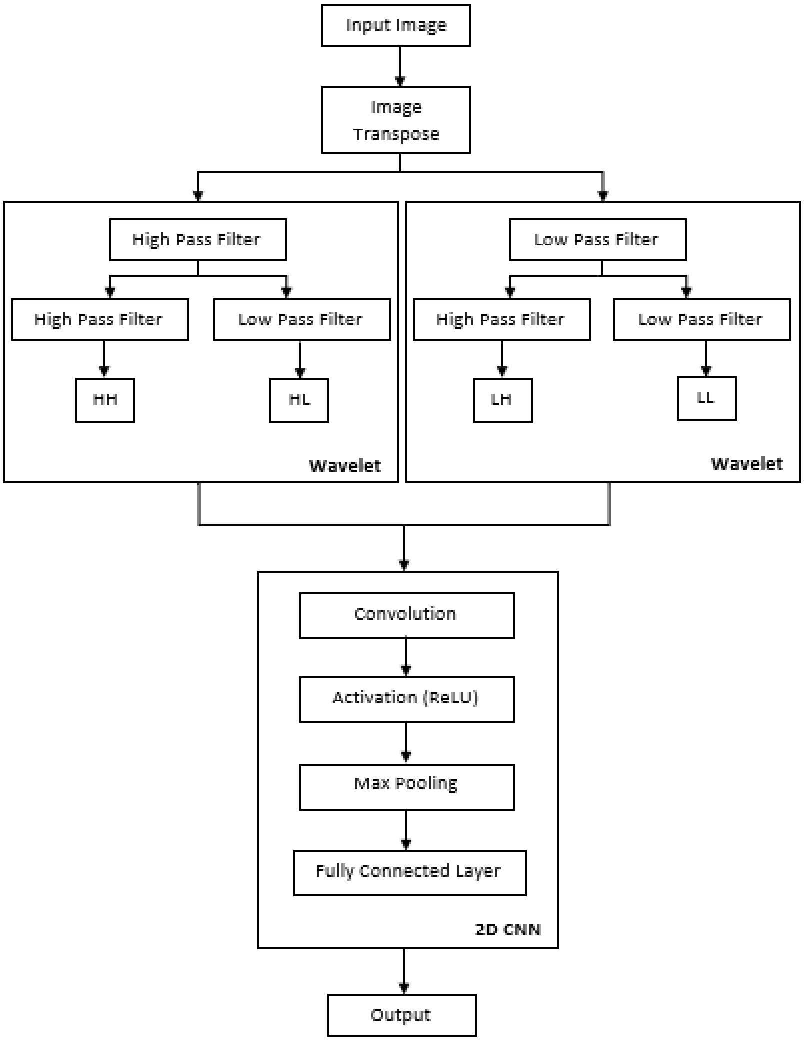

Fig. 1. Wavelet Convolutional Neural Network Flowchart

Figure 2 shows the flow of the classification process using a Wavelet Convolutional Neural Network. First, the image is inserted and then it is transposed from a matrix array to a vector. The inserted image is 224×224 in size. After that enter the filter analysis process, where the High Pass Filter and Low Pass Filter are carried out. Analysis filters are used to obtain approximation and detail. The results of the analysis filter will produce four bands labeled HH, HL, LH, and LL. Then, during preparation, join the Convolutional Neural Network phase, which goes through the convolution layer and uses batch normalization in the network until the activation layer. In both experiments, Adam's optimizer was used, as well as the Rectified Linear Unit (ReLU) as an activation function, and fully connected layer.

3.2. Rectified Linear Units

Activation function using Rectified Linear Units (ReLU), where each negative element is set to 0.0 with no exponential, no multiplication or division operations. The ReLU functions are:

$$f(x) = max(0, x) \tag{1}$$

3.3. Adam Optimizer

Optimization uses Adam's optimization algorithm, where the algorithm is useful for updating weights in neural networks. This algorithm can be used effectively to solve deep learning problems that use large amounts of data (Kingma & Ba, 2015).

4. RESULT AND DISCUSSION

Figure 3 shows the dataset used in this study. The dataset used was 1,943, of which 1,524 were training data and 419 were test data. The dataset contains types of leaf types, namely Aculeate, Biserrate, Crenate, Crenulate, Crispate, Dentate, Denticulate, Incesed, Lecerate, Lobed, Palmatifidus, Palmatilobed, Palmatipartitus, Pinnatifidus, Pinnatilobed, Pinnatisect, Serrate, Serrulate, Sinuate.

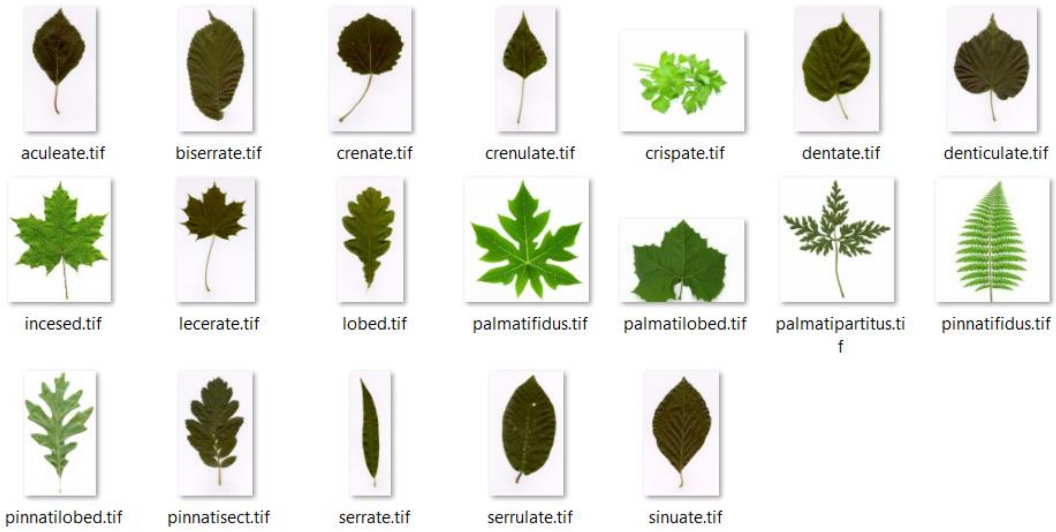

Fig. 2. Dataset

Figure 4 show the dataset after being transformed by the wavelet, a series of sub-band images with different resolutions can be obtained. The far left is a low frequency image, the next three images are a horizontal high frequency, a vertical high frequency, and a diagonal high frequency.

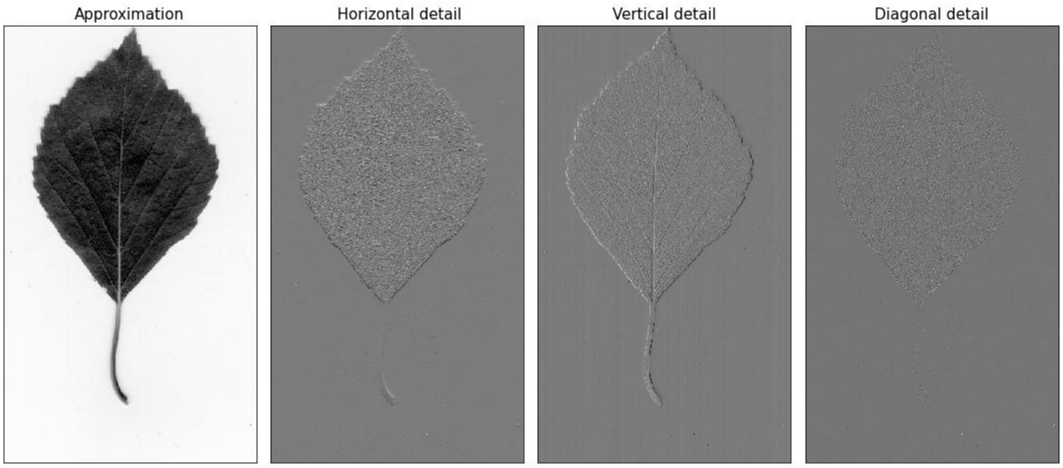

Fig. 4. Wavelet Transformation Results

The blue line reflects the level of accuracy during training, while the yellow line represents the level of accuracy during testing. The classification results give a value of 97.13% using epochs 100 and batch size 32.

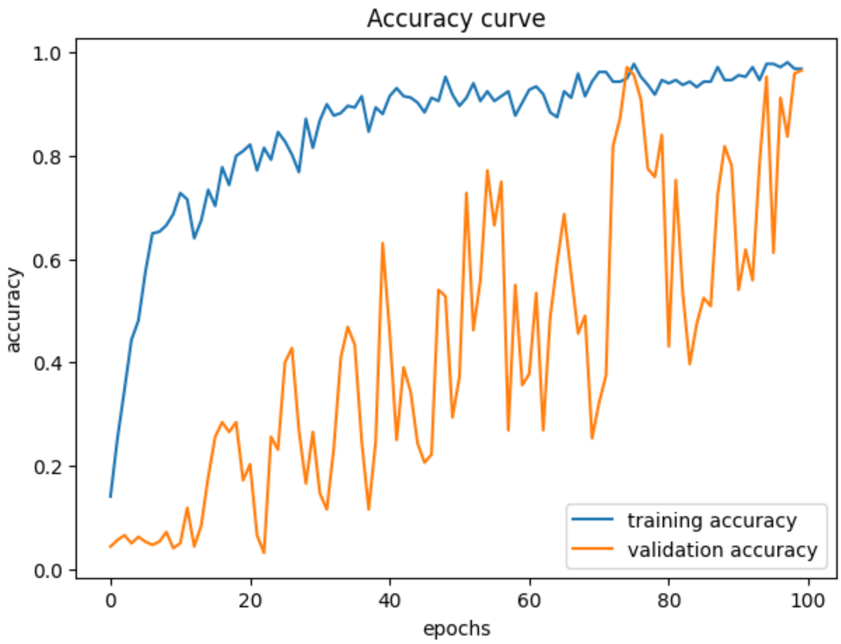

Fig. 5. Accuracy Graph

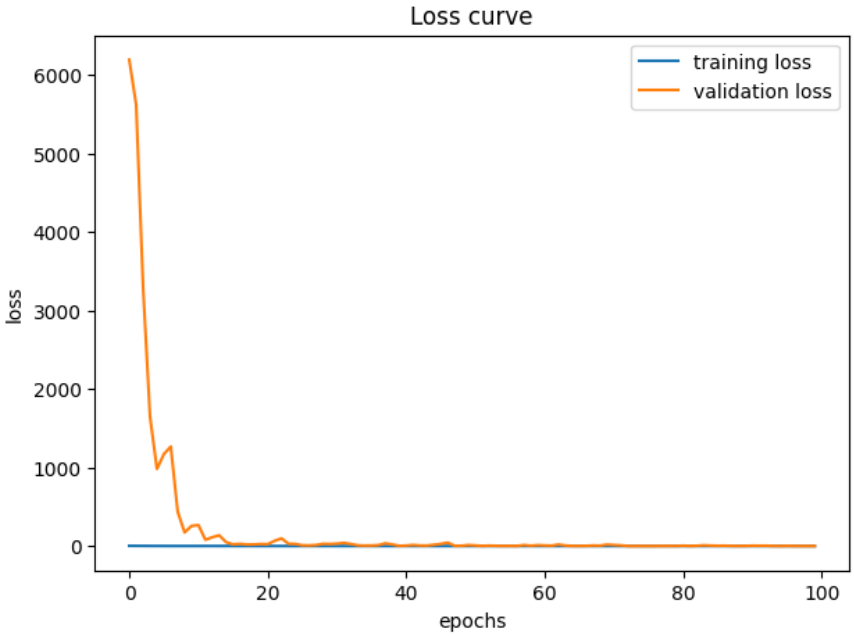

Fig. 6. Loss Graph

Based on the results of image classification using the Wavelet Convolutional Neural Network, the results show that the Convolutional Neural Network Wavelet has the best accuracy of 97.13% at epochs 100 and batch size 32. The classification results are higher than previous studies that classified 22 species of weeds and plants using the Convolutional Neural Network with an accuracy of 88% (Dyrmann et al., 2016), classification of plant leaves using the Convolutional Neural Network. with an accuracy of 87.92% (Liu et al., 2019), classification of plant leaves uses hybrid deep learning with an accuracy of 93%.

5. CONCLUSION

Combining Wavelets as a method for denoising image and Convolutional Neural Network using Adam's optimizer as a leaf classification method based on leaf edge and leaf morphological veins can provide good classification results, proven by the level of accuracy 97.13% and loss of 0.7%.

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