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Fused Random Pooling in Convolutional Neural Network for Herbal Plants Image Classification

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ABSTRACT

Convolutional Neural Network (CNN) faces concerns on overfitting. The CNN model learns during the training process but may not be able to classify new data correctly. Hence, the accuracy is higher in the training set than in the validation set. This occurs despite the breakthrough in CNN even if it is considered state of the art in image analysis. In this study, the fused random pooling is presented to create enhanced pooled feature maps, in that way, reducing overfitting and improving classification accuracy. The dataset utilized in this study consists of 8686 of six herbal plant images collected by actual photos and gathered publicly available online images. A comparison in terms of validation accuracy and validation loss of the average, max, mixed, and fused random pooling methods is presented. Results show that the fused random pooling achieved the highest validation accuracy of 98.21 percent and the lowest validation loss of 5.57 percent among the pooling methods used. The fused random pooling also led in terms of the performance evaluation on the precision, recall, and F1 score and attained results of 98.23 percent, 98.21 percent, and 98.21 percent, respectively. Thus, proving that applying fused random pooling is reliable in the herbal plant image classification.

Key words: Convolutional Neural Network, pooling techniques, image classification, fused random pooling, herbal plants

1. INTRODUCTION

Across history, plant resources remained an important part of human society. Having met the primary needs such as food and shelter, man has sought an effective remedy among plants to cure various diseases. Traditional medicine described as indigenous medicine for maintaining health and preventing, diagnosing and treating physical and mental illnesses [1] [2] mainly in rural areas where locally produced drugs are still used as household remedies for various ailments [3]. The use of herbal medicine, as a supplement and alternative medicine, is growing worldwide though not much is proven about the reasons and factors related to its use [4].

Methods for identifying plant species were used using morphology, anatomy, plant chemical taxonomy, or cell classification which require professional experts in botany; however, there are not enough experts to meet the demand, and plant specialist who knows other plant forms may not be familiar with other plants. This has resulted in increased interest in automating the identification of plants and other related tasks. Clear plant images are easy to collect with the growth and prevalence of digital cameras and computers. Many studies have been done on computer-aided plant identification. The general steps of leaf identification include image preprocessing, feature extraction, and classifier design, for which feature extraction and classifier design are the vital tools [5].

Computer vision researchers have developed plant identification systems that have helped botanists recognize and classify unidentified plant species more quickly. Most studies have so far concentrated on procedures or algorithms that optimize the use of leaf databases for plant predictive modeling. Using Convolutional Neural Network (CNN), useful features of the leaf can be used directly from the raw representations of input data [7].

CNNs are used to classify visual patterns [6] directly from pixel images and to use different forms of multilayer neural networks and are equipped with the back-propagation algorithm [7][8]. CNN embodied a breakthrough in image analysis and considered the state of the art for a number of tasks, including image identification, face recognition, and object detection [9].

Regularization approaches such as weight decomposition, weight binding, and extended training sets are used [10] to prevent overfitting. Stochastic pooling also takes into account activations, which includes the minimum value within the pooling region, while the average or maximum value is considered in mixed pooling. The particular area to be addressed is the pooling of execution [10][11]. Despite these, CNN still faces overfitting problem, which happens when a model learns that the system performance of the new validation data is adversely affected.

In this study, a new pooling technique called fused random pooling in a convolutional neural network is proposed to perform image classification of six herbal plants, namely Clitoria Ternatea, Ginkgo Biloba, Euphorbia Hirta, Curcuma Longa, Garcinia Mangostana and Allium Sativum. Classification metrics on accuracy, recall, precision, and F1 score are used to evaluate the performance of the model with the fused random pooling scheme.

2. REVIEW OF RELATED LITERATURE

2.1. Image Classification Advancements in Herbal Medicines

Plants are the groundwork of all existence on earth which provides food and oxygen. Good plant understanding is essential to help identify new or rare plant species to improve the pharmaceutical industry, balance the ecosystem, agricultural productivity, and sustainability [12].

For key ingredients and compositions of herbal medicines, the physiological components of plants such as leaves, flowers, fruits, nuts, barks, and roots are used. Practitioners of this medicine method and botanists have thrived in studying these plants to benefit the human race. It is important to digitize these useful plant species and their data [5]. This results in massive digital data collection, which initiates the need for classification and retrieval [13][14][15]. Among all organs, the leaf and their characters are studied comprehensively. Computer-based methods have been constructed to support botanists [16][17].

Manual plant species identification has made it difficult for human experts and more difficult for amateurs. A good understanding of shapes, petals, leaf-forms, and the plant's entirety is equally important to help calculate plant conditions and even model climate change using machine learning algorithms [18][19][20].

2.2. Convolutional Neural Network

CNN has proved to be the most dependable result in the classification of images [21][22][23]. The advantage of using CNN is that the kernel can act as a filter, shifting the object from left to right and from top to bottom to move the invariance of the image classification system. Every part of the network will acquire its individual features from the preceding layer. These features will be presented to the fully connected layer for conclusive decisions [24].

Image classification, as well as face recognition is modeled by CNN for temporal and spatial affiliations [25][26][27][28] and uses feature layers such as convolution layers to scale the involvement on all feasible locales in an input matrix. The two primary viewpoints of CNN are to distinguish patches of highlights independent of their position in a location invariance to convert patches of highlights into higher-level representations [29].

Improvements in CNN incorporates AlexNet which has been effectively connected to Large Scale Image Classification [30] and illness location on the tomato plants leaves [26], object recognition [31], semantic division [32], human pose approximation [33], large scale video classification [34], visual tracing [35], among others applications. VGGNet [25] is applied in arbitrary scaling for data augmentation, is a very deep convolutional network for large-scale image recognition utilizing increasing numbers of filters to extract different levels of information. VGGNet has been applied in plant identification [26] and recognition of Dazu Rock Carvings [27]. GoogleNet [29] uses inception modules that use multiple filter sizes at each layer and concatenate the results together, and the recognition accuracy is very high, even for the used small dataset [22]. GoogleNet has been used in programmed detection of basal ganglia hemorrhage [36], abnormality recognition in Chest X-Ray imageries [37], and tuberculosis recognition [38]. SqueezeNet [38] employs weighted cross inventory loss. SqeezeNet is applied in real-time pedestrian recognition and tracing [39] and sickness detection on the leaves of the tomato plants [40]. Region-based Convolutional Neural Network (R-CNN) [31] exceedingly improved the detection operation in terms of mean average precision (MAP) contrasted to models with no deep CNNs. R-CNN is utilized in unconstrained Face Detection [41]. Fast R-CNN develops on the study of R-CNN and progresses training and testing rates while intensifying the detection accuracy. Fast R-CNN substantially decreases the training and testing period [42].

2.3. CNN Pooling Operations

Pooling is another layer in CNN that is commonly placed between two convolutional layers to progressively decrease the spatial component of the feature maps in order to gain computational performance and to address the overfitting problem.

Max pooling uses the maximum element in each pooling region as (1)

$$y_{kij} = \max_{(p,q)\in R_{ij}} x_{kpq} \tag{1}$$

where y_{kij} is the output of the pooling operator associated with the *k*th feature map, x_{kpq} is the element at (p,q) within the pooling region R_{ij} which represents a local neighborhood around the position (i,j) [43].

Average pooling calculate the arithmetic mean for each patch on the pooling region as (2) where ykij is the output of the pooling operator related to the kth feature map, xkpq is the element at (p,q) within the pooling region Rij which indicates a local neighborhood around the position (i,j)where |Rij| stands for the size of the pooling region Rij [44].

$$y_{kij} = \frac{1}{|R_{ij}|} \sum_{(p,q)\in R_{ij}} x_{kpq} \tag{2}$$

Stochastic pooling randomly selects the activations within each pooling region based on a multinomial distribution. This ensures that the non-maximal activations of feature maps are also probable to be used as (3) [10].

$$P_i = \frac{a_i}{\sum_{k \in Rj} a_k} \quad (3)$$

Mixed Pooling randomly selects the conventional max pooling and average pooling operations [11]. Mixed pooling method produces the pooled output with equation (4) where λ is a random value being either 0 or 1, indicating the choice of using the max pooling or average pooling [11].

$$y_{kij} = \lambda . \max_{(p,q) \in R_{ij}} x_{kpq} + (1-\lambda) . \frac{1}{|R_{ij}|} \sum_{(p,q) \in R_{ij}} x_{kpq} \quad (4)$$

3. SIMULATION ANALYSIS AND DISCUSSION

The study uses 8686 collected varied images from actual taken photos by the researchers as well as gathered images from publicly available images online for the six classes of herbal plants specifically, Clitoria Ternatea, Ginkgo Biloba, Euphorbia Hirta, Curcuma Longa, Garcinia Mangostana and Allium Sativum to assess the performance of fused random pooling explored in this paper. Each herbal plant has an image size from 150 x 150 pixels to 300 x 300 pixels. Table 1 shows the distribution of the 6720, 1680, and 286 for the training, validation, and test datasets, respectively.

Clitoria Ternatea is known for antioxidant, antidiabetic, antimicrobial, antihelminthic, hepaprotective and antiasthmatic remedies [45][46]; Ginkgo Biloba is known to treat cerebrovascular diseases, Alzheimer's disease and macroangiopathy [47]; Euphorbia Hirta known to treat mosquito-carried dengue diseases [48]; Curcuma Longa known for to be therapeutic for anti□inflammatory, antihyperlipidemic, and antimicrobial applications [49]; Garcinia Mangostana used as traditional medicine to treat diseases such as diarrhea, abdominal pain, dysentery, wound-infections and chronic ulcer [50]; Allium Sativum know to treat hyperlipidemia and hypertension and prevents cancer and cardiovascular diseases [51][52]. Figure 1 shows some sample images of the herbal plants stated.

In this study, the fused random pooling method is compared with the average pooling, max pooling, and mixed pooling methods for demonstrating performance improvement. This fused random pooling applies random technique within the specified range from the activations of the average of the elements in each pooling region and the highest element of each pooling region, in generating pooled feature map, where β is the random value being any positive integer as shown in equation (5).

$$y_{kij} = \frac{1}{|R_{ij}|} \sum_{(p,q) \in R_{ij}} x_{kpq} + \beta \bmod \max_{(p,q) \in R_{ij}} x_{kpq} \quad (5)$$

In the experiments, the neural network architecture used five convolutional layers, four pooling layers, fully connected layer and a softmax layer as illustrated in Figure. 2. As a regularizer, the data augmentation technique and dropout of 25% were added after each pooling layer during training. This study CNN model used the stochastic gradient descent optimizer [53] with learning a learning rate of 0.01 [54], weight decay of

(a) Clitoria Ternatea (b) Ginkgo Biloba

(c) Euphorbia Hirta (d) Curcuma Longa

(e) Garcinia Mangostana (f) Allium Sativum

Figure 1: Herbal Plants Sample Images Used in this Study

1e-6 [55], momentum of 0.9 [43] and batch size of 32 images [56] were used to make the model efficiently learn. The model is executed in 40 epochs.

All experiments were conducted using Python programming language implementing Keras APIs and tensorflow packages in building the neural network. The convolutional network models were trained on GeForce GTX 1050Ti GPU in a 3.6 GHz Core i7 CPU.

Table 1: Training and Test Herbal Plant Image Dataset Distribution

Herbal Plant	Training Dataset	Validation Dataset	Test Dataset
Clitoria Ternatea	1120	280	50
Ginkgo Biloba	1120	280	48
Euphorbia Hirta	1120	280	47
Curcuma Longa	1120	280	48
Garcinia Mangostana	1120	280	46
Allium Sativum	1120	280	47
Total	6720	1680	286

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

To observe the effectiveness of training using the developed deep neural network shown in Figure. 2, performance evaluation was computed using the equations (6), (7), and (8) to compute for the precision, recall, and F1 score, respectively.

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F1\,score = 2 \times \frac{Precission \times Recall}{Precission + Recall} \quad (8)$$

During the training process, the validation loss and validation accuracy achieved by the described architecture is depicted in Figure 3(a) and Figure 3(b). It can be noted that using fused random pooling method, overfitting problem is successfully resolved and accuracy was improved since fused random pooling hast the lowest validation loss of 5.57% and highest validation accuracy of 98.21%. This indicates that the performance and robustness of the model are considerably observed as shown in the comparative results in Table 2 where fused random pooling led by 1.74% in precision, 1.78% on recall, and 1.79% on F1 score compared to average pooling; a lead of 1.5% on recall, 1.48% on precision, and 1.49% on F1-score with max pooling; and 1.03% on recall, 1.01% on both precision and F1 score on mixed pooling. The confusion matrix and performance results on each herbal plant for the validation data and test data are shown in Figure 4(a) and Figure 4(b), respectively. In the validation data, it can be noted that the precision results ranges from 95.45% to 99.64%; recall from 95.36% to 99.64%; and harmonic F1 score from 96.47% to 99.47%. In the 286 unlabeled images test data, the precision, recall, and F1 score ranges from 97.83% to 100%.

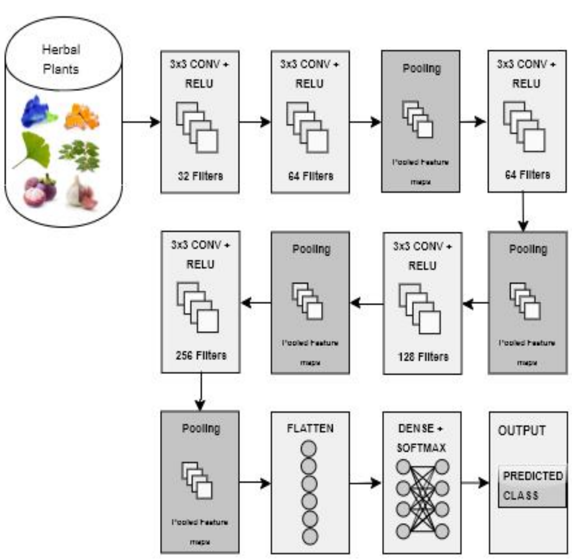

Figure 2: CNN Architecture Used in this Study

Table 2: Comparative Classification Performance for Various Pooling Method on Validation Dataset

Pooling Method	Precision	Recall	F1-Score
Average	96.49%	96.43%	96.42%
Max	96.73%	96.73%	96.72%
Mixed	97.20%	97.20%	97.20%
Fused Random	**98.23%**	**98.21%**	**98.21%**

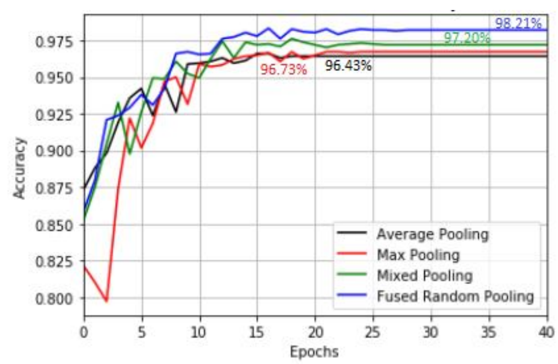

Figure 3(a): Comparison of Validation Accuracy of Each Model

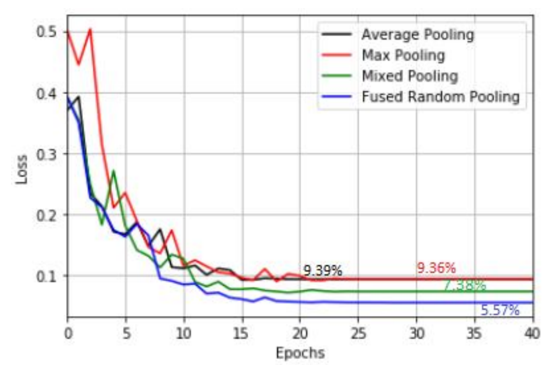

Figure 3(b): Comparison of Validation Loss of Each Model

		Predicted Label							
	Herbal Plants	Clitoria Ternatea	Ginkgo Biloba	Garcinia Mangostana	Allium Sativum	Euphorbia Hirta	Curcuma Longa	Recall	F1-Score
True Label	Clitoria Ternatea	279	0	0	1	0	0	99.64%	98.94%
	Ginkgo Biloba	0	278	0	0	1	1	99.29%	99.11%
	Garcinia mangostana	1	0	274	2	1	2	97.86%	98.74%
	Allium Sativum	4	0	0	273	0	3	97.50%	96.47%
	Euphorbia Hirta	0	1	0	0	279	0	99.64%	99.47%
	Curcuma Longa	0	2	1	10	0	267	95.36%	96.56%
	Precision	98.24%	98.93%	99.64%	95.45%	99.29%	97.80%		

Figure 4(a): Herbal Plants Validation Dataset Confusion Matrix and Performance Results

		Predicted Label							
	Herbal Plants	Clitoria Ternatea	Ginkgo Biloba	Garcinia Mangostana	Allium Sativum	Euphorbia Hirta	Curcuma Longa	Recall	F1-Score
True Label	Clitoria Ternatea	50	0	0	0	0	0	100.00%	100.00%
	Ginkgo Biloba	0	47	0	0	1	0	97.92%	97.92%
	Garcinia mangostana	0	0	46	0	0	1	97.87%	97.87%
	Allium Sativum	0	0	1	47	0	0	97.92%	97.92%
	Euphorbia Hirta	0	1	0	0	45	0	97.83%	97.83%
	Curcuma Longa	0	0	0	1	0	46	97.87%	97.87%
	Precision	100%	97.92%	97.87%	97.92%	97.83%	97.87%		

Figure 4(b): Herbal Plants Test Dataset Confusion Matrix and Performance Results

5. CONCLUSION AND FUTURE WORK

This study presented a fused random pooling method in a convolutional neural network to improve image classification on herbal plant images. Comparative results demonstrate that fused random pooling methods outperforms the average, max, and mixed pooling to address the overfitting problem. Results show that based on the experimental results, fused random pooling lead in all the performance measures on precision, recall and F1 score as applied on the herbal plant dataset. Results also show that in terms of validation loss, the fused random pooling achieved the lowest percentages compared with the other pooling methods in this study. Thus, fused random pooling proved to be reliable in the herbal plant image classification.

It is recommended that this CNN architecture with fused random pooling will be used for future studies to further increase the number of classes and include other herbal plant species in the image classification to further test its reliability.

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