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Herbal Plant Image Classification using Transfer Learning and Fine-Tuning Deep Learning Model

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ABSTRACT

Herbal plants are highly significant to the local community in Malaysia, as the country's fertile land is rich in diverse species that are widely used for various purposes, including traditional medicine, culinary, aromatherapy, and even in the cosmetic industries. This situation demands numerous applications and activities, including plant species identification, medicinal plant research, agriculture research, and environmental monitoring, which makes image classification of herbal plants a substantial task. However, this task is complicated by the complex nature of the plants, particularly includes plants variations in appearance, close similarities between species, and limited availability of labeled data and images. Motivated to mitigate the issues, this paper investigated the use of transfer learning and fine- tuning the deep learning neural network to classify different herbal plant species. Transfer learning is an algorithm that learns to recognize image features in one domain and having the capability to generalize the learnt knowledge to a new domain with a smaller dataset. Additionally, fine-tuning can be used to further improve the performance of the model on the new task with less training time and fewer training data. The authors performed experiments on ResNet-50 which been previously trained with ImageNet dataset. The experiments were carried out on a subset of the MYLPherbs-1 dataset, which consisted of two local perennial herbs plant species. Different hyperparameters were used across the various experiment settings, and the authors observed the behavior and relationships of the distinct models, datasets, and hyperparameters toward the classification task's accuracy. The authors also employed two different transfer learning approaches: (i) using pre-trained models as feature extractors with different classifiers, (ii) fine-tuning the pre-trained model. Based on the results and discussion, fine-tuning the ResNet-50 model on the MYLPherb-1 dataset demonstrated the best overall performance.

Keywords:
Herbal plant; ResNet-50; Transfer Learning; Fine Tuning, Deep Learning; Image Classification

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1. Introduction

Malaysia is a fertile tropical land rich of biodiversity and sacred with abundance flora and fauna. It was ranked at 12th place in the world and 4th in Asia as world largest biodiversity with 15,000 recorded flower plant species [1]. Within the specified numbers, a substantial portion of approximately 1,200 species is categorized as medicinal herbal plants. In this warm and humid tropical climate region, herbal plants flourish and thrive, resulting in their abundant growth. This favourable environment makes these plants easily accessible and extensively utilized by local communities, particularly in culinary practices and traditional medicine. As advancements in technology and herbal knowledge continue to unfold, the usage of herbal plants has gained remarkable momentum, extending its reach into diverse realms such as alternative medicine, aromatherapy, and cosmetics. This expanding interest reflects a growing recognition of the immense potential and holistic benefits offered by herbal plants in various aspects of human well-being.

In order to fully unlock the potential of herbal plants across multiple industries, active research and engagement in herbal plants specifically in Malaysia region is absolutely crucial. Malaysia is a country that is renowned for its abundant variety of herbal plants, boasts a rich diversity of species. However, there remains a limited understanding and recognition of each specific herbal plant species among the general population. This challenge stems from the fact that certain herbal plants exhibit remarkably similar appearances, despite belonging to distinct species [2]. Consequently, accurately and promptly identifying and differentiating these species presents a notable hurdle, particularly for individuals lacking specialized knowledge or experience in this field.

The complex nature of differentiating and discerning among the diverse herbal plant species necessitates the advancement of research in the field of image processing, specifically in the realm of image classification. Image classification for herbal plants capitalizes on the immense potential of deep learning techniques to offer an invaluable solution for automated identification and categorization of various herbal species by leveraging their distinct visual characteristics. Through the meticulous training of a deep learning model on a comprehensive collection of herbal plant images, the system becomes adept at discerning intricate patterns and distinctive characteristics, enabling it to efficiently classify and assign accurate labels to newly encountered herbal images.

Deep learning models have proven to be highly effective in image classification tasks. Among the models, ResNet-50 is one of the popular deep learning model that has been widely used for image classification [3-5]. It is a variant of the ResNet architecture, which stands for Residual Network. ResNet-50 specifically refers to a ResNet model comprises of 50 layers, including convolutional layers, pooling layers, fully connected layers, and skip connections. The authors employed ResNet-50 as the deep learning model due to its outstanding performance in image classification task. Subsequently, transfer learning and fine-tuning approaches is used to enhance the classification performance.

Thus, this study investigates the impact of leveraging transfer learning and fine-tuning deep learning model on a set of herbal plants images. The aim is to observes the performance of the herbal image classification in terms of accuracy.

To further explain on this study, the research paper is organized as follows. In Section 2, the background and motivation of this study will be elaborated. Section 3 describes previous related works done. Section 4 describes methods used to accomplish the experiments. Section 5 presented the results and discussions. Finally, Section 6, outline the conclusion of the study in a comprehensive manner. Acknowledgements and References are included at the last section of this paper.

2. Research Background

The classification of herbal images is a significant research area that focuses on developing algorithms and models to accurately classify images of different herbal plants based on their visual features. The motivation behind this study is to support the evolution of herbal industries which has gained significant raised in interest and demand due to herbal valuable properties. Accurate classification of herbal plants can aid in their identification, quality control, authentication, and conservation. It can also support related activities such as pharmaceutical research, drug discovery, and ensure the safety and efficacy of herbal products [6].

Furthermore, the classification of herbal images faces unique challenges due to the inherent variability and complexity of plant structures [7]. Herbal plants exhibit a wide range of intra-class variations, including variations in leaf shape, color, texture, and other morphological features [8]. These variations can be influenced by factors such as species, growth conditions, and environmental factors, making accurate classification a particularly challenging task [9].

Moreover, the presence of inter-class similarities adds another layer of complexity to herbal image classification [10]. Different herbal plant species may share similar visual characteristics, further complicating the discrimination process. This requires developing robust algorithms capable of capturing subtle differences and extracting discriminative features to accurately differentiate between visually similar plant species.

In the context of Malaysia, the availability and quality of herbal plant image datasets can pose constraints and demand additional effort [11]. Creating comprehensive and diverse datasets that cover a wide range of herbal plant species found in Malaysia requires extensive data collection efforts. Factors such as limited accessibility to certain plant species, variations in lighting conditions, and variations in image quality can further challenge the construction of representative datasets specific to the region.

Addressing these challenges and constraints requires the development of robust image classification algorithms that can effectively handle intra-class variations, inter-class similarities, and the limitations of the available dataset. Integration of advanced techniques, such as deep learning architectures, transfer learning, data augmentation, and fine-tuning becomes crucial to enhance the accuracy and reliability of herbal plant image classification, particularly in the specific context of Malaysia.

3. Literature Review

In the context of herbal image classification in Malaysia, there has been significant research focusing on medicinal leaf images. The contribution by several authors [12-13] to this area, have shedding light on various aspects of the herbal plant images classification process.

In the initial stages of research, Ibrahim *et al.*, [9] conducted a comparative study focusing on three widely used texture features, namely Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and Speeded-Up Robust Features (SURF), in conjunction with a multiclass Support Vector Machine (SVM) classifier. To facilitate their investigation, the authors constructed a novel leaf dataset consisting of samples from ten distinct herbal plants. The experimental findings obtained from this newly constructed dataset, as well as the existing Flavia dataset, revealed that both HOG and LBP exhibited comparable leaf recognition performance, which surpassed the performance achieved by SURF. This study provides valuable insights into the efficacy of different texture features and their suitability for herbal leaf recognition tasks, thereby contributing to the advancement of herbal image classification research.

Subsequently, a prominent study conducted by Muneer *et al.*, [14] compared the performance of two popular algorithms, Support Vector Machine (SVM) and Deep Learning Neural Network (DLNN), for herbal image classification. The research findings demonstrated that DLNN algorithm achieved superior performance compared to SVM algorithm, indicating the potential of deep learning techniques in accurately classifying herbal images.

Another notable work by Suhaila Abdul Halim *et al*., [2] employed Sobel edge detection for image segmentation and utilized SVM to extract shape and texture features from five different herbal plant species. The study aimed to identify distinct features that can contribute to the accurate classification of herbal images. By leveraging these features, the authors successfully differentiated between different plant species, highlighting the importance of shape and texture analysis in herbal image classification.

Investigation on the performance of a convolutional neural network (CNN) on Malaysian medicinal herbs datasets was conducted by Mohd Roslan *et al.*, [13]. The study highlighted the effectiveness of the augmentation technique in enhancing the accuracy of herbal image classification embedded in CNN model. The augmented data, which underwent the augmentation process, outperformed the actual data in terms of classification accuracy. These results demonstrate the potential of data augmentation as a valuable strategy for improving the performance of CNN models in herbal image classification tasks. While another research by Kandelwal *et al*., [15] suggested that deep learning applications mainly lessen the reliance on designs and preprocessing techniques by joining the entire process, hence benefitting the disease diagnosis and classification of herbal plants particularly in medical domain.

In a recent study conducted by Devi *et al*., [16], the authors propose the use of Conv2D Xception Adadelta Gradient Descent (CXAGD) deep learning model for the classification of plant species based on leaflet feature structures. The research leverages a leaf classification dataset from Kaggle, consisting of 4500 plant leaflets representing various species. The CXAGD model is constructed with 36 depth-wise separable convolutional layers and incorporates a maximum pooling layer for each convolution. The results of the study demonstrate that the proposed CXAGD model outperforms existing CNN models in terms of accuracy. The implementation outcomes highlight the effectiveness of the CXAGD model, which is based on the Xception network and utilizes the Adadelta optimizer. The higher accuracy achieved by the CXAGD model showcases its potential for accurate plant species classification based on leaflet feature structures.

4. Methodology

4.1 Dataset

The dataset used in this study is a subset of MYLPherbs-1 introduce by Pushpanathan *et al*., [17] which contains of 2,093 images with 2 different classes. Each class representing a herbal plant species which is Asiatic Pennywort Centella Asiatica and Chinese Gyunera Gynura Pseudochina. This dataset indicating the uncontrolled environment of the real nature surrounding in Malaysia. They were 6 different image acquisition method were setup to three different cameras as follows;

i) Distance of the camera from the leaf : 5cm,10cm,15cm,20cm,25cm and 30cm
ii) Tilt of the camera : 45 degree to left and right with reference to the leaf at 10cm, 20cm and 30cm
iii) Zoom from a distance of 30cm from the leaf : 1x, 1.5x, 2x, 2.5x, 3x, 3.5x and 4x
iv) White balance : Sun,Cloudy,Incandescent and Fluorescent
v) ISO : 100, 200, 400 and 800
vi) Exposure : -2, -1, 0 , +1, +2

4.2 ResNet-50

ResNet-50 is a convolutional neural network (CNN) architecture belongs to the ResNet (Residual Network) family models, which aimed to address the challenge of training deep neural networks with hundreds and not limited to thousands of layers. ResNet-50 refers to the number of layers in the network, including convolutional layers, pooling layers, fully connected layers, and skip connections. The key innovation of ResNet model is the use of residual connections, also known as skip connections, which allow the network to learn residual functions instead of directly learning the desired mapping.

The residual connections in ResNet-50 enable the network to effectively propagate gradients during training, mitigating the problem of vanishing gradients and allowing for the successful training of very deep networks. This design significantly improved the performance of deep CNNs, making it easier to train and achieving better accuracy.

In terms of architecture, ResNet-50 consists of a series of convolutional layers followed by batch normalization, ReLU activations, and residual connections. The network employs a combination of 1x1, 3x3, and 1x1 convolutional filters to capture different levels of spatial information. The use of bottleneck building blocks helps reduce computational complexity while maintaining the representational power of the network.

Overall, ResNet-50's strength lies in its ability to effectively train very deep networks [18], leading to improved accuracy in image classification tasks. The residual connections and architecture design have set a new standard in deep learning models, influencing subsequent advancements in the field.

4.3 Pre-trained Model (ResNet-50)

A pre-trained model is a machine learning model that has been trained on a large dataset and is made available for reuse in different tasks [19]. During the training process, the model learns to capture meaningful patterns, features, and representations from the input data. The learned parameters or weights of the model represent the knowledge gained from this training phase. The authors employed ResNet-50 model that was previously trained with ImageNet dataset. ImageNet is a large-scale dataset of labeled images consists of over a million images across 1,000 different categories, covering a wide range of objects, animals, scenes, and more. ImageNet has been widely used as a benchmark dataset for image classification tasks. Pre-trained ResNet-50 model was downloaded from Tensorflow deep learning framework. The pre-trained ResNet-50 architecture consists of the following;

i. Input Layer: Accepts input images of a fixed size, typically 224x224 pixels with three color channels (RGB).
ii. Convolutional Layers: The input image goes through a series of convolutional layers with different filter sizes, typically 1x1, 3x3, and occasionally 1x1 again. These layers extract visual features from the input image.
iii. Batch Normalization: After each convolutional layer, batch normalization is applied to normalize the activations and improve training stability.
iv. Activation Function: Rectified Linear Unit (ReLU) activation functions are applied to introduce non-linearity and capture complex features.
v. Max Pooling Layers: Periodic max pooling layers are used to down sample the spatial dimensions of the feature maps, reducing computational complexity and capturing more abstract features.

vi. Residual Blocks: ResNet-50 employs several residual blocks, each containing multiple convolutional layers. The residual blocks utilize skip connections that bypass some layers and allow the network to learn residual functions. These skip connections facilitate gradient flow and help address the vanishing gradient problem.
vii. Global Average Pooling: Towards the end of the network, global average pooling is applied to convert the spatial dimensions of the feature maps into a vector representation. This pooling operation aggregates the feature maps' spatial information while reducing dimensionality.
viii. Fully Connected Layers: Following global average pooling, fully connected layers process the aggregated features and produce the final predictions. The number of neurons in the final fully connected layer corresponds to the number of output classes in the specific classification task.
ix. Softmax Activation: A softmax activation function is applied to the final layer, generating a probability distribution over the output classes.

4.4 Transfer Learning

Transfer learning is a technique in machine learning that uses the model developed from previous task to solve the problem in the current task [20]. The main goal of transfer learning is optimization in order to speed up processes as well as minimizing the use of computational resources [21]. On top of that, this technique allows the training of deep neural networks using small amount of data. In this study, the authors used pre-trained ResNet-50 model that was trained with ImageNet as the based model to classify the image dataset.

In this approach, the authors used pre-trained model as feature extractor with different classifiers. Instead of training a model from scratch, the pre-trained model is employed to extract meaningful features from input data, which are then fed into a separate classifier for the final classification task. The process typically involves freezing the pre-trained model's weights to preserve its learned representations while training only the classifier's weights. In order to accomplish the processes, the authors set the base model weights as “False” as well as the top layers which present the classifiers layers in ResNet-50 as ‘False’. Following that, new fully connected layers representing two classes from the dataset as the classifiers on top of the ResNet-50 architecture.

This approach leverages the pre-trained model as a fixed feature generator, extracting highly informative features from the input data. The feature extractor captures rich representations that encode meaningful patterns and structures. Subsequently, the classifier learns to effectively utilize these extracted features, enabling accurate classification based on the discriminative information encoded within the features.

4.5 Fine-tuning

Fine-tuning in image classification is a powerful technique that leverages the capability of a pre-trained model, and adapts it to a smaller, domain-specific dataset [22]. By utilizing pre-existing knowledge and learned representations, fine-tuning eliminates the need to start the training process from scratch, enabling faster convergence and superior performance. This approach capitalizes on the pre-trained model's understanding of visual features and patterns, while fine-tuning the model's parameters to align seamlessly with the intricacies and characteristics of the target dataset. This efficient knowledge transfer not only saves valuable computational resources but also expedites the development of highly accurate and robust image classification systems, facilitating advancements in various domains and applications.

The authors implemented two approaches in the experiments. The first approach is fine-tuning the pre-trained ResNet-50 model by unfreezing the last block of the model. This is referring to fourth residual block in the fourth stage of the model architecture (Stage 4, Block 3). The fourth stage consists of three residual blocks numbered as Block 1, Block 2, and Block 3. The second approach is fine tuning the fourth stage (Stage 4, Block 1). In this approach, the whole Stage 4 block was unfreeze.

5. Results & Discussion

This section will describe the results and discussion from the experiments conducted.

Table 1
Comparison based on accuracy using the following hyperparameters; Input shape: 224 x 224 x 3, Epoch: 50, Batch size:32

	Transfer Learning as feature extractor	Fine-tuning unfreeze (Stage 4,Block 3)	Fine-tuning unfreeze (Stage 4, Block 1)
Accuracy(%)	88.45	90.01	92.7

Table 2
Comparison based on accuracy using the following hyperparameters; Input shape: 224 x 224 x 3, Epoch: 100, Batch size:32

	Transfer Learning as feature extractor	Fine-tuning unfreeze (Stage 4,Block 3)	Fine-tuning unfreeze (Stage 4, Block 1)
Accuracy(%)	92.2	92.1	93.9

Table 3
Comparison based on accuracy using the following hyperparameters; Input shape: 224 x 224 x 3, Epoch: 150, Batch size:32

	Transfer Learning as feature extractor	Fine-tuning unfreeze (Stage 4,Block 3)	Fine-tuning unfreeze (Stage 4, Block 1)
Accuracy(%)	93.18	93.9	96.1

Table 4
Comparison based on accuracy using the following hyperparameters; Input shape: 224 x 224 x 3, Epoch: 50, Batch size:64

	Transfer Learning as feature extractor	Fine-tuning unfreeze (Stage 4,Block 3)	Fine-tuning unfreeze (Stage 4, Block 1)
Accuracy(%)	89.32	91.47	92.79

Table 5
Comparison based on accuracy using the following hyperparameters; Input shape: 224 x 224 x 3, Epoch: 100, Batch size:64

	Transfer Learning as feature extractor	Fine-tuning unfreeze (Stage 4,Block 3)	Fine-tuning unfreeze (Stage 4, Block 1)
Accuracy(%)	92.01	92.18	94.57

Table 6
Comparison based on accuracy using the following hyperparameters; Input shape: 224 x 224 x 3, Epoch: 150, Batch size:64

	Transfer Learning as feature extractor	Fine-tuning unfreeze (Stage 4,Block 3)	Fine-tuning unfreeze (Stage 4, Block 1)
Accuracy(%)	93.82	94.82	97.08

Based on the results of the experiments conducted with different hyperparameter settings, the highest accuracy of 97.08% was achieved using the fine-tuning approach (unfreeze layer in Stage 4 starting from Block 1), as shown in Table 6. On the other hand, the lowest accuracy of 88.45% was obtained when using transfer learning as a feature extractor, as reflected in Table 1.

Unfreezing the layers in the model architecture, starting from Stage 4, Block 1, led to the best accuracy. This process allows the network to adjust its weightage and relearn and adapt to the features present in the new herbal plant image dataset.

Furthermore, increasing the number of epochs improved the accuracy, indicating that a sufficient number of training iterations is necessary for the model to converge and capture the patterns in the data. However, the batch size did not significantly impact the accuracy.

6. Conclusions

In conclusion, the experiments conducted with various hyperparameter settings have provided valuable insights into the performance of different approaches for image classification. Among the tested methods, the fine-tuning approach and increasing the number of epochs, emerged as the most effective strategy for achieving high accuracy.

The fine-tuning approach allowed the model to adapt its weights and learn from the new dataset, leveraging the knowledge gained from pre-training on a larger dataset such as ImageNet. By selectively unfreezing layers starting from Stage 4, Block 1 in Resnet-50 the model was able to focus on refining higher-level features specific to the target task, leading to improved accuracy. This highlights the importance of considering the depth and architecture of the model when fine-tuning, as different layers capture different levels of abstraction in the data.

Moreover, the positive correlation between the number of epochs and accuracy suggests that sufficient training iterations are crucial for the model to converge and capture intricate patterns in the data. Increasing the number of epochs allows the model to refine its representations and fine-tune the learned features, resulting in better classification performance.

Additionally, it is noteworthy that the batch size did not have a significant impact on the accuracy in these experiments. However, it is important to note that the impact of batch size can vary depending on the specific dataset, model complexity, and computational resources available.

Overall, these findings underscore the importance of thoughtful hyperparameter selection and training strategies in achieving optimal performance in image classification tasks. By carefully considering factors such as the fine-tuning approach, layer selection for unfreezing, number of epochs, and batch size, could contribute to the robustness of the model specifically for image classification task.

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