An Effective Deep Neural Network in Edge Computing Enabled Internet of Things for Plant Diseases Monitoring

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Abstract

With the rise of the Internet of Things technology, smart agriculture and the corresponding technology, namely, Taiwan 's agriculture 4.0 has been developed. A large number of large-scale planted agricultural areas have been created in recent years. Unmanned aircraft traveling over the farmland combined with widely distributed smart sensors monitor crop growth, and manage plant disease. Among them, orchids are very suitable as ornamental flowers, and they are flowers with high economic value. Therefore, orchids have become one of the most important agricultural products for export in Taiwan. However, the environment for planting orchids and disease control are very important to prevent the diseases. If orchids become infected, they must immediately make a correct diagnosis of the disease in order to effectively find the way of prevention and treatment measures and minimize the loss. This project intends to study the problem about " An effective deep neural network in edge computing enabled internet of things for plant diseases monitoring", and proposes an effective method for detecting and identifying orchid diseases. It will integrate local and global features in the disease symptoms to the disease attribute and type learning, respectively. Under the automated planting IoT environment, real-time surveillance images are used to identify orchid diseases, and the system can improve identification performance by integrating deep learning neural networks. The main research topics includes: A. Construct an image database of orchid infected leaves, and construct information about the feature type of the disease and the corresponding attributes according to the lesions in different periods. B. Construct a deep learning integration model to obtain mid-to-high-level image features, which can resist the multiple characteristics of orchid lesions, and the influence of environmental variability factors. C. Develop an integrated test prototype system, use a monitoring device in the IoT environment to perform verification, and test the performance of the orchid disease identification.

1. Introduction

The planting environment and disease control significantly interfere with plant growth and can even lead to plant mortality. Consequently, this can impact the yield and market prices of crops. Given that the majority of the world's food supply relies on plant sources, addressing issues related to the planting environment and diseases has long been a focal point of technological research for humans.In recent years, the impact of aging rural populations and declining birth rates has resulted in a substantial shortage of agricultural labor. However, with the rise of Internet of Things (IoT) technology, the era of Agriculture 4.0 has been ushered in. This has led to the emergence of extensive agricultural zones dedicated to large-scale crop cultivation. These areas are equipped with unmanned aerial vehicles (UAVs) and a widespread network of smart sensors, enabling real-time remote monitoring of crop growth conditions. Simultaneously, data collected from these sensors can be transmitted to the cloud for analysis, facilitating tasks such as disease control, fertilizer application, water resource management, and cost analysis. Farmers can easily manage their agricultural activities by connecting to cloud platforms through mobile devices, such as smartphones or tablets [1].

Orchids, which are mostly found in tropical and subtropical regions between the latitudes of 30 degrees north and south, exhibit a wide variety of shapes, colors, and sizes in their flowers. Each orchid species possesses its unique appearance and characteristics, making them highly attractive to a vast number of enthusiasts. Due to their aesthetic appeal and individuality, orchids are exceptionally well-suited for ornamental purposes and have become high-value ornamental flowers. The cultivation of orchids requires precise environmental control, including factors such as temperature, humidity, light, and ventilation, all of which are crucial. The ideal temperature for orchids typically falls in the range of 15 to 30 degrees Celsius. Humidity levels should be relatively high, but it's essential to maintain good ventilation. When it comes to lighting, orchids have a preference for lower levels of light, as excessive exposure to sunlight can lead to wilting and damage. Caring for orchids demands consistent human attention over an extended period. It is essential to prevent diseases and maintain the health of their leaves. In cases where orchids do contract diseases, it is imperative to promptly and accurately diagnose the issue. This facilitates the development of appropriate prevention and treatment measures to address the specific problem [2] [3].

This research aims to develop a deep learning neural network that integrates disease categories and attributes for image-based plant disease recognition within the context of the Internet of Things (IoT) and edge computing environments. While plant disease recognition technology has been developed for several years in the field of computer vision, the vast diversity of plant species and the wide-ranging characteristics of diseases often pose challenges for automated recognition technologies.

Therefore, this paper focuses on the study of orchids, which have high economic value and a higher likelihood of encountering pests and diseases. This research leverages IoT deep learning networks in conjunction with edge and cloud computing models to perform plant disease detection tasks and subsequent dynamic learning. Throughout this process, the deployment strategy must be dynamically adjusted based on the characteristics of the deep neural network model and the network state and computing capacity of edge nodes. The edge nodes are responsible for executing regional feature extraction, while cloud computing handles global feature extraction. The integration of deep learning networks effectively utilizes all available resources to achieve the goal of high-precision plant disease recognition. The problems to be addressed include: A. Changes in the lighting conditions within the scene, such as the impact of direct environmental lighting and the direction of illumination. B. Image capture in an IoT environment may introduce noise, particularly in cases of poor sampling channels or low lighting conditions. Both training and testing images may deviate from their original appearance. C. In actual environments where orchid leaves can move freely, the orientation of the images can be highly complex, necessitating a deep learning model with strong adaptability. D. The appearance and shapes of orchid disease symptoms are highly diverse, including scenarios where disease patches merge into larger patches. E. When converting three-dimensional spatial image information into a two-dimensional image plane, some information is lost. The challenge is to utilize edge computing to process data in a full three-dimensional manner, addressing issues related to large data volumes and excessive computation time.

The literature review of the current important research results in related topics are addressed in Section 2. Section 3 proposes the proposed method based on deep learning network. Conclusions are described in Section 4.

2. Literature Review

In the field of machine learning, Artificial Neural Networks (ANNs) represent one of the fundamental areas of research. These techniques have been applied to tasks involving the learning, classification, and recognition of image data. The design of ANNs is inspired by the structure and function of the human brain's neural system. They employ a large number of neurons and abundant training data to demonstrate their capabilities in learning, recall, and inductive reasoning. Additionally, ANNs have shown promising results in addressing image recognition, classification, normalization, optimization, and other problems.

Arivazhagan and his colleagues [1] used the RGB color channels for image acquisition. They then converted the images to the HSI color space to facilitate the labeling of green areas. The labeled areas were subsequently removed, leaving behind non-green regions. The useful image blocks were then extracted, and color co-occurrence methodology was employed to calculate the color texture features of these image blocks. Finally, an Artificial Neural Network (ANN) was used for recognition. This method was applied to the recognition of tree leaves from nine different plant species, identifying 1 to 2 types of diseases caused by bacterial infections or environmental factors. The accuracy achieved was 87%. However, it's important to note that the sample size and the variety of diseases tested were relatively limited in this study.

Mainkar and his colleagues [4] applied a method similar to the one mentioned above for plant disease recognition. In the preprocessing stage, they introduced the K-means method for pixel clustering in the CIELAB color space, which improved the accuracy of color interpretation. Additionally, in terms of feature extraction, they utilized the Gray-Level Co-occurrence Matrix to compute the statistical entropy of feature information. These details were then input into an Artificial Neural Network (ANN) for classification to distinguish symptoms of tomato leaf spot diseases, including sunburn, cottony mold, black spots, or brown spots, among others. Dheeb and his colleagues [5] developed a plant disease recognition technology based on Feedforward and Back-propagation algorithms. In their experiments, they tested the recognition of plant diseases such as early blight, powdery mildew, late blight, and small white spots. The system provided an effective recognition solution with an accuracy of approximately 93%.

Keyvan and his colleagues [6] focused on the ANN algorithm to study image features of cucumber plant diseases caused by fungi, including diseases like downy mildew and powdery mildew. They successfully designed an ANN model for improving the identification accuracy of these two disease types. Mrunmayee and his colleagues [7] also utilized the Back-propagation algorithm to develop a plant disease recognition system. Their system successfully identified and classified diseases in pomegranate plants, including leaf spot diseases, bacterial blight, fruit spot, and fruit rot. The experimental results indicated an accuracy of approximately 90%. Ramakrishnan and his colleagues [8] presented research on peanut plant disease identification. They used a Back-propagation ANN network to design a disease recognition method that could successfully identify four diseases within leaf spot diseases. The experimental results, which involved 100 images of diseased leaves, showed a system accuracy of 97.41%. Rashmi and his colleagues [9] conducted research on pomegranate plants and constructed an ANN-based plant disease recognition algorithm. In their experiments, the accuracy reached 90%.

The Convolutional Neural Network (CNN) is a type of feedforward neural network known for its effectiveness in image processing. CNN's artificial neurons can respond to units within a partial coverage area. The architecture of a CNN typically includes multiple layers, such as the input layer, convolutional layer, pooling layer, and can include multiple repeating convolutional and pooling layers to achieve deep learning. It is then followed by fully connected layers for training to produce output predictions. With a substantial amount of training data, CNNs often yield excellent recognition results. CNN models are trained using the backpropagation algorithm, and they have a relatively small number of parameters, making them an attractive deep learning structure. In the context of plant disease recognition, previous research by Srdjan and colleagues [10] employed deep convolutional neural networks for the identification of plant leaf images. The method not only had the capability to recognize healthy plant leaves and distinguish background objects but could also identify 13 different types of plant diseases commonly found in fruits like pears, peaches, apples, and grapes, among others.

Amara and colleagues [11] introduced a method based on LeNet combined with Stochastic Gradient Descent for the automatic recognition and classification of diseases in banana leaves. By inputting images of banana leaves afflicted with disease, the system could automatically identify the type of banana disease. Taking real-world operational considerations into account, the authors tested the system with various lighting conditions and complex background scenes. Different scenarios yielded varying levels of accuracy, effectively addressing challenges related to leaf size, pose, and orientation during image acquisition. The experimental results demonstrated that in color images, the accuracy exceeded 92%, while grayscale images achieved an accuracy of 85%.

Srdjan and his colleagues [10] designed a plant disease classification technology using a CNN architecture capable of detecting diseases in leaves of various fruits, including peaches, cherries, pears, apples, and grapes. The system could differentiate between healthy leaves and diseased ones. They trained the models using over 30,000 images and constructed models for 13 different diseases. Experimental data for each category indicated accuracies ranging from 91% to 98%, with an overall average accuracy of 96.3%.

Sharada and his colleagues [12] utilized a publicly available image database containing a total of 54,306 images, including images of 14 different crops and 26 diseases. They trained deep learning neural networks to detect plant diseases, achieving an accuracy of 99.35% when using 20% of the test data and 98.2% when using 80% of the test data. Serawork and his colleagues [13] designed a CNN model capable of identifying three different soybean plant diseases. In experiments, their trained CNN classifier achieved 99.32% accuracy in classifying 12,673 leaf images across four categories. Konstantinos and his colleagues [14] developed a CNN classification technology for recognizing 58 different crop diseases. They successfully tested their CNN classifier on 87,848 images from 25 different plant species, achieving a testing accuracy of 99.53%. As described above, deep learning has proven to be highly effective in plant disease detection.

3. THE PROPOSED METHOD

The causes of plant diseases can be broadly categorized into four main groups: bacteria, viruses, fungi, and environmental factors. When it comes to orchids, each of these main categories can be further divided into several to dozens of specific subcategories. The diversity of plant diseases and the overlapping characteristics among them can significantly impact the accuracy of image-based disease recognition. For instance, take anthracnose as an example. This disease is caused by a pathogenic fungus that thrives in high humidity conditions and can affect orchids. In its early stages, anthracnose leads to the formation of small brown sunken spots on the leaves. These spots gradually expand into circular or irregular-shaped lesions. In many cases, these lesions may merge to form larger lesions. In severe cases, the center of the lesion may develop necrosis.

Depending on the specific orchid species, anthracnose may also produce elongated and discontinuous brown necrotic patches or distinct rings. The diversity and complexity of these symptoms can lead to misclassification and pose a significant challenge for image-based recognition techniques.

To analyze the features for orchid disease recognition, the research team has identified three main categories of image visual features based on an exploration of numerous plant disease recognition studies. These categories represent different levels of image content and serve as the foundation for recognition technology:

A. Low-Level Primitive Features in Images: This category includes characteristics such as color, texture patterns, and shapes. These features serve as the most direct evidence for recognition. However, due to the diversity of orchid disease symptoms, particularly when images are obtained in IoT (Internet of Things) environments, the variability can affect the stability of these features.

B. Intermediate-Level Logical Inference Features: Building on the identification of low-level features in images, this category involves combining specific types of objects into multiple logical features for pattern recognition. For example, it may involve recognizing relationships between orchid leaf disease spots, yellowing, leaf curling, and their corresponding patterns.

C. High-Level Semantic Content Features in Images: This category encompasses abstract speculations about objects within images. It allows for in-depth conceptual judgments about certain behaviors in images. For instance, it can be used to analyze patterns formed by the merging of orchid leaf disease spots or the types of leaf wilting and color changes.

These three levels of features are essential for building a comprehensive image-based recognition system for orchid diseases, taking into account the complexity and variations in disease symptoms.

The research approach begins with capturing real-time orchid leaf images using an array of cameras within an Internet of Things (IoT) framework. Image data is processed at the edge through edge computing. Initially, traditional image processing is applied to extract low-level features from the images. Subsequently, these low-level features are combined to generate high-level features using deep learning networks within the IoT environment. These high-level features are then used, along with a non-linear classifier such as Softmax [15], to obtain recognition results. This methodology allows for the construction of mid-to-high-level image features within a very short computation time by combining edge computing with deep learning. The goal is to enhance the efficiency of the recognition system through this approach. The subsequent deep learning network is built upon the foundation of a Convolutional Neural Network (CNN) model. Its primary purpose is to focus on the fusion of low-level images and the extraction of high-level image features. This approach is designed to mitigate the effects of environmental changes, unstable lighting conditions, and the diversity of disease symptoms.

In this study, global and local image features from orchid leaf images are extracted and integrated using deep learning. A multi-layer neural network is employed to perform deep learning, accurately distinguishing different disease symptoms' characteristic appearances in the images. It also aims to mitigate variations in the image features of the same disease symptom during the infection process. Based on the characteristics of disease symptoms on orchid leaves, the research proposes an IoT-based deep learning network. The data flow is divided into two parts: an attribute learning network and a type learning network. Edge computing and cloud computing are integrated for learning. This enables the deep learning network to learn more discriminative descriptive features, including global features and local features. Specifically, we use attribute prediction as additional hints for orchid disease identification. Considering the relationship between orchid diseases and the attributes of corresponding disease symptoms, we first readjust the weighted values for attribute prediction. Then, we construct an identification mechanism based on these new weighted attribute descriptor values.

Next, the two learning processes of global and local feature descriptions will be integrated into a neural network model under the Internet of Things. Therefore, we plan to adopt a method similar to co-training [16] for deep learning. In the original co-training, semi-supervised learning techniques were used, with two different feature sets used to describe each sample data. These feature sets can provide additional complementary information about the sample instances. In an ideal scenario, the two feature sets for each sample instance in a category are conditionally independent, and each description can accurately predict the classification of the sample instance. Co-training first uses labeled sample instances to generate separate classifiers through a learning process. Each classifier then provides the most confident predictions for other unlabeled data, and an iterative approach is used to construct other labeled training datasets. This method not only generates a large amount of training data but also enhances recognition accuracy using complementary information. Figure 1 shows the network for combining global and local features to achieve the identification.

4. CONCLUSION

This paper leverages the Internet of Things infrastructure, combining edge computing with deep learning net-

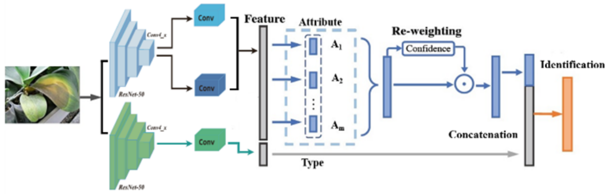

Figure 1. The network for combining global and local features.

works to develop an image-based orchid disease recognition technology, achieving the following results. Constructing an orchid disease image database, annotating the characteristics and attributes of orchid leaf lesions, providing multiple training image sources, and integrating them into usable information for subsequent recognition. Building a deep learning-based image-based plant disease monitoring Internet of Things integration model for edge computing to obtain high-level image features, mitigating the impact of environmental changes such as unstable light sources and the diversity of orchid disease symptoms. Extracting low-level image features through edge computing and developing an integrated network for both low and high-level image features to perform recognition, meeting the requirements for stable performance. Developing an integrated testing prototype system to verify the effectiveness of orchid disease recognition using automated feature extraction with IoT devices combined with edge computing.

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