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Smart Farmer: Deep Learning-Based Surveillance Application for Home Gardeners

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***Abstract* - This paper presents a smart farming system designed for home farmers to identify deficiencies, pests, and weeds in their crops. The proposed system employs deep learning and image processing techniques to analyze images captured using a mobile phone camera. The system comprises four components, each responsible for identifying a specific type of damage. The isolated component is then analyzed using a deep learning model to determine the type of damage and provide remedial actions. The proposed system has the potential to improve crop health, increase yield, and reduce costs associated with ineffective remedial actions. The results of our experiments demonstrate the effectiveness of the proposed system in identifying and diagnosing crop damage.**

Keywords: Image processing, Machine learning CNN, Deficiency identification, Pest damage identification, weed identification.

I. INTRODUCTION

The agricultural sector of Sri Lanka is crucial in ensuring food security and meeting the growing demand for agricultural products. However, growers face several challenges in maintaining plant health, identifying pest and disease damages, and controlling weeds, which can lead to reduced yield and quality. To address these challenges, this study proposes a comprehensive solution using deep learning and image processing techniques.

This mobile application is designed for garden and home farmers to identify problems with their crops. Often, farmers are unsure whether a problem is due to a deficiency, pest damage, or weeds. The app addresses this by allowing the user to take an image of the plant or plant parts, which is then processed using image processing techniques to isolate the component suspected of damage. The system comprises four components: identifying deficiencies damages, identifying pest damages, and identifying weeds.

Using a deep learning model, the isolated component is analyzed to identify the type of damage and suggest appropriate remedial actions. This methodology has the potential to improve plant health, increase yield, and reduce costs associated with ineffective remedial actions. By enabling growers to identify problems accurately and quickly, this app could contribute significantly to the overall success of the agricultural sector.

II. LITERATURE REVIEW

[1] Focuses on the development of a nutrient management technique using Ion Selective Electrodes (ISEs) and a computer-controlled fertilizer pump. Lettuce was grown in a greenhouse using this automated system, and the concentrations of three ions, NO3, Ca, and K, were controlled to reach target concentrations. [2] Evaluates and develops a computer-controlled ISE-based system for direct macronutrient measurement in hydroponic solutions. ISE array having PVC-based membrane along with the computer-controlled system is tested for direct measurement of NO3-N, Ca, and K for paprika hydroponics. [3] Describes the design of an automated robotic vehicle that recognizes nutrient deficiency in plants just by taking a picture of plant leaves. The captured picture is processed by utilizing convolutional neural networks (CNN) to compare it with the available dataset to determine the type of deficiency and the appropriate amount of compost to be used. [4] Focuses on the automatic deficiency detection of Ca, Boron (B), K, and Iron (Fe) by using shape and surface descriptors in pictures of coffee tree leaves. The acquired image is used for training neural networks, Naïve Bayes, and KNN classifiers using the properties extracted to determine the type of deficiency presented in each investigated picture. [5] uses Fourier-transform infrared (FTIR) micro-spectroscopy based on synchrotron radiation to detect Ca deficiencies in fixed and live tissues of plant Commelina communis. This type of procedure would be highly useful for wider nutrient screening applications as well as identifying other abiotic stresses. [6] focuses on developing an on-location ion monitoring system based on ISEs to identify any imbalance that may occur in hydroponic solutions. Performance was evaluated using

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hydroponic arrangements prepared for growing paprika crops in nurseries.

Identifying pests and controlling them is essential in-home farming. However, many growers find it challenging to distinguish one pest damage from another in the field, leading to a failure to apply specific control methods. To solve this problem, a system has been developed based on deep learning and image processing technologies to identify pests according to their damage patterns and suggest related control methods. Several studies have focused on using deep learning for the automatic detection and classification of plant diseases. Vyas et al. (2020) proposed a deep learning approach for the automatic detection and classification of plant diseases using convolutional neural networks (CNNs). The system was trained using a large dataset of plant disease images and achieved high accuracy in identifying diseases [7]. Zheng et al. (2021) proposed a novel pest recognition method based on deep learning and an attention mechanism. The proposed method uses a CNN to extract features from pest images, followed by an attention mechanism to focus on the most important regions. The system achieved high accuracy in recognizing different pest types, demonstrating the effectiveness of the proposed method [8]. Pratama et al. (2021) developed a system for identifying pest damage in plants using deep learning and image processing techniques. The system analyzes plant images to detect pest damage and classify the type of pest based on the damage pattern. The proposed system achieved high accuracy in identifying pests and their associated damage [9]. Gharibi et al. (2021) proposed a system for identifying pest-damaged almond leaves using deep learning and image processing techniques. The system uses a CNN to extract features from the images and a decision tree algorithm to classify the type of damage. The proposed system achieved high accuracy in identifying pest damage in almond leaves [10]. Aminu et al. (2021) proposed a system for the automatic identification and classification of agricultural pest images using deep learning. The system uses a pre-trained CNN to extract features from the images, followed by a support vector machine (SVM) algorithm to classify the pests. The proposed system achieved high accuracy in identifying and classifying different types of agricultural pests [11]. In summary, deep learning and image processing techniques have shown great potential in identifying pests and controlling them in agriculture. These techniques can help growers identify pests more accurately and apply appropriate control methods, thereby improving crop yield and reducing the use of pesticides.

Unwanted plants are referred to as weeds. There is no botanical classification for weeds because a plant that is referred to as a weed in one source may not be a weed when it grows in a desired location. Any plant that grows or aggressively reproduces, or that is outside of its natural habitat, is subject to this term [12]. Low-cost RGB cameras are able to capture photos with good resolution and distinguish between different plants depending on their shape, texture, and color. The soil and plant cover will be distinguished in the image by segmentation. The plant is shown in the image as a white region, while the soil is shown as a black region. The appearance of the leaves can be used to determine the species of the plant. To determine the geometry of the crops and weeds, image analysis software is used. Ten Weed species with broad and narrow leaves are identified, and a database of images is produced. When identifying the shape of the leaves, an accuracy of 90%–98% was attained. In the weed's early stages of growth, this technique was quite effective. [13]. In a field, weeds can develop in a variety of ways. Sometimes, they may completely overrun a section of the field, while other times, they may only grow in the gaps between the crops. Large weed patches are able to be easily identified using ground-based or remote sensing-based approaches, and the necessary steps are able to then be taken. [14]. Several features can be retrieved from the camera-captured images using machine vision algorithms, and these features are helpful for accurately identifying weeds and plants [15]. Texture, form, and color are a few of the features that can be taken off. Both the weed and the crop are able to be easily differentiated when their colors are different from those of the main crop. Tang et al. identified weeds with distinctive colors with 92.5% accuracy [16]. Unless there is a leaf overlap, it is simple to distinguish between photos of weed and crop when the individual leaf shape is distinct from the crop leaf [17]. The ability of DT-based ensemble learning methods, like RF, to automatically offer estimates of feature relevance from a trained prediction model, is one advantage of adopting them. Typically, a feature's significance score represents how helpful it was in developing the DTs included in the model. The important calculations, however, heavily rely on ensemble approaches (such as bagging [18] or boosting [19]) [20]. Around 35% of the workforce in Sri Lanka is employed in the agricultural industry, which also accounts for about 19% of the country's GDP. In extreme situations, weeds can reduce crop yields (quantity) by as much as 50%, which is a significant barrier to high productivity and self-sufficiency in agriculture. Additionally, weeds lower the quality of crop products, which lowers the overall productivity of the land and farmers' agricultural income [21]. Due to current economic crisis in Sri Lanka trend as Organic Farming has been became popular in urban areas. Lack of time and knowledge about agriculture was a major barrier to this trend and information technology has provided better solutions to this issue via various applications such as KRUSHI ADVISOR and CROP LOOK including details about weather, crop, weed, pest, and diseases with Agriculture Ministry.

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III. METHODOLOGY

A) Identify Deficiencies and Damages

Identifying component deficiencies is crucial in agriculture to prevent yield loss and ensure healthy plant growth. However, it can be challenging for growers to identify deficiencies accurately, leading to ineffective remedies or additional expenses. To address this issue, this study proposes a deep learning and image processing-based system that accurately identifies deficiencies in plant components and suggests appropriate remedial actions. The proposed system utilizes a mobile phone camera to capture images of the relevant plant or plant parts. The image is then processed using image processing techniques to isolate the component suspected of a deficiency. The isolated component is further analyzed using a deep learning model that accurately identifies the type of deficiency. The deep learning model is trained using a dataset of images of plants with known deficiencies. The dataset is collected through field surveys and laboratory experiments. The deep learning model is trained using a convolutional neural network (CNN) that can accurately identify patterns in the images to detect the presence of deficiencies. Once the deficiency is identified, the system suggests appropriate remedial actions. The remedial actions are determined based on the type of deficiency and can range from applying specific fertilizers or nutrients to removing the plant entirely. Additionally, the system accurately calculates the area of the plant affected by the deficiency to determine the severity of the problem. In summary, the proposed methodology involves capturing images of the plant or plant parts, processing the image using image processing techniques to isolate the component suspected of a deficiency, analyzing the isolated component using a deep learning model to identify the type of deficiency, suggesting remedial actions based on the type of deficiency, and calculating the area of the plant affected by the deficiency to determine the severity of the problem. This methodology has the potential to improve plant health, increase yield, and reduce costs associated with ineffective remedial actions.

B) Identify Pest Damages

Identifying pests and controlling them is a very important step in home farming. Many growers find it difficult to distinguish one pest damage from another pest damage in the field. Because of this, they fail to apply control methods specific to each pest damage. As a solution to that, this system identifies the pests according to the pest damage pattern and suggests related control methods. Accordingly, this system has been developed based on deep learning and image processing technologies. First, the mobile phone camera takes pictures of the relevant plant or plant parts. After that, the part suspected of pest damage is selected from the image. The suspicious part is further analyzed by a deep learning model and the relevant pest damage is correctly identified. Accordingly, the relevant control method is suggested according to the pest damage that has occurred.

C) Identify Weeds

In the agriculture sector, weed identification and classification play a crucial economical and technical role. Weeds compete for resources with crops and provide lodge to pest. Therefore, weed control provide resources to crop as well as maintain disease and pest free crops. Weeds identification and control increase the productivity on a wide scale, improving income. [22]. Due to economic crisis in Sri Lanka urban people developed a trend to cultivate in their land organically and unfortunately, they do not have experience and knowledge about Agriculture. Even though several studies have been done in weed identification, public do not have idea about them. But currently, this field of the research has made more progress via its association with the information technology. Developing mobile application using concepts such as image processing is really important to weed identification [23]. Urban people do not have time to meet resource people to identify weeds and ask control measurements. The developed web application is convenient to identify weeds. Because almost every grower in urban area have smart phone and have adequate knowledge about capturing images and uploading. After uploading the image of weed all the information about the uploaded weed for instance; Generic Name, Scientific Name are available on the screen. Then they are able to obtain better knowledge about weed. Even farmer enter the image of dirty weed with muddy or sand, developed web application is able to identify the weed. Not only is that, but also farmers able to upload images in top view, side view or any stage of the weed. This developed system is able to identify all of these kinds of images with high accuracy. The same control method is not suitable for every weed. Therefore; web application which helps to identify weeds with high precision and suggest specific control methods is developed. When weed spread vastly for long time, applying herbicide is efficient. After identifying weeds application is suggested specific biological, physical, chemical control mechanism for particular weed. Then growers can apply any control mechanism as their preference. It is another added facility provided through this application.

IV. TECHNOLOGIES

The most appropriate technologies have been used to develop the system to increase its efficiency and accuracy of the system. Basically, python is used for system development.

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Thus, the main Python libraries used are NumPy, Scikit-learn, and Pandas. The deep learning model's development has been done using the TensorFlow framework. Google Colab has been used to train the relevant models. React-native has been used to develop the mobile app. Applications are hosted in AWS Cloud.

A) Identify Deficiencies and Damages

To identify deficiency damages in plants, we employed a combination of deep learning and image processing techniques. First, we used the selective search algorithm to extract regions of interest (ROIs) from the input image. Each ROI was then passed through a convolutional neural network (CNN) to identify the plant part and determine whether it was healthy or damaged.

For the CNN, we experimented with several architectures, including ResNet_v2_50, EfficientNet, Inception_v3, MobileNet_v2_130_224, and Inception_resnet_v2. We evaluated the accuracy of each model and found that EfficientNet achieved the highest accuracy at 89%.

Table 1: Testing Accuracies for Each Architecture (%)

DL Architectures	Accuracy
Resnet_v2_50	75%
Efficient net model	89%
Inception_v3	68%
Mobilenet_v2_130_224	50%
Inception_resnet_v2	65%

After the CNN identified the ROIs, we used a region-based CNN (r-CNN) model to further analyze the ROIs and classify them as either deficient or non-deficient. The r-CNN model was trained on a dataset of labeled images of plant parts with and without deficiency damages. The model used a combination of a region proposal network (RPN) and a fast R-CNN to generate a set of candidate regions and classify them.

The final step in the deficiency identification process involved using a set of equations to determine the severity of the deficiency. We used the following equations to calculate the severity index for each identified deficiency.

$$SI = (1 - (CI / TCI))$$

$$CI = (N / A)$$

Where SI is the severity index, CI is the chlorophyll index, TCI is the total chlorophyll index for the plant species, N is the number of pixels in the ROI with low chlorophyll content, and A is the total number of pixels in the ROI.

The proposed deficiency identification system has the potential to improve plant health and increase yield by enabling home farmers to quickly and accurately identify and address nutrient deficiencies in their crops.

B) Identify Pest Damages

The proposed technology employs the YOLOV8 algorithm to detect suspicious areas in plant parts captured by a camera. Upon detection of a suspicious area, a bounding box is created around it. The bounding box is then segmented and sent to multiple convolutional neural networks (CNN) models for identification. The system selects the model with the highest accuracy to determine the type and extent of the damage caused by pests. To evaluate the accuracy of the models, the researchers used various evaluation metrics on a specific dataset that represented real-world scenarios. The below deep learning models use for the system.

Table 2: Testing Accuracies for Each Architecture (%)

DL Architectures	Accuracy
ResNet 50	81%
Efficient Net Model	77%
Inception_v3_ Model	70%
Mobilenet_v2_130_224	74%
Cropnet Model	56%

The system recommends pest control methods to the user based on the type and extent of damage caused by the pests. Most of the time, the system suggests natural pest control methods. In conclusion, the proposed technology shows promise in accurately detecting and identifying pest damage in plants. The use of multiple models and careful evaluation of the accuracy of each model ensures that the system provides accurate results. Further research is needed to determine the practicality and effectiveness of the recommended pest control methods.

C) Identify Weeds

In accordance with the objective of this study, we propose a methodology to build a system design that can identify weeds via an Ensemble model. With this, identification is done when an image of a weed is presented either from the top view or from the side view. For this, separate models have been implemented for top view and side view. Resnet152v2 architecture has been used for that implementation.

Table 3: Testing Accuracies for Each Architecture (%)

DL Architectures	Side View	Top View
EfficientNetB0	98%	88%
ResNet152V2	99%	84%
ResNet250	100%	87%
InceptionV3	99%	84%

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To improve the accuracy of the prediction, it is always better to create multiple models Instead of creating a single model. Both traditional ensemble method and snapshot ensemble methods have been used in this research. Single data set is trained on different classifiers. Multiple models classified the same data and different predictions were obtained. The predictions from the base models are then combined by taking their average. This can be done by adding the predictions and dividing by the total number of base models, or by using weighted averaging, where different weights are assigned to the predictions of different base models based on their performance or expertise. The averaged prediction obtained from the ensemble of base models is used as the final prediction or decision. The accuracy of this model is 88.39%. The core of Snapshot Ensembling is an optimization process that visits through a number of local minima before converging toward a final solution. At these various minima, model snapshots have been captured and at the test time average their predictions have been taken. When individual models do not overlap in the pool of examples they misclassify and have low, test error ensembles perform best [24]. Our method was motivated by the finding that training neural networks for dropping learning rate sooner and less epochs had slight effect on final test error [25]. This seems to imply that after just a few epochs, the local minima along the optimization path start to look promising (according to the generalization error) [24].

Cyclic cosine annealing schedule was followed in this study as proposed by Loshchilov & Hutter in 2016. The learning rate was first decreased at a fast pace to encourage convergence to the first local minimum. Following that, the optimization process was carried out at a higher learning rate, which disturbs the model and causes it to deviate from the minimum. In order to get many convergences, this technique was done several times. Even with a high initial learning rate, the convergence of short cycles was improved by updating the learning rate at each iteration using a monotonically decreasing function, such as shifted cosine function [24].

A snapshot of model weights was collected when model reaches a local minimum with regard to the training loss at end of each training cycle. The final ensemble used M model snapshots that were obtained after M training cycles. M snapshots were required the same amount of time to train a model as a regular schedule was required. Ensembling at test time involves averaging the softmax outputs of the last m ($m \leq M$) models, where m is chosen based on the desired ensemble size, as these models tend to have the lowest test error. As these models often have the lowest test error, ensembling at test time entails averaging softmax outputs of last m models ($m \leq M$), where m was selected based on desired ensemble size [25]. The accuracy of this model is 89.21%. This is more optimal.

V. CONCLUSION

Developing Mobile applications such as this system for small smart farmers in urban area based on solutions for their current problems in farming is brought Sri Lanka forward in the technology field. Because Agriculture sector in Sri Lanka is traditional and integration with Information Technology is currently not popular. Many advantages can be realized with the installation of this application to smart farmers in urban area as well as economy in Sri Lanka. To be able to solve the problems that arise in the cultivation on the spot and at the same time without any delay, decrease the living cost in Sri Lankan, increasing motivation of smart farmers to cultivate, emergence of a self-sustaining economic system, absence of need for agricultural officers in all areas in Sri Lanka are some of the key advantages. Even though there are some limitations such as not being able to operate without an internet connection, this mobile application is convenient to use as well as productive and effective. Moreover, latest technologies such as deep learning have been used in developing this system. Thus, this system is cutting edge in terms of technology. Another core component of developing an efficient, productive system that also inspires smart farmers is the use of better and latest technologies. With the previously mentioned details, it is clear that this system will work well for all smart farmers in Sri Lanka in the future because it is not only effective and productive but also user-friendly and convenience in a number of ways.

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