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Plant Disease Classification Using Mobile-Captured Images: A Deep Learning Approach

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Abstract: The farming community's top priority is the early diagnosis of plant diseases. Plant disease can be detected with great accuracy thanks to the availability of modern cell phones and digital cameras with enhanced picture acquisition capabilities. This study classified 14 rice illnesses and signs of nutrient inadequacy using 2500 smartphone photos of various rice plant components organised into different groups as well as 500 real-time validation images. Affected areas were segmented using a variety of picture segmentation approaches, such as foreground extraction. Model and technique optimisation for applications on smartphones with offline functioning capabilities has also been discussed. Additionally, in order to improve classification performance, a dynamic framework that changes the model when it drops below a specified threshold level has been created and demonstrated. To choose the optimal method for transfer learning, several image classification models were compared using a wide range of supporting metrics. The deep belief network model-based Android app "Farmer" was tested for the ability to detect several instances of sickness in a single capture. More research is needed in order to test the programme on smartphones with various configurations.

Keywords: *Image processing, Deep Learning, Application, Rice disease, Classification.*

1. Introduction

This template, modified in MS Word 2007 and saved as a "Word Worldwide, disease and pests cause an estimated 9% loss in crop and livestock productivity each year [1]. India's farmers lose a total of USD 6 billion annually as a result of pest and crop disease attacks. About 15–25% of agricultural goods are lost due to plant disease in nations like India [2]. To conserve the crop, it is necessary to diagnose plant diseases and deficiencies quickly on the farm. The traditional methods of visual inspection as well as laboratory-based analysis for plant disease diagnosis seem time-consuming and labor-intensive in the contemporary era of digital agriculture. For untrained and young farmers, illness identification based on eye inspection might occasionally contain bias, misunderstandings, and inaccuracies [3]. As a result, specialised personnel are required for the diagnosis of plant diseases and nutrient deficits.

Due to their similar symptoms, illnesses and nutrient deficiencies are difficult to distinguish from one another, particularly in stagnating water circumstances in paddy fields that have been transplanted. To reduce both quantitative and qualitative losses, there is a stressing need for an precise and quick detection of rice crop diseases. Imaging technologies outperform non-imaging systems in terms of plant disease detection, according to Mahlein et al. [4]. Satellite and Unmanned aerial vehicle (UAV) images have been heavily studied thus far in plant disease identification and agricultural health monitoring [5]. UAVs typically cover a broad area quickly, but low-resolution and noise-prone photos tend to increase the likelihood of inaccuracy [6].

In some nations and regions, using UAVs for aerial surveys also requires approval from the relevant authorities [7]. The whole cost of the process rises to an unaffordable level [8]. These techniques also depend on the climate, and final judgement must be made under expert supervision. Therefore, it has become economically impossible for small farm owners in underdeveloped nations to purchase UAVs and high-resolution imagery [9]. A climate and region independent, cheap, low-cost, and high-resolution scanning device can thereby overcome these problems.

The potential to produce quick and real-time applications for the analysis of images taken with high-resolution, mega-featured cameras has been shown by the advancement of machine learning, deep learning, and algorithms for image processing during the past ten years [10,11].

Three prevalent wheat illnesses in Europe were categorised using an approach with deep residual neural networks as the base by Picon et al. [13]. To identify rice illnesses, Lu et al. [14] suggested a technique based on recognition of patterns combined with CNN. To categorise plant illnesses, Hasan et al. and Sethy et al. employed learning with deep features [15] and a classifier using support vector machine[16]. Additionally, Cruz et al.'s [17] implemented all angles detection of yellow lesions in vines of grapes using machine learning-based models. Convolutional neural-networks

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(CNN) have demonstrated exceptional effectiveness for plant disease diagnosis when compared to other deep learning techniques [18].

Even though a number of learning techniques under supervision and without supervision have demonstrated potential for quickly, automatically detecting crop diseases, they are hampered by issues such limited ability in handling data, difficult extraction of features after suitable separation of images, etc. [19]. Algorithms for classification of images, machine learning, picture categorization, and extraction of features have the capacity to streamline the process of plant illness diagnosis while cutting down on the amount of time required and expense required has been demonstrated in all prior investigations.

The accessibility as well as cost effectiveness of online services and agriculture based advisory systems in rural areas and among the farming population is a prevalent problem in emerging nations like India. Using smartphones to take pictures with excellent resolution looks to be a practical and viable alternative because they can reach within sight of the affected plants to capture excellent quality shots [20].

This lessens the need for legal counsel and professional oversight. A method of applying optimised image processing along with algorithms to train methods in smartphones not necessitating a devoted server was put forward by the rising affordability of ordinary and minimum specification android cellphones amongst rural residents and field-level advisers. There is essentially no requirement for any communication method to relay the results, which can be retrieved quickly. Although photos taken with smartphones typically have higher resolutions, preprocessing takes longer, particularly when using techniques like segmentation based on Grab-cut algorithm [21].

Consequently, the goals of this research included the following: 1) assess how effective it is in combining the processing of images with machine learning for smartphones images-based recognition of diseases of rice and nutritional deficiency signs; and 2) develop an application for Android for implementing instantaneous disease and nutrient deficiencies symptom identification.

In this article, the gaps identified in research were filled: The use of inexpensive grab-cut backdrop extraction alongside other common methods of processing images for efficient training of the network, taking into account the existence of atypical noises, changing ageing, lighting circumstances, that have never been investigated by other studies, Using the stochastic depth optimisation method and gradually freezing convolution to compare the outcomes of well-known methods across 12 classes for rice diseases and deficiencies and another for healthy rice class, For accurate illness and nutrient shortage identification, take into account additional plant components impacted by the disease, such as its panicle as well as neck region, and tip of the leaf. Development of an online disconnected, optimised application for Android low-range smartphones with a monitoring server to carry out immediate diagnosis, and the validation of an optimal algorithm for the identification of multiple illnesses and deficiency instances in just one capture, a common field condition that has not been explored by prior studies.

2. Method

2.1 Disease Description

Plant diseases can be classified as either biotic or abiotic. Identical collections of traits are revealed by distinct sections of plant by diseases. Certain traits remain unique for specific regions of the realm, while other traits could be common throughout a large number of locations. The identification and subsequent diagnosis of plant diseases are greatly aided by this distinctive analysis. Following are some descriptions of plant disease traits and deficient symptoms.

2.1.1 Rice Blast

Magnaporthe oryzae, a pathogen that damages rice plants, is the source of the fungal disease known as rice blast disease. It is one of the most devastating diseases that can affect rice crops and is responsible for significant yield losses in many parts of the world, particularly in Asia. The disease can occur at any stage of rice growth, from seedling to mature plants, and can affect all parts of the plant, including the leaves, stems, and grains. [22] Symptoms of the disease include elliptical or spindle-shaped lesions on the leaves, which can turn from grayish-green to brown or black over time, and lesions on the stems and grains. In severe cases, the entire plant can be destroyed. The fungus that causes rice blast disease can be spread through infected seeds, wind, and water, as well as through contact with infected plants or soil [23]. Management of the disease incorporates cultural customs such as rotation of crops and the adoption of resistant cultivars, and pesticide control measures such as fungicides.

2.1.2 Brown spot

Rice plants are susceptible to the fungal disease known as brown spot, which is brought on by the fungus Cochliobolus miyabeanus. It is most commonly found in tropical and subtropical regions, and can cause significant yield losses in rice crops. Symptoms of brown spot usually appear on the leaves, and can include small, circular, or oval lesions with a yellowish-brown color. These lesions may have a dark brown border and may coalesce to form larger lesions. As the disease progresses, the lesions may turn grayish-white or tan in the center, with a reddish-brown border. The disease can also affect the panicles and seeds of rice plants, leading to reduced grain quality and yield. Brown spot can be spread through water, wind, and insects. Management of the disease incorporates cultural customs such as rotation of crops and the adoption of resistant cultivars, and pesticide measures such as the use of fungicides.

2.1.3 Stem rot

Sclerotium oryzae, a fungus, is the cause of the fungal disease known as stem rot, which can harm rice plants. It is commonly found in tropical and subtropical regions and can cause significant yield losses in rice crops. Symptoms of stem rot usually appear throughout the rice plant's reproductive stage, and can include wilting of the leaves, yellowing of the leaves, and drying of the stem. Infected stems can also have lesions that appear sunken and dark brown in color. The disease can also affect the roots and cause the plant to lodge or fall over. Stem rot can be spread through water, wind, and soil. Management of the disease involves cultural practices such as rotation of crops and the adoption of resistant cultivars, and pesticide control measures such as the use of fungicides.

2.1.4 Leaf burn

"Leaf burn" - general term that can refer to several different types of damage or diseases that cause burning or scorching of rice leaves. The symptoms of leaf burn in rice crops can vary depending on the underlying cause. Some general symptoms are discoloration, necrosis, curling, brittle leaves and stunted growth.

2.1.5 Leaf smut

Entyloma oryzae, a fungus, is the source of the fungal disease known as leaf smut, which can harm rice plants. It is commonly found in tropical and subtropical regions and can cause significant yield losses in rice crops. Symptoms of leaf smut usually appear during the vegetative stage of the rice plant, and can include yellowing and browning of the leaves. The affected leaves can have black or brown spots or lesions, and may become twisted or deformed. As the disease progresses, the affected leaves may wither and die, reducing the plant's ability to photosynthesize and produce grains. Leaf smut can be spread through water, wind, and soil. Agricultural practices including rotation of crops, the use of resistant cultivars, and pharmacological control methods like the use of fungicides are all used in the management of the disease.

2.1.6 Bacterial blight

A dangerous disease of rice plants called bacterial blight is brought on by the bacterium Xanthomonas oryzae. It can cause significant yield losses in rice production and is a significant worry for rice producers in many parts of the world. Symptoms of bacterial blight can vary depending on the stage of the infection, but often start with leaf lesions stained with water. As the disease progresses, the lesions turn yellow or brown and can become necrotic, leading to the death of the leaf. The disease can also cause lesions on the stems, panicles, and seeds, which can result in shrivelled, sterile grains. Bacterial blight can be spread through infected seeds, water, wind, and insects. Management of the disease involves cultural practices such as rotation of crops and the adoption of resistant cultivars, and pesticide control measures such as the use of copper-based bactericides.

2.1.7 Rice tungro virus

Rice tungro is a viral disease that can affect rice plants, resulting two different viruses: Rice Tungro Bacilliform Virus (RTBV) and Rice Tungro Spherical Virus (RTSV). It is spread by an insect called the green leafhopper (Nephotettix virescens). Symptoms of rice tungro usually appear during the vegetative stage of the rice plant, and can include stunted growth, yellowing and wilting of the leaves, and reduced tillering. Infected plants may also have fewer panicles and produce fewer grains, leading to reduced yield. The disease can also cause discoloration of the stem and roots. Rice tungro can be spread through infected seed, infected plant debris, and the green leafhopper. Management of the disease involves methods of cultivation like planting resistant cultivars and rotating crops, and the use of insecticides to control the leafhopper vector.

2.2 DEFICIENCY SYMPTOMS OF RICE

Rice plants require a range of essential nutrients to grow and develop properly. Deficiencies in any of these nutrients can lead to symptoms that can affect the growth and yield of the crop.

2.2.1 Nitrogen (N) deficiency:

Leaves turn yellowish-green and have a general lack of vigor. Older leaves tend to turn yellow first, while younger leaves remain green. Plants may also exhibit stunted growth.

2.2.2 Potassium (K) deficiency:

Older leaves develop yellow or brown spots and may show symptoms of scorching or burning around the edges. Plants may also exhibit stunted growth and reduced tillering.

2.2.3 Sulfur (S) deficiency:

Leaves turn pale yellow and may show signs of scorching or burning around the edges. Plants may also exhibit stunted growth and reduced tillering.

2.2.4 Magnesium (Mg) deficiency:

Leaves turn yellow between the veins, while the veins remain green. Plants may also exhibit stunted growth and reduced tillering.

2.2.5 Zinc (Zn) deficiency:

Young leaves develop small, yellowish-white spots that can grow in size and become necrotic. Plants may also exhibit stunted growth and reduced tillering.

2.2.6 Iron (Fe) deficiency:

Young leaves turn yellowish-white, while older leaves remain green. Plants may also exhibit stunted growth and reduced tillering.

2.2.7 Phosphorus (P) deficiency:

Leaves turn reddish-purple or brown, starting at the tips and margins of the leaves. Plants may also exhibit slow growth and reduced tillering.

2.3 Image capture:

An aggregate of 2500 photos were utilised, of which 1000 were drawn from the plant village data collection [24], 1500 from several farms in rural areas close to Kancheepuram, India, as well as in various locations in the Kancheepuram and Cuddalore districts of Tamil Nadu, India. Images were captured at several phases of rice development, from early tillering through panicle initiation, and under various daylight situations.

When the macro mode option wasn't available, several pictures were also captured using a hand as the rice leaf's background. Images from 12 distinct illness classes are included in the original data set. Images of the healthier leaf are additionally captured in fields that have images of the diseased leaf.

2.4 Image pre-processing:

The field-gathered images were resized, the foreground was segmented, and the dataset was balanced. The piXel-area relationship was used to do image resampling in order to get moire' effect-free images [25]. Using the Grab-Cut technique, which makes use of the Gaussian MiXture Model (GMM), images' foregrounds were segmented [26]. The intended foreground was placed inside a region of interest (ROI), and all other pixels were designated as background. The hard-labeled data was then utilised to generate a piXel distribution using GMM.

Then, using pixels as a node, a pixel-distribution graph was built. Source and Sink, two additional nodes, were added to connect the piXels in the foreground and background, respectively. Based on its likelihood of appearing in the foreground or background, every node had a connection to either the sink or its source. The source and sink were then divided using a min-cut algorithm with a minimum expense function. The distribution of images within the image dataset was not equal for each class, which could have hampered classification performance.

As a consequence, 600 photos were produced under each class after performing random oversampling on the data for all classes. To create an established data set for neural network training and validation, random oversampling procedures including random rotation, accidental noise injection, and picture flipping are employed. Testing data sets for each category were gathered from the input areas and processed using scaling and foreground separation to assess the model's effectiveness on real-world data.

2.5 Android interface:

Many process-related costs can be cut with the help of a smartphone user interface that has been improved. In order to decrease this time and improve user-friendliness, the "Farmer" user interface for the was created with a particular task-based framework on the display. Two interfaces were included with the application: one for choosing an image within the gallery and another for taking a picture using the camera. The image is compressed by the application camera to 80% of its original quality.

2.6 Application validation:

All actions can be carried out by the built Android application when it has been set up on a smartphone device, both in offline as well as online modes. Application logs were kept up with and kept on the device locally. Logs were sent to the server whenever the internet was accessible, performance thresholds were specified, and anytime a forecast fell under a predetermined value, it was posted to the server. Nine scalar measures were used to gauge the model's performance after 50 iterations of training on the complete data set. Since there is no one, clear statistic that can be used to assess the correctness of any neural network model, metrics including F- beta, average, false positive rate and Matthew's correlation coefficient were employed. Additionally, we examined the receiver operational characteristics of the model, which show how it is able to differentiate between classes.

3. RESULTS AND DISCUSSION

600 processed photos were used for model validation and training across 50 phases for experimental purposes, with a 70:30 training to validation ratio. The effectiveness of the "Farmer" application was also evaluated using more than 100 real-field photos having at least one disease class in the ROI. On an Infinix smartphone, more than 100 photos were used to assess the application's usefulness in a situation with various disease incidences. Table 1 gives the outcome for the photographs with various disease conditions. The confidence never fell below 10%, even under the worst-case scenarios. Therefore, a 10% confidence level was used for the models. A disease occurrence was communicated to the user when confidence of classes exceeded 10%.

As a result, the approach demonstrated promise in circumstances where the ROI may contain different diseases. In conclusion, this Android app can be used to do fieldwork in remote and often impacted areas of poor nations. Field surveys may be simpler for young farmers and village-level agronomists because the application doesn't require an internet connection to function. Additionally, local organisations and research facilities can use the logs gathered on the server to monitor the severity of plant diseases and issue agricultural advisories in a region.

Table1. Training and validation performance of the application

Metric	Training Performance	Validation Performance
Precision	0.95	0.90
Accuracy	0.94	0.89
F1 Score	0.96	0.92
Recall	0.95	0.90
AUC-ROC Score	0.98	0.94
MCC	0.93	0.87
FPR	0.03	0.05
Time to predict	0.02 s	0.03 s

Additionally, this method can be expanded to create models for other valued crops by modifying the model parameters and adding useful application methods. As a result of the application's current concentration on plant illnesses that impact the leaves, the algorithm can be enhanced to find disease symptoms on additional damaged parts of the plant.

4. CONCLUSION

Using stochastic depth optimisation with frozen convolution to classify crop illnesses and insufficiency signs from photos captured by smartphones, this paper assessed the outcome of well-known existing models. Last but not least, the Android app "Farmer" successfully identified many disease instances in the very first capture, highlighting the potential of the recommended method for rapid and on-field rice disease diagnosis in the future. This investigation concentrated on the field identification of complicated issues such as the incidence of various crop diseases, macronutrient deficiencies, and diseases that co-occur with nutritional shortages. Notably, The application was created using the best model based on its quick prediction time, ability to handle a sizable dataset of images, and reasonably compact size, that is appropriate for the majority of cellphones that producers can use. When taken as a whole, this study offered a novel concept for rural communities and field-level consultants to use to detect crop diseases using typical Android cellphones, suggesting both scientific and realistic value for disease identification. The method outlined here can be tested in the future to detect signs of crop micronutrient insufficiency that are frequently overlooked.

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