CHENNAI
INSTITUTE OF TECHNOLOGY
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Title:

“DEEP - LEARNING - BASED CLASSIFICATION DETECTION IN PRECISION AGRICULTURE"

A CORE COURSE PROJECT REPORT

Submitted By

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE AND ENGINEERING

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CHENNAI INSTITUTE OF TECHNOLOGY

(Autonomous)

Sarathy Nagar, Kundrathur, Chennai-600069

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CERTIFICATE

This is to certify that the " **Core Course Project**" Submitted by **Name: ROHITH NARAYANAN (Reg no : 23CS192)** and **Name: NIJANDHAN S (Reg no: 23CS144)** is a work done by him/her and submitted during **2023-2024** academic year, in partial fulfilment of the requirements for the award of the degree of **BACHELOR OF ENGINEERING** in **DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**, at Chennai Institute of Technology.

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(Name and Designation)

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PREFACE

I, a student in the Department of Computer Science and Engineering need to undertake a project to expand my knowledge. The main goal of my Core Course Project is to acquaint me with the practical application of the theoretical concepts I’ve learned during my course.

It was a valuable opportunity to closely compare theoretical concepts with realworld applications. This report may depict deficiencies on my part but still it is an account of my effort.

The results of my analysis are presented in the form of an industrial Project, and the report provides a detailed account of the sequence of these findings. This report is my Core Course Project, developed as part of my 2nd year project. As an engineer, it is my responsibility to contribute to society by applying my knowledge to create innovative solutions that address their changes.

DEEP - LEARNING - BASED CLASSIFICATION AND

DETECTION IN PRECISION AGRICULTURE

1. Introduction

Any disease that causes enough morphological and physiological changes in crop plants can be a good candidate for remote sensing detection. As an early example from the late 1920s, an ordinary film-based camera was used from an airplane to capture aerial photographs of cotton fields that were infested by cotton root rot, a soilborne disease caused by the fungus *Phymatotrichopsis omnivore* . Stimulus for more applications of aerial photography for crop disease detection occurred after extensive experiments to examine spectral reflectance characteristics of healthy and stressed crops and to determine optimum film and camera parameters for identifying and differentiating certain cereal crop diseases .

Since then, numerous studies had been conducted on the use of aerial photography for identifying crop diseases that could be generally grouped into four major types: airborne, insect-borne, seed-borne, and soilborne. Although film-based aerial photography is no longer used today, it was a primary remote sensing tool until satellite imagery and airborne imaging systems became more widely available.

Airborne imaging systems with multispectral and hyperspectral cameras have been used for detecting mapping crop diseases for a few decades. The feasibility of airborne color-infrared (CIR) videography was demonstrated for detecting Phymatotrichum root rot in cotton and root-knot nematodes in kenaf . Airborne digital multispectral imagery was evaluated for detecting Phytophthora foot rot in citrus orchards , mapping late blight in tomato fields , and mapping cotton root rot in cotton fields .

Airborne hyperspectral imagery was evaluated for identifying yellow rust in wheat , grapevine leafroll virus and yellow leaf curl on tomatoes . Aerial multispectral and hyperspectral imaging techniques were used for detecting citrus greasy spot , cotton root rot , and huanglongbing or citrus greening .

Satellite imagery has also been evaluated for mapping crop diseases. Landsat imagery, even with 30 m spatial resolution, was able to map severe infestations of the take-all disease in wheat . Advances in satellite sensors have greatly improved image spatial resolution. QuickBird satellite imagery was used for detecting powdery mildew and leaf rust in winter wheat, and high accuracies were achieved with severe infections at late growth stages .

QuickBird imagery was also used to map and identify basal stem rot in oil palms . SPOT 6 satellite imagery was used for mapping powdery mildew in winter wheat in multiple regions . The feasibility of WorldView-2 satellite imagery for the detection of huanglongbing was examined . More recently, unmanned aircraft systems have been evaluated for the detection of crop diseases such as citrus greening , *Flavescence dorée* grapevine disease , and root rot in alfalfa .

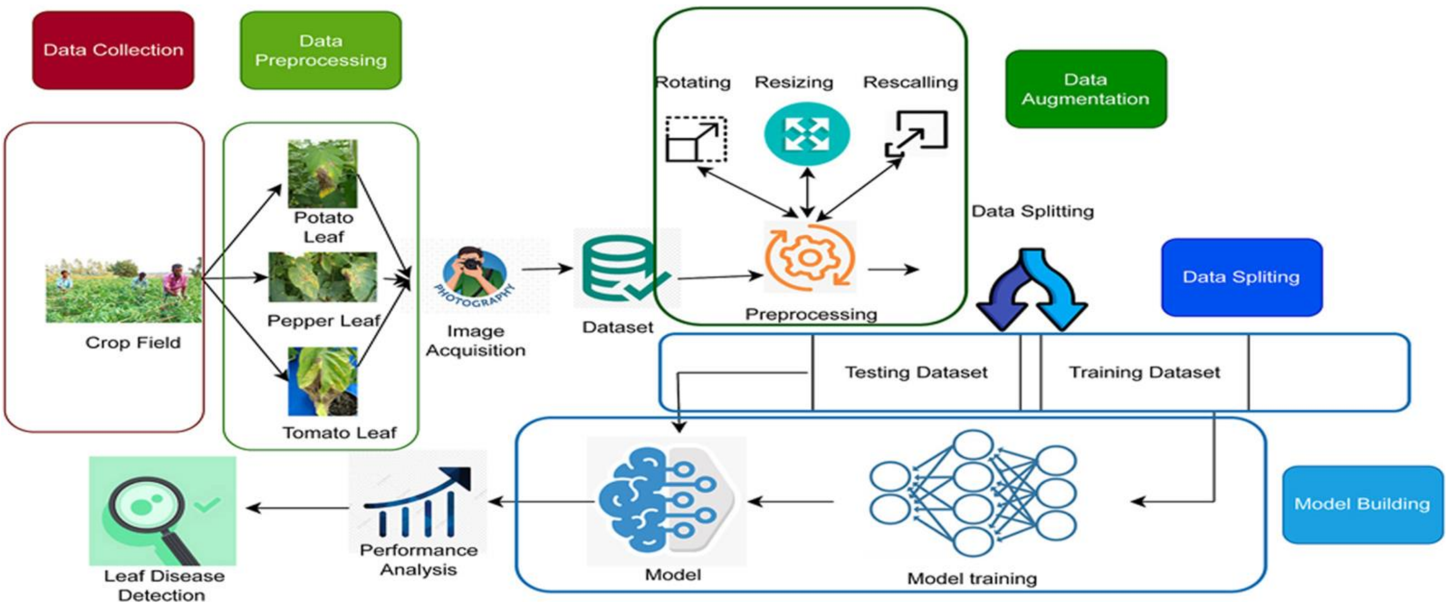
Although both airborne and satellite images have been successfully used to detect and map many crop diseases, early detection is still a challenge. In most cases, by the time remote sensing imagery can reveal any disease symptoms, damage may have already been done to the crop. This delayed detection may be early enough to reduce further damage with certain measures for some crops; for others, it may be too late to stop the infection for the current growing season. For example, once the plant is infected with cotton root rot, it will die within days.

In fact, remote sensing has commonly been used to estimate the extent and severity of the damage caused by disease. Moreover, imagery obtained in the current growing season can be used for the management of recurring diseases, such as cotton root rot, in future growing seasons. Fungicides are widely used for disease control to reduce crop yield loss and quality degradation. Uniform fungicide application has been commonly used, since many diseases tend to spread quickly across the field. However, site-specific and variable rate application can be more effective for the management of some diseases that are stable either within the season or across different seasons. If a disease tends to occur in similar areas within the field across different seasons, site-specific application can be made before the initiation of the disease, based on infestation maps from previous years. Cotton root rot is one such disease that has affected the cotton industry for over a century.

The US Department of Agriculture's Aerial Application Technology Research Unit in College Station, Texas, started to collect aerial imagery to monitor the distribution and severity of cotton root rot in south Texas in 2000 and in central Texas in 2010. Images from 2000–2002 and 2010–2017 have shown that this disease tends to occur in similar areas within fields across different years . The recurrent pattern of the disease provides strong evidence for the usefulness of imagery for creating prescription maps. Therefore, a three-year field study was conducted to demonstrate how to implement site-specific fungicide application using historical imagery and variable rate technology .

The rest of this article uses cotton root rot as an example to illustrate how remote sensing and precision agriculture technologies can be used for the detection and site-specific management of this disease. Specifically, image selection and acquisition, prescription map creation, variable rate application, and performance evaluation are discussed so that the methodologies can be directly used or modified for similar crop diseases.

Graphical abstract



2. Image selection and acquisition

Both airborne and satellite imagery can be used to map cotton root rot infestations . Airborne imagery has fine pixel size, but its availability varies by location and time of year. High-resolution satellite imagery is another important image source because of its short revisit time and large ground coverage. Landsat imagery is free, but the spatial resolution is too low for accurately mapping smaller infestations.

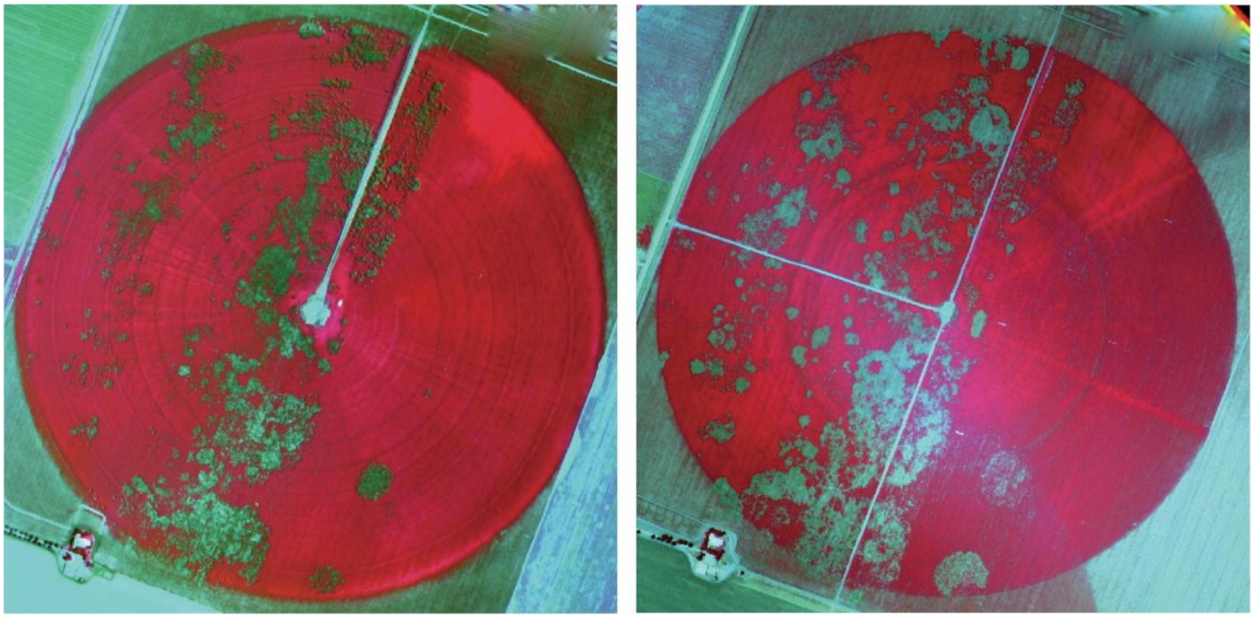
Satellite imagery with a pixel size of 5 m or less would be more appropriate. There are a number of such satellite sensors, including GeoEye-1, Pleiades, WorldView-3 and -4, and GaoJing-1. If such imagery is not available or is too expensive for the fields under investigation, imagery with resolutions of 5–10 m, such as RapidEye, SPOT 6 and 7, and Sentinel-2, can be used.Three airborne multispectral imaging systems (three-camera, four-camera, and two-camera) and one satellite sensor (Geoeye-1) were used for image acquisition for the cotton root rot project over the years.

The three-camera imaging consisted of three digital cameras with visible to near-infrared (NIR) sensitivity to obtain 8 bit images with 1024 × 1024 pixels . The three cameras were filtered in the green (560 ± 5) nm, red (630 ± 5) nm, and NIR (851 ± 6) nm bands, respectively. The four-camera imaging system consisted of four digital cameras to capture 12 bit imagery with 2048 × 2048 pixels in four spectral bands with a bandwidth of 40 nm and center wavelengths of 450, 550, 650, and 830 nm, respectively .

The two-camera system consisted of two identical consumer-grade Nikon D810 cameras with a pixel array of 7360 × 4912. The first camera was used to obtain normal red–green–blue (RGB) images, while the second camera was modified to capture NIR images by replacing the original NIR blocking filter with an 830 nm long-pass filter. A Cessna 206 airplane was used for image acquisition at altitudes of approximately 3050 m above ground level.

All airborne images were taken between 1000 and 1500 h. Pixel size was 1.3, 1.0, and 0.8 m for the three-, four-, and two-camera systems, respectively. The GeoEye-1 satellite image had a spatial resolution of 2 m and a pixel depth of 11 bit, and contained three visible bands (RGB) and one NIR band. All the airborne and satellite imagery was rectified to the Universal Transverse Mercator coordinate system.

It presents two airborne CIR images taken from a 102 hm^2 cotton field in south Texas toward the end of the growing seasons in 2001 and 2011, respectively. Non-infested areas have a reddish color, while infested areas exhibit a greenish or light blue tone. Cotton root rot infestations can be readily differentiated from healthy plants on the CIR images. Although there were some differences in infestations between the two years, the overall patterns of the infestations were similar. Image classification results showed that the infested areas accounted for about 14% and 18% of the total field area in 2001 and 2011, respectively .



(a) (b)

Comparison of cotton root rot infestations in a 102 hm^2 cotton field in south Texas between

(a) 2001

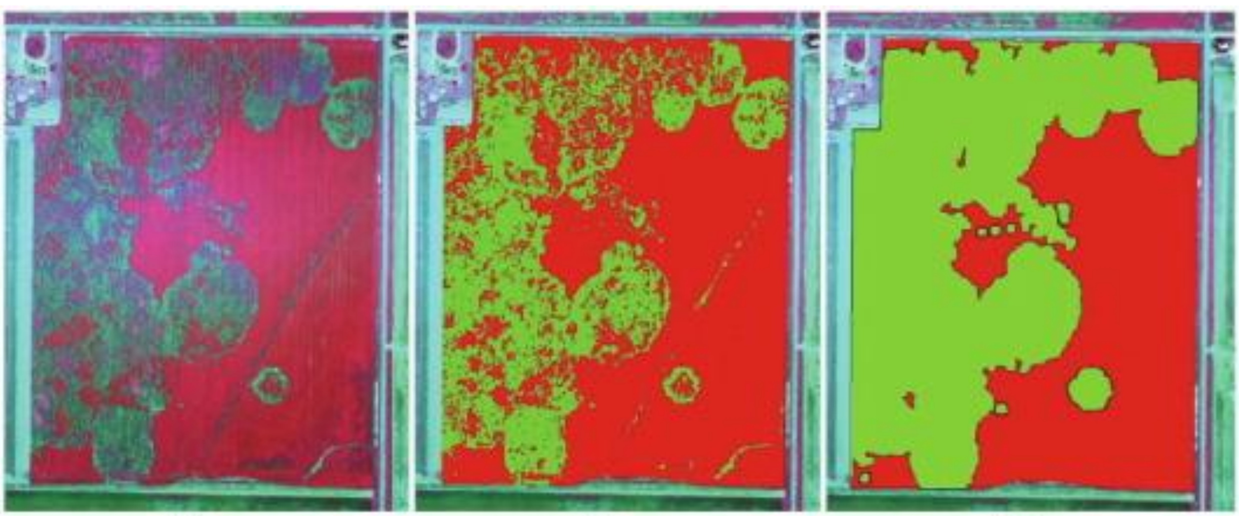
(b) 2011

3. Prescription map creation

For site-specific management of cotton root rot, it is necessary to delineate the infested areas within a field from an airborne or satellite image. Most image-processing software packages such as Erdas Imagine and ENVI can be used to classify the image and then create the prescription map for use by a variable rate control system. Moreover, other less expensive software products such as Trimble Ag Software and AgLeader SMS, which have been used in agriculture, can be used for this purpose. In addition, free image-processing software such as QGIS is available for image processing and prescription map creation.
For the cotton root rot project, numerous classification techniques were evaluated to differentiate infested from non-infested areas in airborne imagery.

Two unsupervised and six supervised classification classifiers were compared for identifying cotton root rot from airborne imagery . The evaluation results showed that although all eight methods were equally accurate, the two unsupervised methods were easy to use; these methods were therefore recommended for cotton root rot identification. The two unsupervised methods can be implemented by applying iterative self-organizing data analysis to a multispectral image or to the normalized difference vegetation index image derived from the multispectral image. To consider the potential expansion of the disease, a 3–10 m buffer can be added around the infested areas as part of the treatment zone in the prescription map . presents an airborne CIR image, the unsupervised classification map, and the prescription map with a 5 m buffer for a 45 hm^2 cotton field near San Angelo, Texas.

The classification map effectively separates the cotton root rot-infested areas within the field. Nevertheless, some non-infested areas such as the linear feature and the bare soil exposure toward the lower right portion of the field were classified as infested areas; these areas were then removed before the buffer was added. The classification map indicated that about one-third of the field was infested, while the prescription map with a 5 m buffer showed that 57% of the field needed to be treated.



(a) (b) (c)

Process to create a prescription map from an airborne image for a 45 hm^2 cotton field in south Texas.

(a) Airborne image acquired on 30 July 2010;

(b) classification map, infested = 33%, noninfested = 67%;

(c) prescription map, treated = 57%, nontreated = 43% .

4. Variable rate application

Variable rate technology allows farming inputs (i.e., fertilizers, herbicides, and fungicides) to be applied to address the specific needs for each area of the field. Extensive publications are available that document research and commercial activities in this technology and in other precision agriculture technologies around the world. Variable rate application does not change the basic functionality of existing applicators, but it does require the addition of a control system that can read a prescription map to adjust the application rate automatically. Different control systems are available for variable rate application, but flow-based control systems are simple and commonly used; these systems deliver the desired rate across the boom or swath with an electronic controller.

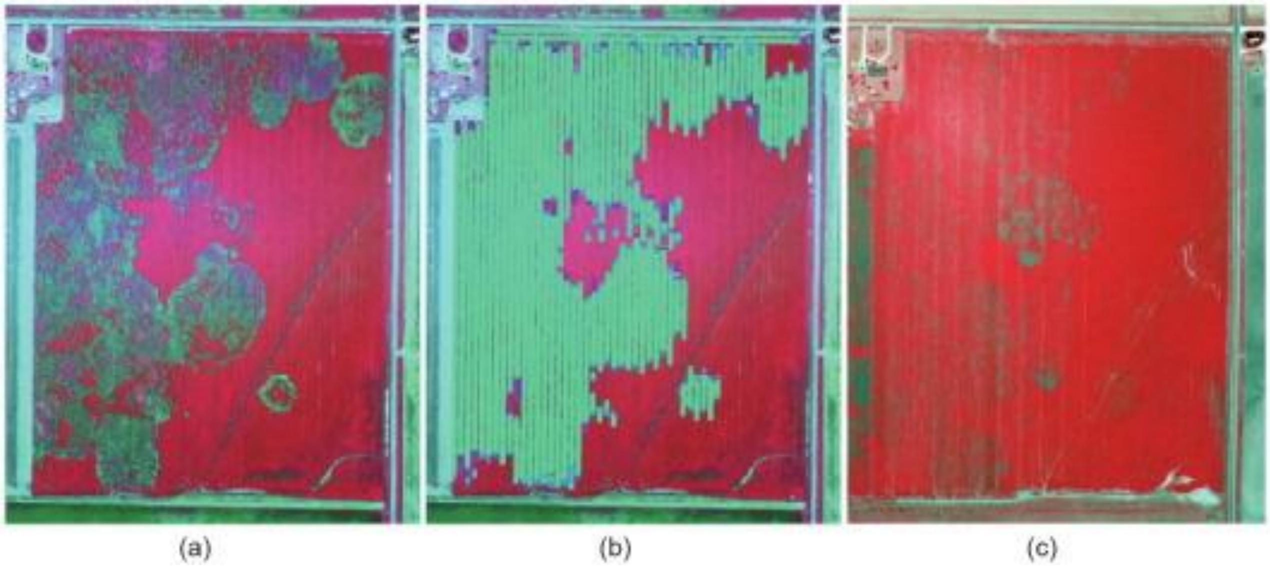
Two flow-based control systems—a John Deere controller and a Trimble controller—were selected for our research. The John Deere control system consisted of a controller, a servo valve, a flowmeter, and a shutoff valve and was added to a John Deere tractor owned by a farmer near Edroy, Texas. The Trimble system, with similar components, was adapted to a John Deere tractor owned by a producer in San Angelo, Texas. Both tractors were already equipped with the StarFire real time kinematic global positioning system receiver. The John Deere system required a John Deere GreenStar display and the Trimble control system required a Trimble FMX display. Both displays were already integrated on the respective tractors for automatic guidance and other field operations. The prescription maps were uploaded to the displays and each system was calibrated for the desired rates prior to fungicide application over multiple fields in 2015–2017.

5. Evaluation of application performance and treatment efficacy

Both as-applied maps and post-application aerial imagery along with ground observations can be used to assess the performance of variable rate application. The actual rate and target rate for each small area are generally recorded in the as-applied maps during field application.

Aerial imagery taken during the growing season will be able to detect any root rot from the treated fields. shows a pre-treatment CIR image taken in 2010, the as-applied map overlaid on the CIR image, and a post-treatment CIR image for the 45 hm^2 cotton field.

Overall, the John Deere control system used for this field accurately applied the product to the prescribed areas. Spatial analysis showed that the actual treatment area was only 1.5% smaller than the target treatment area, while the actual application rate was 4.1% higher than the desired rate for the field .



Comparison of (a) a no-treatment airborne image acquired in 30 July 2010 with natural infestation, (b) the as-applied map, and (c) an airborne image acquired in 5 August 2015 after the site-specific treatment of Topguard Terra fungicide for a 45 ha cotton field in south Texas.

Obviously, site-specific treatment effectively controlled the cotton root rot in the treatment areas, as can be seen from the post-treatment CIR image. However, root rot showed up in a few small, non-treated areas near the center of the field. As the image that was used to create the prescription map was taken in 2010, root rot may have expanded since then. The prescription map can be modified with the addition of the new infestations for the coming years. It should be noted that the rectangular area along the west border of the field was not treated, and almost all the plants in that area died during the flowering stage in the season.
The fungicide used to treat cotton root rot, Topguard Terra, is very expensive.

The cost at full application rate is 50 USD·acre^{-1} (1 acre = 4046.9 m^2) or 124 USD·hm^{-2}. For example, if the whole 45 hm^2 field had been treated uniformly at full rate, the fungicide cost for the field would have been 5580 USD (45 hm^2 × 124 USD·hm^{-2}). As only 57% of the field needed treatment, the amount saved on fungicide, in comparison with uniform treatment, was 2400 USD, or 43%. The cost to adapt a variable rate control system to the existing tractor or planter was about 4000–5000 USD.

This initial investment can easily be recovered, as long as site-specific treatment can reduce the treatment area by 32–40 hm^2 in a single season. Our aerial surveys indicate that most fields with a history of cotton root rot infestations contain 20%–40% infested areas, although infested areas within fields can reach 75%. Clearly, the potential for savings on fungicide is tremendous with site-specific application.

6. Challenges and research needs

This brief review uses the successful cotton root rot story as an example to illustrate how remote sensing and variable rate technology can be used for disease detection and site-specific management. Diseases with distinct spectral signatures can be easily distinguished, as in the case of cotton root rot, but some diseases are difficult to detect, especially when multiple biotic and abiotic conditions with similar spectral characteristics exist within the same field.

With advances in imaging sensor technology and image-processing techniques, it is necessary to evaluate advanced imaging sensors and analytical methodologies for differentiating diseases from other confounding factors.

Although many crop diseases, as discussed in the introduction section, can be successfully detected and mapped using airborne or satellite imagery, the understanding of how to convert remote sensing data to practical prescription maps is still lacking. More research is needed to develop operational procedures for transforming image classification maps to applications maps.

Each disease has its own characteristics and requires different procedures for detection and management, although the cotton root rot project presented in this article should provide some guidance. For diseases that tend to recur year after year in similar areas, historical imagery can be used to document the spatial and temporal consistency and dynamics of the infestations, which will be useful for the creation of prescription maps.

Variable rate fungicide application has great potential to reduce fungicide use and increase profitability, as demonstrated by the cotton root rot project, but many technologies are necessary for the implementation of site-specific application. This can present a great challenge, as not many farmers have the knowledge and skills required to integrate all the technologies into a disease-management system. Farmers with some experience with image processing may be able to create their own prescription maps.

If this is not practical, farmers can always use a commercial image-processing service to create prescription maps. At present, many agricultural dealerships provide services for image acquisition, prescription map creation, and variable rate application. Nevertheless, not all diseases are suitable for site-specific application, and uniform rate application is still effective for many crop diseases. More research should also be devoted to the identification of diseases that are more suitable for variable rate application.

7. Application areas of the proposed work

This research is noteworthy because of the contributions it makes to agricultural research its potential application can be summarized as follows:

AI-enabled leaf disease detection system: This proposal creates an opportunity to quickly and accurately identify diseased leaves by integrating a deep learning model. Our research improves the accuracy of predicting diseases. This can help experts make more accurate diagnoses, which in turn can improve harvest results.

Automated preventive measures: The results of this study have practical applications in any environment where a web browser is available. By promptly uploading images of diseased crops, farmers can take corrective measures to enhance agricultural productivity.

Advancement in machine learning techniques: Our research aids the development of deep learning models for use in the smart agricultural industry of any country. The findings of this research can be used to improve crop disease prediction and prognosis using deep-learning models that are both accurate and easy to interpret.

8. Conclusions

Plant and Leaf disease detection and classification problems are crucial and challenging problems in agriculture worldwide. This study utilized Convolutional neural networks-based architecture to identify leaf disease and its source. Several models, such as CNN, VGG-16, VGG-19, and ResNet-50 architectures, are adopted to detect leaf conditions. Extensive experiments were conducted with the freely available “plant-village” plant disease dataset. In the experiment, we got the accuracy rate of 98.60%, 92.39%, 96.15%, and 98.98% for CNN, VGG-16, VGG-19 and ResNet-50 models respectively. Among all models, RestNet50 provides a better accuracy rate to detect leaf disease efficiently. So, we employed the proposed higher accuracy model for our web app development to correctly detect plant leaf disease. The web application provides a smart agriculture system for detecting the disease. Hence, the proposed method produced better outcomes for estimating symptom severity than earlier investigations of plant leaf disease.

In the future, we want to improve the accuracy rate by developing a new hybrid deep-learning architecture using an attention-based mechanism as well as plant leaf disease area identification or developing a localization method to identify the area of disease in the leaf. Besides, we will use better multiple-leaf disease datasets so that it includes all the plant-leaf diseases.

9.PROGRAM CODE :

```
import os
os.listdir("../input/plant-diseases-classification-using-alexnet")
```

Building CNN Based On AlexNet Architecture

```
# Importing Keras libraries and packages
from keras.models import Sequential
from keras.layers import Convolution2D
from keras.layers import MaxPooling2D
from keras.layers import Flatten
from keras.layers import Dense
from keras.layers import Dropout
from keras.layers.normalization
import BatchNormalization

# Initializing the CNN
classifier = Sequential()

# Convolution Step 1
classifier.add(Convolution2D(96, 11, strides = (4, 4), padding = 'valid',
input_shape=(224, 224, 3), activation = 'relu'))

# Max Pooling Step 1
classifier.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2), padding = 'valid'))
classifier.add(BatchNormalization())

# Convolution Step 2
classifier.add(Convolution2D(256, 11, strides = (1, 1), padding='valid', activation
= 'relu'))

# Max Pooling Step 2
classifier.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2), padding='valid'))
classifier.add(BatchNormalization())
```

```
# Convolution Step 3
classifier.add(Convolution2D(384, 3, strides = (1, 1), padding='valid', activation =
'relu'))
classifier.add(BatchNormalization())

# Convolution Step 4
classifier.add(Convolution2D(384, 3, strides = (1, 1), padding='valid', activation =
'relu'))
classifier.add(BatchNormalization())

# Convolution Step 5
classifier.add(Convolution2D(256, 3, strides=(1,1), padding='valid', activation =
'relu'))

# Max Pooling Step 3
classifier.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2), padding = 'valid'))
classifier.add(BatchNormalization())

# Flattening Step
classifier.add(Flatten())

# Full Connection Step
classifier.add(Dense(units = 4096, activation = 'relu'))
classifier.add(Dropout(0.4))
classifier.add(BatchNormalization())
classifier.add(Dense(units = 4096, activation = 'relu'))
classifier.add(Dropout(0.4))
classifier.add(BatchNormalization())
classifier.add(Dense(units = 1000, activation = 'relu'))
classifier.add(Dropout(0.2))
classifier.add(BatchNormalization())
classifier.add(Dense(units = 38, activation = 'softmax'))
classifier.summary()
```

Loading Weights To The Model :

```
classifier.load_weights('../input/plant-diseases-classification-using-
alexnet/best_weights_9.hdf5')
```

Fine Tuning By Freezing Some Layers Of Our Model

```
# let's visualize layer names and layer indices to see how many layers
# we should freeze:
from keras import layers
for i, layer in enumerate(classifier.layers):
   print(i, layer.name)

# we chose to train the top 2 conv blocks, i.e. we will freeze
# the first 8 layers and unfreeze the rest:
print("Freezed layers:")
for i, layer in enumerate(classifier.layers[:20]):
    print(i, layer.name)
    layer.trainable = False
```

Model Summary After Freezing

```
#trainable parameters decrease after freezing some bottom layers
classifier.summary()
```

Compiling the Model

```
# Compiling the Model
from keras import optimizers
classifier.compile(optimizer=optimizers.SGD(lr=0.001, momentum=0.9,
decay=0.005),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Image Preprocessing

In [ ]:

```
# image preprocessing
from keras.preprocessing.image import ImageDataGenerator

train_datagen = ImageDataGenerator(rescale=1./255,
                                   shear_range=0.2,
                                   zoom_range=0.2,
                                   width_shift_range=0.2,
                                   height_shift_range=0.2,
                                   fill_mode='nearest')

valid_datagen = ImageDataGenerator(rescale=1./255)

batch_size = 128
base_dir = "../input/new-plant-diseases-dataset/new plant diseases dataset(augmented)/New Plant Diseases Dataset(Augmented)"

training_set = train_datagen.flow_from_directory(base_dir+'/train',
                                                 target_size=(224, 224),
                                                 batch_size=batch_size,
                                                 class_mode='categorical')

valid_set = valid_datagen.flow_from_directory(base_dir+'/valid',
                                              target_size=(224, 224),
                                              batch_size=batch_size,
                                              class_mode='categorical')

class_dict = training_set.class_indices
print(class_dict)

li = list(class_dict.keys())
print(li)

train_num = training_set.samples
valid_num = valid_set.samples

# checkpoint
```

```python
from keras.callbacks import ModelCheckpoint
weightpath = "best_weights_9.hdf5"
checkpoint = ModelCheckpoint(weightpath, monitor='val_acc', verbose=1,
save_best_only=True, save_weights_only=True, mode='max')
callbacks_list = [checkpoint]

#fitting images to CNN
history = classifier.fit_generator(training_set,
                         steps_per_epoch=train_num//batch_size,
                         validation_data=valid_set,
                         epochs=25,
                         validation_steps=valid_num//batch_size,
                         callbacks=callbacks_list)
#saving model
filepath="AlexNetModel.hdf5"
classifier.save(filepath)
```

Visualising Training Progress

```python
#plotting training values
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)

#accuracy plot
plt.plot(epochs, acc, color='green', label='Training Accuracy')
plt.plot(epochs, val_acc, color='blue', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
```

```
plt.figure()
#loss plot
plt.plot(epochs, loss, color='pink', label='Training Loss')
plt.plot(epochs, val_loss, color='red', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.show()
```

Predicting New Test Image(s)

```
# predicting an image
from keras.preprocessing import image
import numpy as np
image_path = "../input/new-plant-diseases-
dataset/test/test/TomatoEarlyBlight1.JPG"
new_img = image.load_img(image_path, target_size=(224, 224))
img = image.img_to_array(new_img)
img = np.expand_dims(img, axis=0)
img = img/255

print("Following is our prediction:")
prediction = classifier.predict(img)
# decode the results into a list of tuples (class, description, probability)
# (one such list for each sample in the batch)
d = prediction.flatten()
j = d.max()
for index,item in enumerate(d):
    if item == j:
        class_name = li[index]

##Another way
# img_class = classifier.predict_classes(img)
# img_prob = classifier.predict_proba(img)
# print(img_class ,img_prob )
```

```
#ploting image with predicted class name
plt.figure(figsize = (4,4))
plt.imshow(new_img)
plt.axis('off')
plt.title(class_name)
plt.show()
```

10. References

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