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DIGITAL DISEASE MAPPING OF CITRUS CANKER FROM SELECTED CITRUS ORCHARDS IN POTHOWAR

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ABSTRACT

Agriculture is one of the essential sectors for the survival of humankind. Adapting technology as well as digitalization is very crucial for the field of agriculture to benefit the farmer as well as the consumer. Crop growth and yield are essential aspects that influence the field of agriculture as well as farmer economically and socially. So, it is necessary to have close monitoring at various stages of crop growth to identify the diseases at right time. But, humans naked may not be sufficient and sometimes it would be misleading scenarios arise. In this aspect, automatic recognition and classification of various diseases of a specific crop are necessary for accurate identification. This thought gave inspiration for the present proposed framework

Pakistan confers with a broad range of agro-climatic position, diverse from tropical to temperate, allowing 20 different types of fruits to grow. Citrus is an important fruit within the economically important family *Rutaceae* and is cultivated in Pakistan on a 20.0461 thousand ha with an annual production of 2.29 million tons. According to intentional reports published during 2015, Pakistan stands 16th country of world for production of good quality of citrus crops. However, during 2016 CABI released a report indicating a serious disease of citrus fruits like canker, causing higher losses in citrus production caused by gram negative bacteria *Xanthomonasaxonopodis.* Conventionally method for plant diseases diagnosis using hand lenses till to isolation lab techniques are laborious and not predictive for fungicidal application time to time, and make some treatment to control the diseases. By applying Artificial Intelligence techniques 4 to 5 thousands picture of Citrus canker spots from different orchards from different plant parts fruit

and leaves at different location from pothowar were obtained . Then resize the images and retain images in convolutional neural network (CNN) by using python as computer language were applied . A model of *Citrus Fruits Detection (Multi Classification).ipynb*(CFD) was developed, that is able to detects the Citrus canker disease on Citrus Plant, and provides data at its initial stages (Low Infection) or at final stage (Severe Infection).
Keywords: Citrus, *Xanthomonasaxonopodis*, Artificial, Intelligence ,CNN

INTRODUCTION

The distribution of crop diseases can affect the economy badly. The manual diagnoses of crop diseases are time-consuming and risk errors. Digital revolution is reinventing agriculture, which integrates advanced technologies, digital tools, information, and communication technologies to enhance the opportunities for agriculture improvement and performance. Digital agriculture is currently emerging as a consequence of several technological developments in artificial intelligence, remote sensing, and robotic systems. Such systems allow farmers to provide broad, precise, and accessible traditional agricultural products at the national and regional levels, and boost yield and quality while limiting environmental impact. It can also provide ease to the farmers for detecting plant disease, pests and weeds (Adaskaveg and Foster, 2004 ; Aruoma et al., 2012).

Citrus is producing in all the four provinces of Pakistan , But mainly in Province Punjab five districts, Sargodha (Bhalwal), Toba Tek Singh, MandiBahauddin, Sahiwal, Khanewal, Cover total area under cultivation 60% and production of Citrus is 65%. (Deqiu, 1993; Devatkal, and Naveena, 2010).). In Pakistan area and production of fruit increased by 22.8% and 21%, respectively, in the year 2005 better growth received by the growers, 0.8 million hectares area under fruit trees. (MINFAL, 2006; Franke and Menz, 2006; Gerhards and Oebel, 2006). Among fruits, citrus was cultivated on 192,274 hectares with annual production of 2,458,381 tons during

2005. Since the best growth of Kinnow (*Citrus reticulate*.), Pakistan produced 1.62 million tones citrus (Jeliazkova and D. Percival, 2003), which increased to 2.4 million tons in 2014 and 2015. (FAO, 2016), its production has been fistedly increasing to fulfill the demand in the country and abroad (Khan, 1992; Gliever and Slaughter, 2001; González-Molina et al., 2010).

The citrus stand first in area and production among all fruits produced worldwide. It is highly prized and remunerative fruit cultivated in more than 50 countries worldwide (Kl, 1993; Lin et al., 2009; Luo et al., 2008). The major fruit producers are China, Brazil, USA, and Mexico and contribute 47% of total citrus world production (Youseif et al., 2014; Mukti ansd Biswas , 2019). Brazil is the biggest citrus fruit production country in the world and most of the oranges are produced here (Wali et al., 2013; Nutter et al., 2006; Parvat et al.,2017). Global production of citrus has been considerably increased during the past few years and reached 3.2 metric million tons during 2016-17. The Oranges accounts for about 50 million tons (USDA, 2017). The availability of Pakistani kinnow in the European market is irregular and is mainly used as a raw material for juice. The Pakistan is exporting only 10% of its total Kinnow production which can be increased thrice by providing local farming better knowledge about growth to post harvest stages . It exported 372,160 tons Kinnow during the year 2015-16 and major international markets were Afghanistan, Azerbaijan, Indonesia, Mauritius, Oman and Philippines (Trade Development Authority of Pakistan, 2017).

In scientific literature, several techniques have been proposed to tackle the complex challenges in agriculture, such as decision support systems, plant disease detection, and other artificial intelligence-based techniques. Deep learning has shown most promising results for agricultural image processing such as plant disease detection, pesticides detection, plant type classification, etc. For instance, the study proposed the detection of *Fusarium* head blight disease in wheat crops (Sankaran, 2016) . Here, deep con volutional neural network (CNN) and image processing techniques are employed to detect the diseased part of wheat leaf images. The authors in exploit Bayesian deep learning for approximating the probability density for crop disease detection problems. Another deep CNN-based work suggests deploying a pre-trained model learned from usual massive datasets, and transferring it into a specific task trained with their data, like VGG Net and Image Net (Selvaraj et al., 2006;).

An automated wheat disease diagnostic system implementable on mobile devices to conduct a real-time diagnosis is based on deep learning and multiple instances learning (MIL). Their method uses four deep learning models, VGG-FCN-VD16, VGG-FCN-S, VGG-CNN-S, VGG-CNN-VD16, and are implemented on the leaf images dataset. The accuracies of VGG-CNN-VD16 and VGG-CNN-S are 73.00%, and 93.27%, respectively. However, the suggested model cannot detect the last stage of disease of the plant. Authors of applied the neural network, support vector machine, and fuzzy classifier for plant disease detection problems. They suggested that there is a need to work on diseases stage identification and quantification, real-world applications, and the reliability of a fully automatic system in agricultural sector. proposes the detection of the *Fusarium*head blight, a wheat crop disease (Saville, 2006) . They developed a deep convolutional neural network (DCNN) capable of extracting distinct wheat stems from a single image with a complicated environment. They also suggest a new method for identifying *Fusarium* head blight infected regions in each spike. In training, the model accurately detects the crop's diseased part, and the mean average precision is 0.9201. The results are better than k-means and Otsu's methods. However, this model requires a large dataset to detect the diseased part more accurately (Shahzadi et al., 2016; Shaw and Royle, 1989).

A novel plant leaf disease detection model bases on deep CNN is proposed in(Lin et al., 2009). Transfer learning and deep CNN are used for the leaf disease detection problem. The deep CNN model could accurately differentiate 38 different groups of diseased and healthy plants using leaf images with 96.46% accuracy (Sunny and Peter, 2016) and used texture-based segmentation and simpler linear iterative clustering (SLIC) to capture and recognize the diseases and pests at early stages in corn crops. Classification is done through binary support vector machine (BSVM) and multi-class support vector machine (MSVM). The accuracy achieved for pest detection is 52%, which can be extendable used ResNet-101, VGG-16, and ResNet-50 can see blurred images, and yolov3 for pest and disease detection in rice crop, and detected blurred boundaries and irregular shapes. However, the model showed poor performance for fewer features present in the image frames (Thangadurai and Padmavathi , 2015).

The results presented by Mukti and Biswas (2019) suggested the use of image acquisition, image preprocessing, image segmentation, feature extraction, and classification techniques for the ginger plant disease detection problem. The system is linked with a digital/web camera, allowing farmers to take images of plant leaves. The collected images are processed using image processing techniques to identify diseases symptoms, disease type and notify the farmers about disease type through global system for mobile communications (GSM) interface. Then, relay turns on the pump installed in the device to release medicine to the infected plant according to the infected disease. However, the study does not consider a standard dataset of the ginger plant leaf images, and some diseases of ginger plants and pests are not discussed (Zaman et al., 2011).

This study focuses on making an autonomous system that detects ginger plant diseases, pest patterns, and deficiency nutrients through deep artificial neural network and learning techniques, namely VGG-16, CNN and MobileNetV2 in real-time circumstances. The study also involves developing a large-scale ginger plant dataset based on different stages. We present the classification of various diseases and nutrient deficiencies, and investigate the pest patterns in the leaf images. In addition, we exhibit the performance and ability of the model to predict diseases with high accuracy. This study hopes to present the first step towards deep learning-based citrus canker disease detection. This research study presents the following key contributions. • To develop a standard dataset of leaves and fruits ofcitrus at healthy stage, citrus canker at initial stage and citrus canker at final stage.

MATERIAL AND METHODS

Data Collection

Collection of the images of Citrus fruits and leaves were collected at different stages twice in a month from emergence of canker spots at Knoot Research Farm, Pir Mehr Ali Shah Arid Agriculture University Rawalpindi at Chakwal and Panj Katha village in Attock. The size of data was almost 4000 images of canker spots by using Sensor (Iphone8 mobile Camera with 12-megapixel wide-angle f/1.8 camera with a larger. Data was taken from a specific distance of 01ft from infected sample to image collecting devices.

Image Acquisition and Description

To detect canker spotsinreal□time, there was three stages Healthy Citrus (Healthy images of Fruits and Leaves), Canker at Initial Level (Canker spots on leaves and fruits at Initial level), Canker at Final Stage (Canker Spots on leaves and fruits at Final Stage).

RESULTS AND DISCUSSION

After collecting data, images were processed as 1.5 × 1.4□m subject of view PNG documents within the Google Colab Note Book in Google drive. A detailed description of dataset distribution is provided in Table 1.

Table 1. A detailed description of dataset distribution

Sr. No	Stages of Citrus	Training 80%		Total	Testing 20%
		Leaves Data	Fruits Data		
01	Citrus Healthy	512	512	1024	
02	Citrus Canker (Initial)	512	512	1024	768
03	Citrus Canker (Final)	512	512	1024	
04	Total	1536	1536	3072	3840

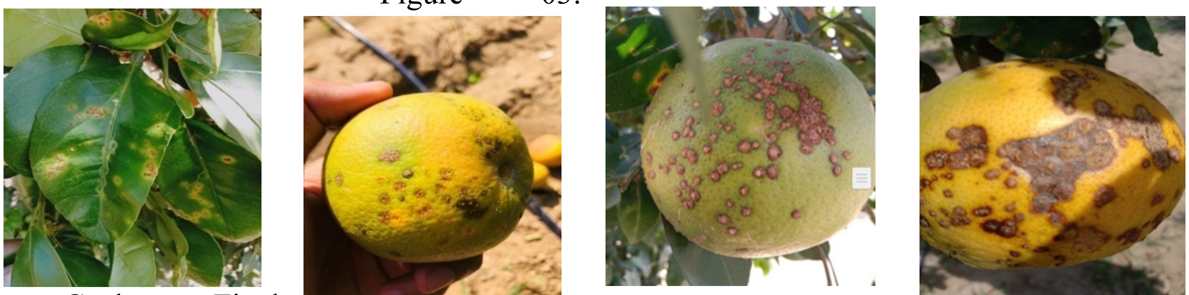
Data Augmentation and Processing

Data augmentation is a method of creating new training data from field data. We apply domain-specific techniques to samples from the training data to generate unique and distinct training instances. In this study, we augment the images by rescaling, rotating the images, changing the width and height shifts, zooming the images, and doing the horizontal flip. All the images are renamed by python code, resized by the cv2 library, and converted into RGB images for further data processing. The dimensions of the images are (150 × 150 × 3), height and width are 150 and 150, and 3 represents RGB channel (Red, Green, Blue).

Figure 1. Citrus at Healthy stage.

Figure2. Canker on citrus leaves

Figure 03:



Citrus Canker at Final Stage in the field.

Classification

This step trains images of Citrus Canker disease. We use 80% data for training and the remaining 20% data for testing a detailed description of the deep learning algorithms is provided in the following table 2.

Table 2. Detail description of images use during algorithm.

Sr. No	Stages of Citrus	Training 80%		Total	Testing 20%
		Leaves Data	Fruits Data		
01	Citrus Healthy	512	512	1024	
02	Citrus Canker (Initial)	512	512	1024	768
03	Citrus Canker (Final)	512	512	1024	
04	Total	1536	1536	3072	3840

CNN Model

CNN is widely employed in the field of study. Image is represented by a three dimensional matrix is presented to CNN. Then, the convolutional layer extracts the characteristics of the image. Convolutional layer also includes ReLU activation, which reduces all negative values to zero. After convolution, the pooling layer is utilized to minimize the spatial volume of the input image. Then max pooling is used to minimize the spatial volume of the input image, and the 4 × 4 dimension input has been reduced to 2 × 2 dimensions. Then there is a fully connected layer, and the last is the logistic layer. The label, which is one-hot encoded, is contained in the output layer. A sequential model is used with Relu activation function. Dropout rate is 0.2 to reduce the over-fitting of the algorithm and sigmoid is used in the last layer. The hyper parameters used for CNN are given in Table 3.

Table 3. Hyper parameters tuning used for CNN.

Dataset ratio	There are three classes for citrus canker disease detection, Citrus (Healthy Stage), Citrus canker (Initial Stage), Citrus canker (Final Stage) fruits and leaves. 80% data is used for training and 20% data for testing for all detection cases.
Pre-processing	Images are renamed and resized to 150 × 150
Batch size	Batch size is 32 for training the CNN
Epochs	Epochs are set to 60 to train the CNN.algorithm
Learning rate	Learning rate of 0.001 is set for the proposed model
Optimization algorithm	The CNN model is trained by Adam optimizer.

The convolutions are a fixed size of 150 × 150 RGB (Red Green Blue) images during training. The pre-processing performed here removes the typical RGB value computed on the training phase-out of each pixel. The image is processed using a stack of convolutional layers, which employ filters with a small field of 3 × 3. It is more complex and has nonlinear effects but has fewer parameters. In one of the settings, 1 × 1 convolution filters are used, which may be thought of as a linear modification of the input channels. For 3 × 3 convolution layers, the convolution phase and spatial padding of convolution input are kept to 1 pixel, ensuring that the spatial resolution is retrained after convolution.

Spatial pooling is helped by five max-pooling layers that follow part of the convolution layers. Max pooling is done with stride 2 across a 2 × 2-pixel frame. After a stack of convolution layers, there are three fully connected (FC) layers. The first two each have 4096 channels, whereas the third uses 1000 way ILSVRC classification and hence has 1000 channels, one for each class. The Softmax layer is the last layer. However, because of binary classification study.

The last layer used here is the sigmoid layer. In all networks, the configuration of the ultimately linked layers is the same.

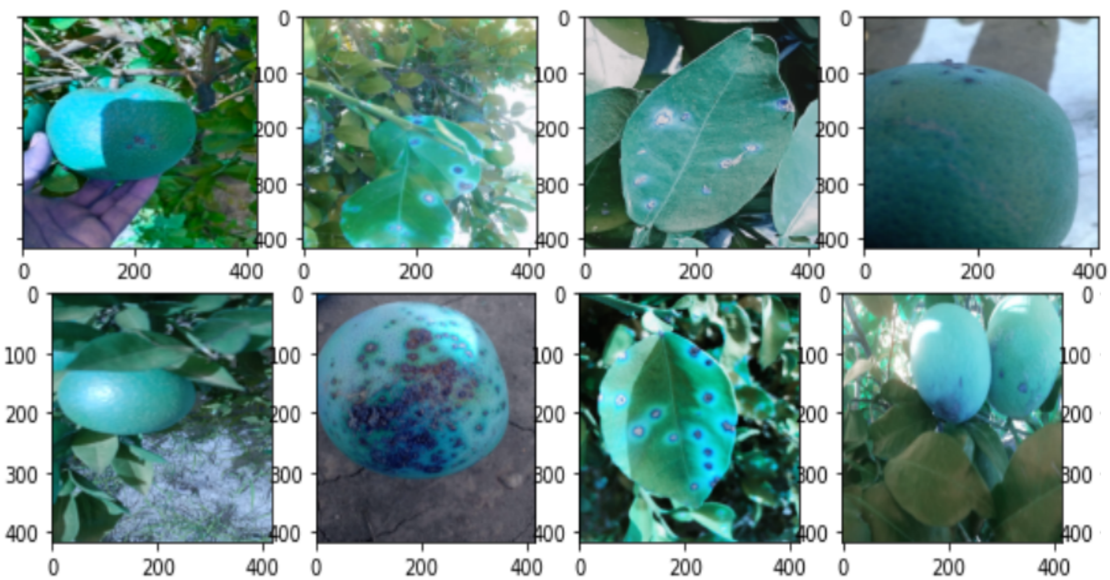


Figure 4. Training Data of Citrus (Healthy), Citrus canker (Initial Stage), Citrus canker (Final Stage).

This section presents the results of pest pattern detection. The dataset was split into three classes' pest pattern and healthy having 3072 images of training and 768 images for testing. Accuracy for CNN is shown in Figure 5. The number of epochs was represented on the x-axis, and it can be defined as the algorithm will learn in the number of times of the entire dataset. The y-axis represents the accuracy of the models, and accuracy is the ratio of the number of accurate predictions to the overall number of correct predictions. VGG-16 achieves better validation accuracy of 92% in disease detection.

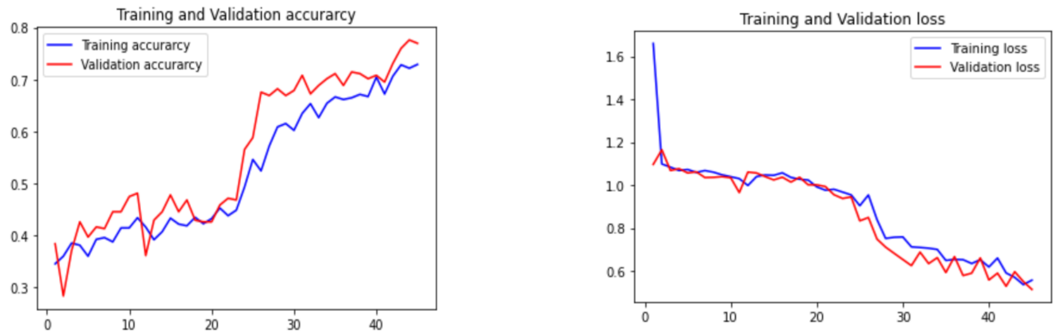


Figure 5. Accuracy of CNN when epoch size is 45 and training accuracy is 92%. Algorithm CNN shows the accuracy 92%, loss was 0.3%, precision was 95%.

CONCLUSION

Citrus plant plays an important role in agriculture and medical field. So, this research represents an approach for canker detection in citrus. Digital image processing techniques can be employed to detect canker infected leaf diseases with accuracy compared to the traditional methods. The proposed CNN based leaf disease identification model *Citrus Fruits Detection (Multi Classification).ipynb*(CFD) developed, that detects the Citrus canker disease on Citrus Plant, and also detects and gives data about it that is it at initial stage (Low Infection) or at final stage (Severe Infection). Mapping of citrus canker disease done from four orchards at two different locations in pothowar region.In future we can add the management factor at all the stages for the citrus canker. To early manage the disease and also develop an application. Also develop a Mobile Application for the access of each farmer or citrus grower, for early detection of citrus canker and its proper management.

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