Automatic Detection and Recognition of Citrus Fruit & Leaves Diseases for Precision Agriculture

Ashok Kumar Saini
(Manipal University Jaipur, Rajasthan, India
https://orcid.org/0000-0003-2699-9134, shksaini@gmail.com)

Roheet Bhatnagar
(Manipal University Jaipur, Rajasthan, India
https://orcid.org/0000-0001-9098-3378, roheetbhatnagar@yahoo.com)

Devesh Kumar Srivastava
(Manipal University Jaipur, Rajasthan, India
(https://orcid.org/0000-0002-7400-8641, devesh988@yahoo.com)

Abstract: Machine learning is a branch of computer science concerned with developing algorithms & models capable of 'learning through data and iterations'. Deep learning simulates the structure and function of human organs and diseases using artificial neural networks with more than one hidden layer. The primary purpose of this work is to develop and test computer vision and machine learning algorithms for classifying Huanglongbing (HLB)-infected, healthy, and unhealthy leaves and fruits of the citrus plant. The images were segmented using a normalized graph cut, and texture information was extracted using a co-occurrence matrix. The collected attributes were used for classification and support vector machine (SVM), and deep learning methods were employed. When rating the classification outcomes, the accuracy of the classification and the number of false positives and false negatives were considered. The result shows that Deep Learning could create categories up to 96.8% of HLB-infected leaves and fruits. Despite a broad variance in intensity from leaves collected in North India, this method suggests it could be beneficial in diagnosing HLB.

1 Introduction

Crop plant diseases are a matter of serious concern and various diseases and pests wreak havoc on India's agriculture, the country's prime source of GDP. India is an agriculture-driven economy, and a lot of research is being done in this sector for the benefit of all stakeholders. Agricultural research automation using new technologies needs to be investigated for the benefit of society. This paper discusses citrus leaves and fruits diseases and explores the use of advanced modern technology. Research is conducted on citrus plants for growth and production despite abundant land suitable for citrus plantations. In the past, specialists saw and diagnosed such plant diseases and pests with their own eyes. However, a loss of low-level accuracy has been attributed to naked-eye diagnosis. As a result of the high demand, several modern technologies were

used to develop systems to detect plant diseases and pests. The decline in plant diseases led to an increase in production, which boosted the economy. The increase in citrus crop production was critical to India's economic, social, and environmental development.

The use of technology has improved the precision and dependability of detection and analysis processes. New technologies can aid in the treatment of unexpected diseases. The use of cutting-edge technology has put a stop to the diseases. Infectious crop diseases can cause droughts and famine, putting human lives in danger. Agribusiness may suffer significant losses. The use of computer vision (CV) and machine learning may aid in diagnosing and treating specific diseases. AI uses computers to perceive and comprehend its surroundings. However, it has also been used to identify and analyse materials in medical procedures. Using computer vision to avoid plant diseases improves food security.

CV has helped determine the severity of the disease. Deep learning can predict diseases in plants and animals with high accuracy [Janarthan, 2020] [Jiménez-Bello, 2015]. It is used to prevent diseases from emerging too late and classify diseases. Unlike that of human, a plant's disease is not contagious. The commonality of diseases is due to a variety of causes. Human-to-plant diseases, on the other hand, are uncommon. It is possible to improve the current technology by studying the data about it. Photographs of leaves and other plant components can be used to diagnose plant problems [Hosseinimehr, 2003]. Among other things, this technology could be used to analyse images of people and detect diseases and their eradication rates. This research paper aims to investigate how image-based technologies could be used to diagnose citrus plant diseases and make recommendations for future research.

In recent years, machine vision and learning have been used to detect and classify plant diseases [Khattak, 2021] [Zeng, 2020] [Pan, 2019]. Such actions are required to ensure agriculture's long-term viability and avoid significant economic losses. Citrus canker, Huanglongbing (HLB), and citrus greening are the three major citrus diseases that threaten citric acid output (Candidatus Liberibacter asiaticus). Citrus conditions affect many countries. Citrus growers in India are constantly working to prevent and manage disease outbreaks. Pesticide spraying and plant damage are used to treat the Asian citrus psyllid (Diaphorina citri Kuwayama). To prevent disease spread, an effective diagnostic tool must be developed.

To diagnose unhealthy leaves in the laboratory using polymerase chain reaction (PCR), extensive scouting for diseased trees and frequent field inspections for symptoms are required. Using machine vision technologies in the field can help improve disease prevention. Scouting can be aided by machine vision and PCR analysis. It also lowers the cost of detecting illness because fewer samples are required for PCR analysis. According to an automated vision system, the leaves of citrus fruits grown under controlled laboratory conditions had the greasy spot, Milanese, and scabs. The researchers had completed their work.

[Cao, 2019] provided and proposed features for identifying citrus diseases using colour co-occurrence matrix (CCM) characteristics. Colour and texture qualities have been identified as necessary in disease diagnosis. Because conventional imaging methods cannot gather as much spatial and spectral information as fluorescent imaging spectroscopy, a field-use sensing methodology is required. These advancements have improved their utility in field situations.

1.1   Problem Statement

Because the world's population continues to grow at an alarming rate, governments throughout the world are concerned about plant disease automation in agriculture science. Plants and animals can be diagnosed with more precision and efficiency, thanks to today's more widespread adoption of technology. To stop and prevent a disease's transmission, the first step is the discovery of the sickness. Animal-to-human transmission of illnesses makes worldwide eradication harder. Researchers have been studying the most prevalent diseases in people and plants for decades. The detection and discovery procedures are far from complete, even though certain components have been accomplished. Some diseases have become pandemics because medical science has not been able to recognize them in a timely way. It is our goal to apply artificial intelligence to explain the disease's idiosyncrasies and learn how to identify the condition when it first shows up.

2   Literature review

Machine learning (ML) technology enables robots to interact and learn from humans. As a result, robots can act on behalf of humans and make decisions just as humans can. Recently, it has been a leading industry for growth. Machine learning may be used to classify plant diseases. This technique marks a turning point in the fight against plant diseases by providing a substantial first step. It has boosted agricultural yields. After three years of development, the technology that incorporates visualization approaches has achieved its present level. It is possible to relieve many of the world's present issues if illnesses can be recognized and treated early on. The popularity of machine learning (ML) is increasing throughout the globe. ML and DL specialists use several methods to diagnose patients [Ok, 2018]. Existing diagnostic equipment for these disorders has limitations in terms of its usefulness and precision.

Aside from the temporal complexity of ML and DL, many of the technologies used to diagnose these diseases are obsolete or rely on historical data, resulting in significant diagnostic ambiguity. Another issue is the sensitivity of segmentation [Luque, 2020]. High Precision and sensitivity are required to achieve the desired results (RoI). Second, a language barrier has an impact on how the technology is used. Another impediment to the adoption of this technology is a lack of resources. Most ML and DL procedures necessitate many resources. Commercial and public funds are frequently used to support research into human and plant diseases.

Citrus Plants have grown in importance over time. Science and technology have long recognized citrus plants' critical roles in human health, energy production, and global warming [Somers, 2009]. When there are fewer plants on Earth, global warming is more likely [Tits, 2014]. Several research initiatives have been launched to assist scientists in the development of a cutting-edge convolutional system for image detection and plant disease classification. Image recognition can assist in distinguishing between healthy and diseased leaves. To detect anomalies in plant images, convolutional neural networks (CNNs) may be used. Using images of healthy and sick plants, researchers can compare their findings.

Deep Learning can detect risks to human and plant health. To detect infections, the leaves of infected plants are pixel-by-pixel examined. Researchers can use this

information to determine which diseases affect plants and how to prevent their spread [La Rosa, 2020]. It has been demonstrated that DL technology can improve accuracy by up to 98.59 percent. Plant pathology has made significant advances in disease control and global temperature reduction. To effectively use image detection technology, one must first understand how the leaves of sick plants differ from those of healthy plants. Some of the leaves may have black spots or dry edges. The stiffness of the dried parts makes it easy to see when they have folded. Machine learning attempts to find these distinctions without the use of humans.

Artificial neural networks (ANN), decision trees, support vector machines (SVM), and K-means have all been used to diagnose diseases [Hazarika, 2020]. Compatibility difficulties prevent computers from using photographs taken in the field. During the conversion process, images are transformed into data that computers and machines can interpret. For the technology to work, images must be converted into computer-readable data. You need a basic understanding of computer science and programming to excel here.

Image-based disease detection and recognition in humans can aid in discovering diseases that affect specific regions of the body, in addition to knowledge application in plants and timely diagnosis of diseases. Some human diseases result in severe tissue and organ damage. One of the most common types of prostate cancer is adenocarcinoma. Doctors can detect the disease by scanning a patient's body for abnormalities. [Delalieux, 2014] One in every nine men will develop prostate cancer at some point in their lives. The most reliable method for diagnosing cancer in men is subjective tissue evaluation. To be effective, the Gleason method [Zhang, 2019] necessitates extensive tissue research. The Gleason scale's inaccuracy has been addressed and how it might be used to treat prostate cancer patients. Artificial intelligence is being used to assess the cancer impact of prostatectomy specimens. The appearance of body organs must be considered both before and after a disease such as cancer. Computers outperform humans in distinguishing between organs of varying sizes and shapes. Early detection of illness has the potential to save lives.

Image-based disease detection is beneficial to some plants, such as cassava. Drought-tolerant crops, such as cassava, are critical to agriculture's ability to control food supply and nutrients [Ali, 1977]. Several of these crops are threatened by diseases, making it difficult for agriculture departments to meet their targets. Knowing more about the disease may help us avoid problems in the future. The use of CNN enables accurate disease analysis. [Liu, 2016], This method is precise and dependable. Diseases have been classified based on affecting leaves and other plant parts [Su, 2021]. Some diseases attack specific parts of a leaf, whereas others attack the entire leaf or even the stem. Images of leaf samples can be analysed to determine which category best corresponds to a given illness.

Many countries, notably in Sub-Saharan Africa, rely on cassava as a staple food. Despite this, it has lost most of its nutritional content as a result of viral infections. As of 2014, there were 145 million tonnes of cassava harvested in Africa. The vast majority of food safety devices on the market today are geared at maximizing efficiency rather than decreasing it. Food shortages can be alleviated by using cutting-edge technology to identify and cure illnesses that impede production. Raw materials from the majority of plants are utilized in different industrial processes. These plants are prone to yield subpar goods if they are of poor quality.

2.1 Literature Survey on Types of Plant Diseases

Plant disease features are difficult to elicit during the diagnostic procedure. Visual features such as texture, shape, colour, and motion can be utilized to diagnose the symptoms of disease. Disease feature extraction necessitates the use of these features as well [Perry, 1980]. A novel approach based on colour and texture signals were developed by Raza and his colleagues to detect disease spots. [Hu, 2021(a)] created the D-S evidence theory and multifeature fusion to improve D-S evidence theory judgement techniques. This was followed by the introduction of variance into the D-S evidence theory selection criteria. The Local Binary Patterns (LBP) approach has been enhanced by [García-Cruz, 2019] to use the original LBP local quadratic value to transform an image into grayscale and process the R and G channels of an image by considering both the overall and region. According to Li and colleagues [Mignani, 2016], a deep migrating learning model was employed to extract IoT properties for the smart city. Creating a music app that extracts crucial audio components to make the visuals responsive to music is an example of this. In recent years, new methods for extracting characteristics have emerged. The researchers devised two novel estimators for spectrum estimation in the context of the complicated task of detecting important and distinguishing features from EEG data. According to [Tits, 2011], a residual neural network (SCR)[Guillén-Climent, 2013] was used to extract the high-dimensional time-frequency spectrum features.

2.2 Image Segmentation

Identifying plant disease features is tough. Textures, form, colour, and motion can all help diagnose sickness. These features are essential for disease extraction. [Mignani, 2016] In this study, Raza and his team used colour and texture clues to detect illness spots. [Hu, 2021(b)] improved D-S evidence theory assessment techniques by combining multifeatures. The outcomes of the D-S evidence theory selection criteria were then varied. To process an image's R and G channels, Turkoglu developed an update to the Local Binary Patterns (LBP) approach that employs the original LBP local quadratic value to turn the picture into grayscale. [Thakur, 2021]. A smart city IoT feature extraction model. Extraction of essential audio components to make visuals responsive to music is one example. In recent years, new strategies for extracting characteristics have been developed. To detect relevant and distinguishing aspects in EEG data, the researchers constructed two novel spectrum estimators [Aparisi, 2021]. The residual neural network was used to recover the high-dimensional time-frequency spectrum features [Mills, 2021]. (SCR). [Marjańska, 2017], A technique proposed by [Edan, 1991], may quantify milling tool wear.

2.3 Feature Extraction

Throughout the diagnostic process, extracting plant disease traits is challenging. Texture, shape, colour, and motion are all visual characteristics that can identify illness abnormalities in a patient's body. These characteristics are also crucial for extracting disease features. In [Xiaomei, 2019], colour and textural cues were used to create a novel method for detecting illness spots. [Senthilkumar, 2019] developed this multifeature fusion and Dumpster–Shafer (D-S) evidence theory to improve D-S evidence theory judgement methods. The D-S evidence theory selection criteria were

then refined by incorporating variance. On the other hand, Turkoglu has presented an updated version of the Local Binary Patterns approach that employs the original LBP local quadratic value to transform an image into grayscale, processing the R and G channels of an image by considering both the overall and region. Li and colleagues used a deep migrating learning model to extract IoT features for the smart city [Hasan, 2021]. This has been demonstrated by the development of a music application that extracts important audio components to make the images responsive to the music. In recent studies, several novel techniques for extracting characteristics have been developed and used. In addition, the researchers developed two novel estimators for spectrum estimation in the context of the difficult problem of detecting significant and distinguishable properties in EEG data [Zheng, 2021(b)]. The residual neural network described by Liu and colleagues [Senthilkumar, 2020] was used to extract the high-dimensional time-frequency spectrum characteristics. (SCR). [Chuquizuta Trigoso, 2020] Xu and colleagues describe a method for measuring milling tool wear in their paper.

2.4   Disease Identification

A wide range of methods is being developed and tested to ensure that reliable results for exact identification can be obtained. The identification model describes the development of an image classification system that uses class labels for training images. According to [Song, 2020], they developed a hybrid clustering-based identification method for plant disease leaf images. (CBIR) technique in 2017 [Wen, 2020] extracts texture characteristics and colour information using a support vector machine (SVM) classifier. In these investigations, the images and classification algorithms generated in this work were used to extract and identify feature information. The development of new approaches has improved diagnostic precision and accuracy. Researchers used a novel approach based on photographs and brief written descriptions to diagnose previously identified plant diseases using a remote desktop computer, smartphone, or personal digital assistant [Chen, 2019]. [Soriano, 2021] used mobile phones to capture real-time images of sick plants in the field. Their use of mobile devices, for example, aided them in developing an improved K-means algorithm for leaf image segmentation and disease detection. It used the decision tree confusion matrix and synergistic judgement of texture and shape features to develop a system for microscope image identification [Tang, 2020].

It is also routinely used to diagnose a wide range of diseases using a convolutional neural network. [Dongmei, 2020] Images taken in the field can be used to detect disease in maize plants. Trained deep convolution neural network on 1632 images of maize kernels. According to [Hu, 2021(a)], deep convolutional neural networks (CNNs) can detect rice diseases and pests. Deep learning was used by [Adhiwibawa, 2019] to create an image recognition network for agricultural machines. Using deep convolution neural networks, [Maharani, 2021] claims to have improved the detection accuracy of maize leaf disease. The Alex Net and VGG-16 nets were used to identify images, and the results were published in peer-reviewed journals. [La Rosa, 2020] [Yang, 2021] Coulibaly and colleagues proposed that feature extraction could be accomplished through transfer learning. As a result, model training takes an inordinate amount of time, which harms the model's use and marketing. In addition to the pretrained models described in this article, transfer learning models can be used to identify damaged

leaves. The study's findings have resulted in several victories in three different areas. Leaf images are segmented, lesion details are obtained, and disease patterns are identified. Despite the complexity of the environment, diagnosing plant diseases remains difficult.

3   Proposed Methodology

3.1   Deep Convolutional Neural Network

Two convolutional neural network designs are compared: building a shallow one from scratch and fine-tuning the top layers of pretrained networks by transferring training data. This study aims to design a convolutional neural network for illness severity classification with limited training data. A SoftMax normalization is used to complete the network, which has two fully connected layers and a short convolutional layer with a few filters per layer. We use convolutional layers with 2, 4, 6, 8, and 10 convolutions to train external networks. Except for the final 64-filter convolutional layer, which includes 32 3x3 filters, each convolutional layer is followed by a 2x2 max-pooling layer. It has a ReLU activation in the first fully connected layer, followed by a dropout layer with a 50% dropout ratio. Each class's output is fed into a SoftMax layer, which computes the probability output from the SoftMax layer, which is the final fully connected layer.

3.2   Convolutional Neural Network Architecture

CNN architecture consists of an input layer, hidden layer, and an output layer shown in Figure 1. Images of citrus are fed into the input layer, passed to the hidden layers, and classified diseases at the output layer. Model's learning happened during training. Output layer is responsible for providing the labels whether the image is HLB infected, other disease infected, or healthy. In this architecture, citrus images with neurons and weights are augmented and reproduced in the following layers. The output layer is responsible for the estimate tasks for evaluating neurons.
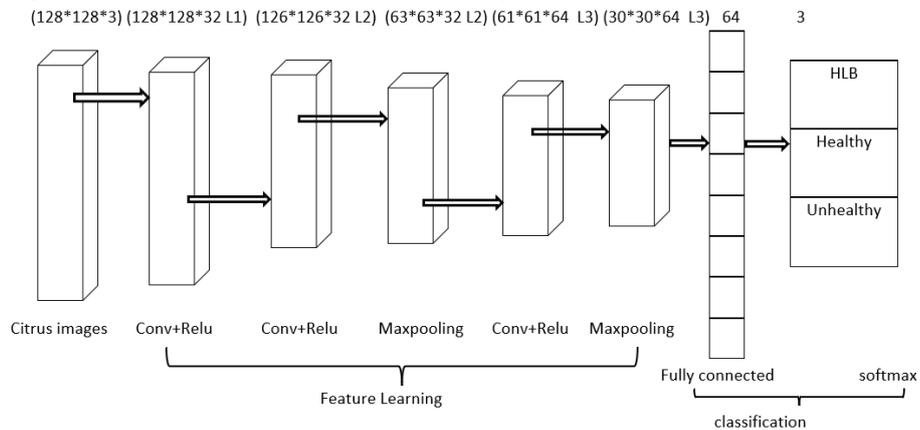

Figure 1: Training and learning of leaf location, image segmentation, disease extraction, and disease detection using a deep learning model

Figure 1 depicts three phases: leaf location, image segmentation, disease extraction, and disease detection using a deep learning model based on citrus plants. By segmenting the picture, plant disease can be extracted and identified. The model used in this study is based on the three phases listed below. Sick leaves can be found by first determining their location. For damaged leaves, RPNs are utilized to train a leaf dataset in a complicated environment, followed by frame regression and classification neural networks.

3.3 Method for Feature Extraction

The Citrus plant disease identification model framework has the following methods: Citrus Images' Sample Digitization. As a result of this research, a technique of data collection was utilized to generate clear images of leaves in the Citrus plant sample database that could then be used for further analysis and processing. A more efficient digitizing system requires a uniform and even light source to be sent to it. The photos taken with a smartphone camera and a digital camera are sent through the computer. PNG files store the digital colour images that may be seen on a computer screen using these gadgets.

3.3.1 Image Data Pre-processing

The first and most fundamental duty in every image processing project is integrating preprocessed pictures into a network. Vectorization, normalization, picture scaling, and image augmentation are all standard image preprocessing activities that may be found in every image processing project. [Zheng, 2021(a)] This study uses the OpenCV package in Python to prepare images for deep learning processing. Data augmentation may also be used to create extra training datasets from real-world data sets to improve data sampling.

3.3.2 Feature Extraction

Deep learning overcomes many shortcomings of machine learning feature extraction, such as manually extracting features, by employing the most effective and dependable approach available, known as a CNN [Hu, 2021(b)]. The layers are employed in the process of acquiring knowledge, as shown in Figure 2. Using a filtering technique, the data is utilized to match and extract the values that are included inside them.
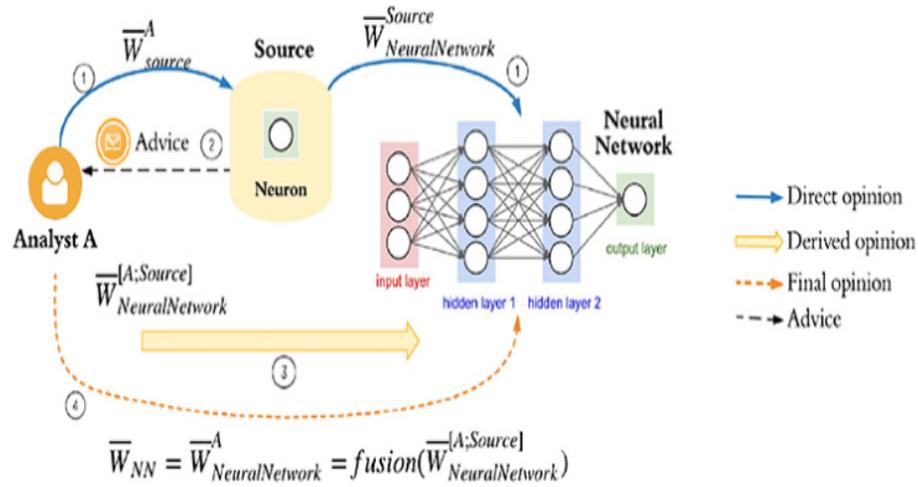
$$\overline{W}_{NN} = \overline{W}^A_{NeuralNetwork} = fusion(\overline{W}^{[A;Source]}_{NeuralNetwork})$$

Figure 2: Method for Feature Extraction in Deep Learning

3.4   Dataset Partitioning and Model Selection Methodology

K-fold cross-validation is used to partition the dataset, which is divided into K values, where K + 1 must be met for the next divisions to be valid. According to the researcher's study, the optimal K value for deep learning is 10. Thus, that is what they used in this study. This means that a 10-fold cross-validation technique, which splits the dataset into 10, is denoted by K = 10. D = 3600/10 = 360 data points are used for each folding. Regularly taking leaf shots yields an 80/20 split, with 80% of the images being used for training and the remaining 20% for testing. Consequently, the approach has been proven to be accurate.

3.5   Dataset Partitioning and Model Selection Methodology

In this study, two distinct image-collecting devices were utilized to acquire images 3600 of citrus leaves/fruits. For implementation, the suggested model was implemented in Python 3.7.3. The model is trained using Keras 2.2.4-to TensorFlow. The suggested system should be developed using TensorFlow 1.14.0. Many experimental sets were used to test the performance (Tkinter). In terms of hardware, the CPU was utilized for training and testing.

3.6   Evaluation Techniques

Methodologies were employed during the creation of the structure, as well as at the conclusion to assess its overall performance. A confusion matrix is used to analyze the prototype's first acquisition, and four evaluation metrics are used to evaluate the confusion matrix reports, including the F1-score, precision, recall, and accuracy for the first acquisition. By putting something through its paces in experimental research, it is possible to make an objective judgement of it. As a final note, the results of the tests suggest that the model may be applied in a variety of situations.

3.7 The Architecture of the Proposed Model

It is important to note that the CNN architecture's feature learning and classification parts are important components. In the example, citrus photos are fed into an input layer and exit through an output layer, which is seen on the right. Overall, Figure 3 demonstrates the multiple strata of the hidden layer that are not visible to the naked eye. It will be necessary to utilize citrus leaf photos as input, and the output will be a class name, also known as the label for citrus leaf illnesses or pests. In this suggested design, pictures of citrus leaves with neurons have substantial weights, which is not always the case in other cases, as is the case in this one.
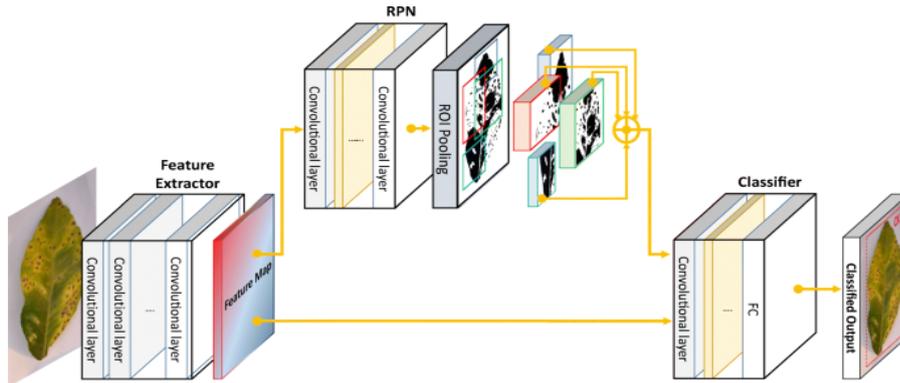

Figure 3: Architecture of the Proposed Model

The adjustment parameters of the boundary regression neural network and the output boundary box may be represented by four-dimensional variables. One boundary box can be represented by one four-dimensional variable (x, y, w, h). (P_x, P_y, P_w, P_h) represents the given boundary box, (H_x, H_y, H_w, H_h) represents the target boundary box, and $(\widehat{H_x}, \widehat{H_y}, \widehat{H_w}, \widehat{H_h})$ represents the predicting boundary box. To find a Happing relationship f of boundary regression neural network, $f(P_x, P_y, P_w, P_h) = (\widehat{H_x}, \widehat{H_y}, \widehat{H_w}, \widehat{H_h})$ and $(\widehat{H_x}, \widehat{H_y}, \widehat{H_w}, \widehat{H_h}) \approx (H_x, H_y, H_{w,}, H_h)$ are defined.

The movements of the border are accomplished via the use of pan and zoom. In this case, (x,y) is the pan's Parameter, assuming that $\Delta x = P_w d_x(P)$ and $\Delta y = P_h d_h(P)$ respectively (P). The following is the formula:

$$\widehat{H_x} = P_w d_w(P) + P_x,$$
$$\widehat{H_y} = P_h d_h(P) + P_y.$$

Parameter used for zoom is (S_w, S_h), which is given by $S_w = \text{exM}(d_w(P))$ and $S_h = \exp(d_h(P))$. The formula is shown as

$$\widehat{H_w} = P_w \exp(d_w(P))$$
$$\widehat{H_h} = P_h \exp(d_h(P))$$

As shown in the preceding equation, the basic learning objectives for the boundary regression neural network $d(P) = \big(d_x(P), d_y(P), d_w(P), d_h(P)\big)$, and it is represented by the variables d(P), and the real transform parameters between the predicting boundary box and artificially marked boundary box are represented by the variables as $t = \big(t_x, t_y, t_w, t_h\big)$ respectively.

$$t_x = \frac{(H_x - P_x)}{P_x},$$

$$t_y = \frac{\big(H_y - P_y\big)}{P_y},$$

$$t_w = \log\left(\frac{H_w}{P_w}\right),$$

$$t_h = \log\left(\frac{H_h}{P_h}\right).$$

The objective function of a boundary regression neural network is d(P)=wT, P, where w is the learning parameter of the boundary regression neural network and T is the training parameter. The following is an illustration of the loss function:

$$\text{Loss} = \sum_{i=1}^{N}(t_i - d_i(P))$$

Each layer's output is processed and then copied to the next layer in the process. The prediction tasks for the calculation of neurons are shown in the output layers.

4   Experimental Results

There were several experiments carried out throughout the experimentation phase to come up with an efficient model. The colour of the dataset, the number of epochs, augmentation, optimizer, and dropout are among the variables that are being analyzed. To put it another way, according to Serawork Wallelign [Dhiman, 2021], the accuracy of RGB augmented images was 15% higher than the accuracy of shots that were not. The following function is used to compute the image feature:

$$E = \mu \, \text{Length}(C)$$
$$+\lambda_1 \iint_{c_1} |u(x,y) - u_1|^2 dxdy + \lambda_2 \iint_{c_2} |u(x,y) - u_2|^2 dxdy$$

For example, $u(x,y)$ represents the image's grey values; u_1 represents the average grey values inside the contour, u_2 represents the average grey value outside the contour, and c_1 indicates the area within the contour. The formulas presented are as follows:

$$F_1 = \lambda_1 \iint_{c_1} |u(x,y) - u_1|^2 dxdy,$$

$$F_2 = \lambda_2 \iint_{c_2} |u(x,y) - u_2|^2 dxdy.$$

When $F_1 \approx 0$ and $F_2 \approx 0$, the computing ends.

To solve, the level set, approach is employed, and the zero level set is used to describe the contour lines. The following functions are introduced: Heaviside's function and Dirac's function

$$T = Y, f(X),$$

$$\delta(\varphi) = \frac{dH}{d\varphi}.$$

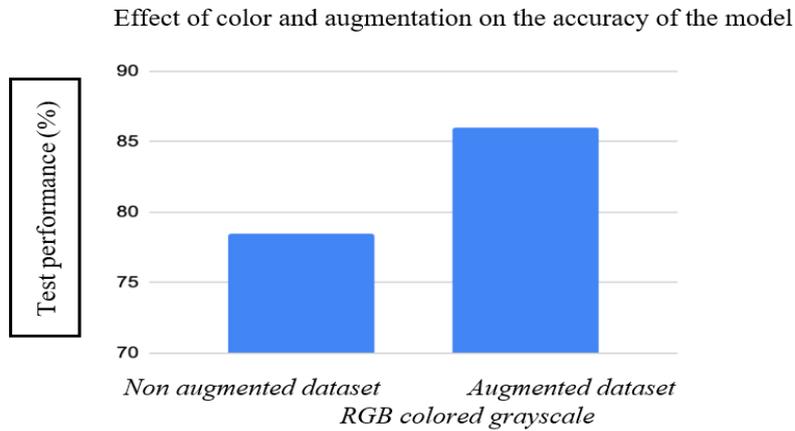The study used three distinct epoch counts to train this novel model: 30, 50, and 100.

Effect of color and augmentation on the accuracy of the model

Figure 4: Effect of color and augmentation on the accuracy of the model

There were 50 epochs in which the model performed ideally, as shown in Figure 5. Due to the improved performance, [Tudose, 2021] implemented a CNN dropout (2.6%). As a consequence, the experiment employed dropout rates of 0.24 and 0.52%, with the 0.5% dropout rate producing the best results out of the three potential possibilities.
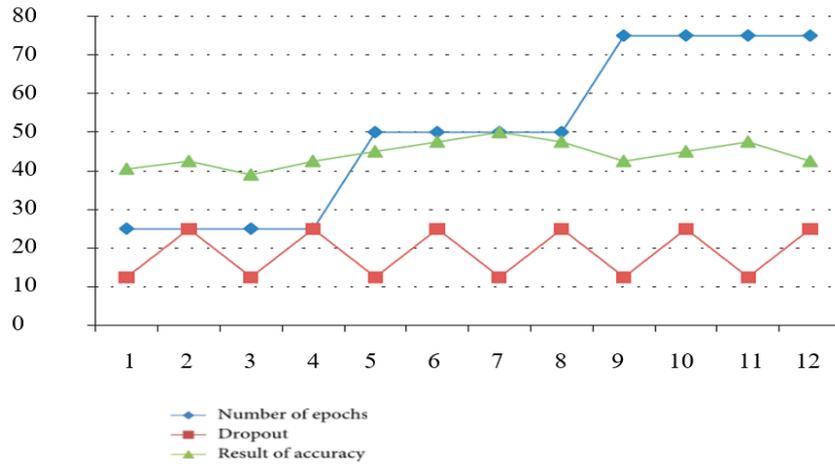
Figure 5: Upshot of epochs and regularization methods through experimentation

A critical investigation was carried out on the regularization approach that optimization algorithms' use may reduce the loss via iterations by updating means according to a gradient. Numbers directly impact epoch and regularization approaches, as seen in Figure 6. RMSProp and adam are utilized in this study, although the adam optimization technique lowers the loss by 2.3%, as seen in Figure 7.
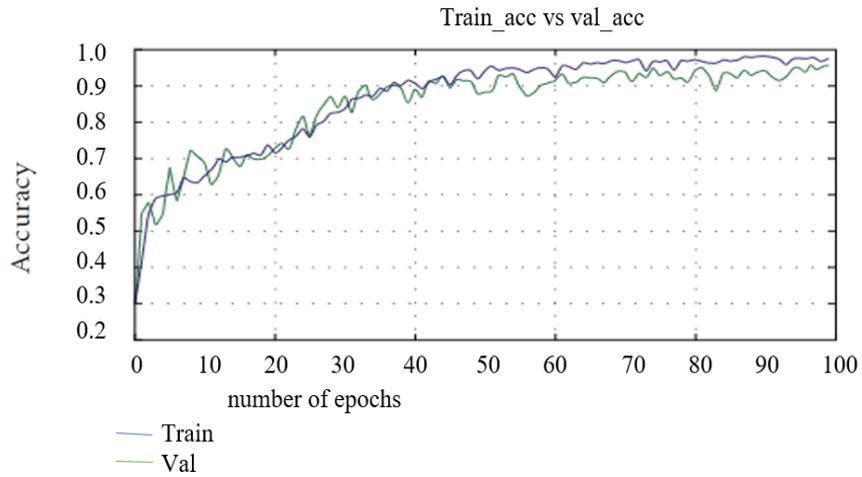

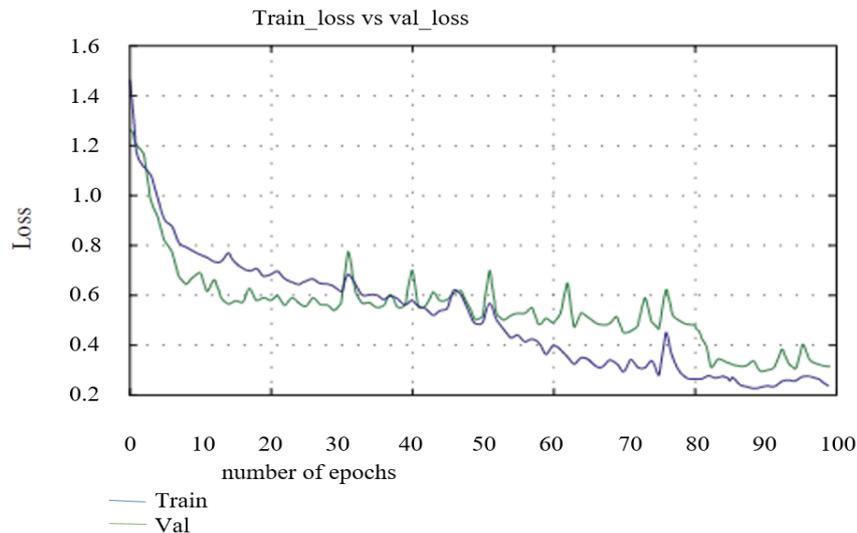*Figure 6: Computation of accuracy of the proposed model with epochs*

Figure 7: Computation of loss of feature in the oroposed model with epochs

The model's performance is evaluated using parameters such as K-fold cross-validation with a total number of 10 folds. Adding the augmentation shown in Figure 4, to the RGB-colored picture dataset increases the model's performance by >10%. 97.6% accuracy was achieved [Kobayashi, 2019] using the grayscale dataset and the transferred learning CNN model. A great lot of effort is required when dealing with coloured datasets to train the model to increase its performance, even when using a complex layer because the colour is the most essential and decisive feature in citrus recognition and classification. With 100 iterations and the adam optimization technique, the model improved its performance by 10.3% and 5.8% above the baseline, respectively. As a result, our newly developed CNN model correctly diagnoses 96.8% of HLB, 95% of healthy, and 96.6% of unhealthy. The researcher has used several preprocessing techniques to eliminate noise from the data. In regard to misclassification in the case of bacterial blight, healthy plants, and leaf miners, the main factors include: The overall accuracy shown in Figure 6, of the model in identifying leaf disease in citrus trees, is 96.8%, according to the confusion matrix.

5   Conclusion

With the help of Python and the Keras module, the Jupiter programming environment, this deep learning-based model was built. Many tests have been conducted as part of this research study to develop an effective model. Several variables, including dataset colour, number of iterations (epochs), augmentation, and regularization techniques, have been tweaked during these tests. An RGB-colored picture dataset with boost proved to be the most effective in the model's evaluation process (15.4%). Results show that increasing the model's performance by 10.4% and 5.8% is primarily dependent on the number of epochs and regularization approaches employed. Compared to other systems, the prototype's highest efficacy was 96.8% for identifying Citrus tree leaf

diseases and pests. Automated techniques are being developed to assist farmers and pest control professionals in identifying citrus diseases and problems by visual signals on the plants' leaves. Farmers will benefit significantly from this approach because of the reduced difficulty, time, commitment, and cost of spotting disease outbreaks in leaves.

References

[Adhiwibawa, 2019] Adhiwibawa, M.A. and Nugroho, W.H.: Detection of Anomalies in Citrus Leaves Using Digital Image Processing and T 2 Hotelling Multivariate Control Chart. *2019 International Conference of Artificial Intelligence and Information Technology (ICAIIT)*, Yogyakarta, Indonesia, 2019, pp. 310-314.doi: 10.1109/ICAIIT.2019.8834453

[Ali, 1977] Ali, M. and Aggarwal, J.K.: Automatic interpretation of infrared aerial color photographs of citrus orchards having infestations of insect pests and diseases. *IEEE Transactions on Geoscience Electronics*, vol. 15, no. 3, pp. *170-179*, July 1977.doi: 10.1109/TGE.1977.6498976

[Aparisi, 2021] Aparisi, P.A., Sánchez, E.F., Rodrigo, L.C., Peris, R.M. and Laguarda-Miro, N.: A Rapid Electrochemical Impedance Spectroscopy and Sensor-Based Method for Monitoring Freeze-Damage in Tangerines. *IEEE Sensors Journal*, vol. 21, no. 10, pp. 12009-12018, 15 May15, 2021.doi: 10.1109/JSEN.2021.3065846

[Cao, 2019] Cao, H., Jia, P., Xu, D., Jiang, Y. and Qiao, S.: Feature extraction of citrus juice during storage for electronic nose based on cellular neural network. *IEEE Sensors Journal*, vol. 20, no. 7, pp. *3803-3812*, 1 April1, 2020.doi: 10.1109/JSEN.2019.2961135

[Chen, 2019] Chen, Q., Liu, X., Dong, C., Tong, T., Yang, C., Chen, R., Zou, T. and Yang, X.: Deep convolutional network for citrus leaf diseases recognition. ," *2019 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom)*, Xiamen, China, 2019, pp. 1490-1494.doi:10.1109/ISPA-BDCloud-SustainCom-SocialCom48970.2019.00215

[Chuquizuta Trigoso, 2020] Chuquizuta Trigoso, T., Oblitas Cruz, J., Arteaga Miñano, H. and Castro Silupu, W.: Application of machine Learning in the discrimination of citrus fruit juices: uses of dielectric spectroscopy. *2020 IEEE Engineering International Research Conference (EIRCON)*, Lima, Peru, 2020, pp. 1-4.doi: 10.1109/EIRCON51178.2020.9253756

[Delalieux, 2014] Delalieux, S., Zarco-Tejada, P.J., Tits, L., Bello, M.Á.J., Intrigliolo, D.S. and Somers, B.: Unmixing-based fusion of hyperspatial and hyperspectral airborne imagery for early detection of vegetation stress. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 7, no. 6, pp. *2571-2582*, June 2014.doi: 10.1109/JSTARS.2014.2330352

[Dhiman, 2021] Dhiman, P., Kukreja, V. and Kaur, A., September. Citrus Fruits Classification and Evaluation using Deep Convolution Neural Networks: An Input Layer Resizing Approach. *2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, Noida, India, 2021, pp. 1-4.doi: 10.1109/ICRITO51393.2021.9596357

[Dongmei, 2020] Dongmei, Z., Ke, W., Hongbo, G., Peng, W., Chao, W. and Shaofeng, P.: Classification and identification of citrus pests based on InceptionV3 convolutional neural network and migration learning. *2020 International Conference on Internet of Things and Intelligent Applications (ITIA)*, Zhenjiang, China, 2020, pp. 1-7.doi: 10.1109/ITIA50152.2020.9312359

[Edan, 1991] Edan, Y., Flash, T., Peiper, U.M., Shmulevich, I. and Sarig, Y.: Near-minimum-time task planning for fruit-picking robots. *IEEE Transactions on Robotics and Automation*, vol. 7, no. 1, pp. 48-56, Feb. 1991.doi: 10.1109/70.68069

[Ehsani, 2016] Ehsani, M., Hamidon, M.N., Toudeshki, A., Abadi, M.S. and Rezaeian, S.: CO_2 gas sensing properties of screen-printed La_2O_3/SnO_2 thick film. *IEEE Sensors Journal*, vol. 16, no. 18, pp. 6839-6845, Sept.15, 2016.doi: 10.1109/JSEN.2016.2587779

[García-Cruz, 2019] García-Cruz, A., Rincón-Enríquez, G., Ilyina, A., Guízar-González, C., Mtz-Enríquez, A.I., Díaz-Jiménez, L., Quiñones-Aguilar, E.E., Enríquez-Vara, J., Ramos-González, R. and Aguilar-González, C.N.: Bactericidal in-vitro effect of zinc ferrite nanoparticles and the orange wax extracts on three phytopathogen microorganisms. *IEEE Transactions on NanoBioscience*, vol. 18, no. 4, pp. 528-534, Oct. 2019.doi: 10.1109/TNB.2019.2937840

[Guillén-Climent, 2013] Guillén-Climent, M.L., Zarco-Tejada, P.J. and Villalobos, F.J.: Estimating radiation interception in heterogeneous orchards using high spatial resolution airborne imagery. *IEEE Geoscience and Remote Sensing Letters*, vol. 11, no. 2, pp. 579-583, Feb. 2014.doi: 10.1109/LGRS.2013.2284660

[Hasan, 2021] Hasan, M.M., Salehin, I., Moon, N.N., Kamruzzaman, T.M. and Hasan, M.: A Computer Vision System for the Categorization of Citrus Fruits Using Convolutional Neural Network. *2021 International Symposium on Electronics and Smart Devices (ISESD)*, Bandung, Indonesia, 2021, pp. 1-6.doi: 10.1109/ISESD53023.2021.9501790

[Hazarika, 2020] Hazarika, S., Choudhury, R., Montazer, B., Medhi, S., Goswami, M.P. and Sarma, U.: Detection of citrus tristeza virus in mandarin orange using a custom-developed electronic nose system. *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 11, pp. *9010-9018*, Nov. 2020.doi: 10.1109/TIM.2020.2997064

[Hoge, 2003] Hoge, W.S.: A subspace identification extension to the phase correlation method [MRI application]. *IEEE Transactions on Medical Imaging*, vol. 22, no. 2, pp. 277-280, Feb. 2003.doi: 10.1109/TMI.2002.808359

[Hosseinimehr, 2003] Hosseinimehr, S.J., Tavakoli, H., Pourheidari, G., Sobhani, A. and Shafiee, A.: Radioprotective Effects of Citrus Extract Against γ; -Irradiation in Mouse Bone Marrow Cells," in *Journal of Radiation Research*, vol. 44, no. 3, pp. *237-241*, Sept. 2003.doi: 10.1269/jrr.44.237.

[Hu, 2021(a)] Hu, X., Wu, J., Yu, H., Lv, S. and Wang, C.: Research on the Location of Citrus Based on RGB-D Binocular Camera. *2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, Chongqing, China, 2021, pp. 2280-2284.doi: 10.1109/IAEAC50856.2021.9390798

[Hu, 2021(b)] Hu, X., Yu, H., Lv, S. and Wu, J.: Design and experiment of a new citrus harvesting robot. *2021 International Conference on Control Science and Electric Power Systems (CSEPS)*, Shanghai, China, 2021, pp. 179-183.doi: 10.1109/CSEPS53726.2021.00043

[Ilan, 1989] Ilan, Y.A.E.L.: Evaluation of innovative projects-an integrative approach. *IEEE Transactions on Engineering Management*, vol. 36, no. 1, pp. 51-54, Feb. 1989.doi: 10.1109/17.19983

[Janarthan, 2020] Janarthan S., Thuseethan S., Rajasegarar S., Lyu Q., Zheng Y., Yearwood J.: Deep metric learning based citrus disease classification with sparse data. in *IEEE Access*, vol. 8, pp. 162588-162600, 2020.doi: 10.1109/ACCESS.2020.3021487

[Jiménez-Bello, 2015] Jiménez-Bello, M.Á., Castel, J.R., Testi, L. and Intrigliolo, D.S.: Assessment of a remote sensing energy balance methodology (SEBAL) using different interpolation methods to determine evapotranspiration in a citrus orchard. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 8(4), pp.1465-1477.

[Khattak, 2021] Khattak, A., Asghar, M.U., Batool, U., Asghar, M.Z., Ullah, H., Al-Rakhami, M. and Gumaei, A.: Automatic detection of citrus fruit and leaves diseases using deep neural network model. in *IEEE Access*, vol. 9, pp. *112942-112954*, 2021.doi: 10.1109/ACCESS.2021.3096895

[Kobayashi, 2019] Kobayashi, F.K., Mattos, A.B., Gemignani, B.H. and Macedo, M.M.: Experimental analysis of citrus tree classification from UAV images. *2019 IEEE International Symposium on Multimedia (ISM)*, San Diego, CA, USA, 2019, pp. 32-327.doi: 10.1109/ISM46

[La Rosa, 2020] La Rosa, L.E.C., Oliveira, D.A., Zortea, M., Gemignani, B.H. and Feitosa, R.Q.: Learning geometric features for improving the automatic detection of citrus plantation rows in UAV images. *IEEE Geoscience and Remote Sensing Letters*. doi: 10.1109/LGRS.2020.3024641

[Liu, 2016] Liu, K., Wang, C., Hu, H., Lei, J. and Han, L.: Indirect treatment effects of water–air MHCD jet on the inactivation of Penicillium Digitatum suspension. *IEEE Transactions on Plasma Science*, vol. 44, no. 11, pp. *2729-2737*, Nov. 2016.doi: 10.1109/TPS.2016.2608926

[Luque, 2020] Luque, P.A., Nava, O., Romo-Cardenas, G., Nieto-Hipolito, J.I., Vilchis-Nestor, A.R., Valdez, K., de Dios Sanchez-Lopez, J., Murrieta-Rico, F.N., Facile zinc oxide nanoparticle green synthesis using Citrus reticulata extract for use in optoelectronic sensors. *IEEE Sensors Journal*, vol. 21, no. 10, pp. *11275-11282*, 15 May15, 2021.doi: 10.1109/JSEN.2020.3011988

[Maharani, 2021] Maharani, S.K.R., Syukur, A., Hindarto, A.N., Zuhri, M.F. and Soeleman, M.A.: Classification of Citrus Type Based on Leaf Image Using Shape Extraction and GLCM with the Decision Tree Method. *2021 International Seminar on Application for Technology of Information and Communication (iSemantic)*, Semarangin, Indonesia, 2021, pp. 335-339. doi: 10.1109/iSemantic52711.2021.9573252

[Marjańska, 2017] Marjańska, E. and Szpakowska, M.: Qualitative and quantitative analysis of selected tonic waters by potentiometric taste sensor with all-solid-state electrodes. *IEEE Sensors Journal*, vol. 18, no. 3, pp. 1250-1255, 1 Feb.1, 2018.doi: 10.1109/JSEN.2017.2780283

[Mignani, 2016] Mignani, A.G., Ciaccheri, L., Mencaglia, A.A., Di Sanzo, R., Carabetta, S. and Russo, M.: Dispersive raman spectroscopy for the nondestructive and rapid assessment of the quality of southern Italian honey types. *Journal of Lightwave Technology*, vol. 34, no. 19, pp. 4479-4485, 1 Oct.1, 2016.doi: 10.1109/JLT.2016.2539550

[Mills, 2021] Mills, R., Marnerides, A.K., Broadbent, M. and Race, N.: Practical Intrusion Detection of Emerging Threats. *IEEE Transactions on Network and Service Management*.doi: 10.1109/TNSM.2021.3091517

[Ok, 2018] Ok, A.O., Ozdarici-Ok, A.: Combining orientation symmetry and LM cues for the detection of citrus trees in orchards from a digital surface model. *IEEE Geoscience and Remote Sensing Letters*, vol. 15, no. 12, pp. 1817-1821, Dec. 2018.doi: 10.1109/LGRS.2018.2865003

[Pan, 2019] Pan, W., Qin, J., Xiang, X., Wu, Y., Tan, Y. and Xiang, L.: A smart mobile diagnosis system for citrus diseases based on densely connected convolutional networks. in *IEEE Access*, vol. 7, pp. *87534-87542*, 2019.doi: 10.1109/ACCESS.2019.2924973

[Perry, 1980] Perry, D.D. and Bolcar, J.P.: Effect on de-greasing solvents on conductive separable connector shields and semiconductive cable shields. *IEEE Transactions on Power Delivery*, vol. 5, no. 2, pp. 781-786, April 1990.doi: 10.1109/61.53083

[Senthilkumar, 2019] Senthilkumar, C. and Kamarasan, M.: Optimal segmentation with back-propagation neural network (BPNN) based citrus leaf disease diagnosis. *2019 International Conference on Smart Systems and Inventive Technology (ICSSIT)*, Tirunelveli, India, 2019, pp. 78-82. doi: 10.1109/ICSSIT46314.2019.8987749

[Senthilkumar, 2020] Senthilkumar, C. and Kamarasan, M.: An optimal weighted segmentation with hough transform based feature extraction and classification model for citrus disease. In *2020 International Conference on Inventive Computation Technologies (ICICT)* (pp. 215-220). IEEE.

[Somers, 2009] Somers, B., Delalieux, S., Verstraeten, W.W., Verbesselt, J., Lhermitte, S. and Coppin, P.: Magnitude-and shape-related feature integration in hyperspectral mixture analysis to monitor weeds in citrus orchards. *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 11, pp. *3630-3642*, Nov. 2009.doi: 10.1109/TGRS.2009.2024207

[Song, 2020] Song, C., Wang, C. and Yang, Y.: Automatic Detection and Image Recognition of Precision Agriculture for Citrus Diseases. *2020 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE)*, Yunlin, Taiwan, 2020, pp. 187-190.doi: 10.1109/ECICE50847.2020.9301932

[Soriano, 2021] Soriano, C.B., Ferrer, D.K., Villaverde, J.F. and Padilla, D.A.: Classification of Citrus Sinensis Peel for Production of Biopolymers Using Probability Distribution Function. *2021 IEEE 7th International Conference on Control Science and Systems Engineering (ICCSSE)*, Qingdao, China, 2021, pp. 319-323.doi: 10.1109/ICCSSE52761.2021.9545158

[Su, 2021] Su, Y., Cheng, T., He, Z. and Li, X.: Joint Waveform Control and Resource Optimization for Maneuvering Targets Tracking in Netted Colocated MIMO Radar Systems. *IEEE Systems Journal*.doi: 10.1109/JSYST.2021.3098622

[Tang, 2020] Tang, Z., Xu, L. and Xie, H.: Picking trajectory planning of citrus based on improved immune algorithm and binocular vision. *2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, Dalian, China, 2020, pp. 6-10.doi: 10.1109/ICAICA50127.2020.9182606

[Thakur, 2021] Thakur, A., Chopra, T. and Devi, P.: Green Synthesized Cu@ Carbon Quantum Dots for Histidine and Arsenate Sensing. *IEEE Sensors Journal*, vol. 21, no. 15, pp. 16464-16468, 1 Aug.1, 2021.doi: 10.1109/JSEN.2021.3081634

[Tits, 2011] Tits, L., Somers, B. and Coppin, P.: The potential and limitations of a clustering approach for the improved efficiency of multiple endmember spectral mixture analysis in plant production system monitoring. *IEEE Transactions on Geoscience and Remote Sensing*, vol. 50, no. 6, pp. 2273-2286, June 2012.doi: 10.1109/TGRS.2011.2173696

[Tits, 2014] Tits, L., Somers, B., Saeys, W. and Coppin, P.: Site-specific plant condition monitoring through hyperspectral alternating least squares unmixing. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 7, no. 8, pp. *3606-3618*, Aug. 2014.doi: 10.1109/JSTARS.2014.2313984

[Tudose, 2021] Tudose, I.V., Rosca, I., Romanitan, C., Ionescu, O.N., Petrotos, K., Zaoutsos, S., Suchea, M.P. and Koudoumas, E.: PLA nanocomposites with antimicrobial action, based on olive fruit polyphenols and citrus fruit extracts encapsulated in Maltodextrin. *2021 International Semiconductor Conference (CAS)*, Romania, 2021, pp. 269-272.doi: 10.1109/CAS52836.2021.9604116

[Wen, 2020] Wen, C., Zhang, H., Li, H., Li, H., Chen, J., Guo, H. and Cheng, S.: Multi-scene citrus detection based on multi-task deep learning network. *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Toronto, ON, Canada, 2020, pp. 912-919.doi: 10.1109/SMC42975.2020.9282909

[Xiaomei, 2019] Xiaomei, H., Bowen, N. and Jianfei, C.: Research on the location of citrus picking point based on structured light camera. In: *2019 IEEE 4th International Conference on Image, Vision and Computing (ICIVC)* (pp. 567-571). IEEE.

[Yang, 2021] Yang, Y., Yu, J. and Kurihara, T.: Immature Yuzu Citrus Detection Based on DSSD Network with Image Tiling approach. *2021 60th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE)*, Tokyo, Japan, 2021, pp. 1128-1133

[Zeng, 2020] Zeng, Q., Ma, X., Cheng, B., Zhou, E. and Pang, W.: Gans-based data augmentation for citrus disease severity detection using deep learning. *IEEE Access*, vol. 8, pp. *172882-172891*, 2020. doi: 10.1109/ACCESS.2020.3025196

[Zhang, 2019] Zhang, M., Liu, S., Yang, F. and Liu, J.: Classification of canker on small datasets using improved deep convolutional generative adversarial networks. *IEEE Access*, vol. 7, pp. *49680-49690*, 2019.doi: 10.1109/ACCESS.2019.2900327

[Zheng, 2021(a)] Zheng, S. and Luo, D.: Recognition and Counting of Citrus Trees Based on UAV Images. *2021 4th International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE)*, Changsha, China, 2021, pp. 703-706.doi: 10.1109/AEMCSE51986.2021.00145

[Zheng, 2021(b)] Zheng, S., Zhiquan, L.I.N., Jiahao, X.I.E., Mingfeng, L.I.A.O., Shujun, G.A.O., Zhang, X. and Tian, Q.I.U.: Maturity recognition of citrus fruits by Yolov4 neural network*2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)*, Nanchang, China, 2021, pp. 564-569.doi: 10.1109/ICBAIE52039.2021.9389879.