IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 1, March 2024

Ensemble Learning Model for Damage Detection Using Deep Convolutional Networks

Dr. Akshay Dhande

Department of Electronics and Telecommunication Engineering,

Lovely Professional University, Punjab, India

akshaydhande126@gmail.com,

https://orcid.org/0000-0002-7340-9806

Abstract: *Damages to crops happen due to natural calamities, irregular fertilization, improper treatment, etc. To perform this estimation of this damage with high accuracy, both satellite & near-field images are needed. Satellite images assists in evaluation of damages due to natural calamities, while near-field images assist in evaluation of damage due to plant diseases. Separate models are designed for processing these images, which limits their correlative analysis; and thereby reduces overall accuracy of damage detection. To remove this drawback, this text proposes a deep convolutional network (DCN) design that integrates both near-field and far-field images in order to perform effective correlation. The model is trained for detection of areas which are infected by natural calamities, thereby assisting farm experts to undertake corrective measures based on specific area. Results of proposed model are compared with some of the recently developed state-of-the-art methods, and it is observed that the former model achieves 10% better accuracy, performance.*

Keywords: Crop, damage, prediction, machine learning, convolution, correlation

I. INTRODUCTION

Natural calamities, improper treatment, and irregular irrigation are some of the reasons for crop damage. Near-field image and satellite images are essential input to accurately estimate the damage mention above for planning and executing corrective actions against it. Satellite imagery helps assess damage from natural disasters, while near-field imagery estimates damage from crop disease. Separate architecture is designed to handle these images, limiting the correlation between them and reducing overall recognition accuracy. In the comparison of the individual models the architecture suggested in this thesis perform better correlation between near-field and far-field images to predict crop damage more efficiently. When compared with some of the most advanced models, our proposed correlation-based model delivers a 10% improvement in accuracy and 8an % improvement in precision. Plus, you'll get 5% more accurate results with less effort. In order to validate the model, it was evaluated on different datasets and crop in multiple ways. This thesis also discusses upcoming research instructionswhich can be consider so that the prediction model can perform more effectively.

Crop damage prediction and detection is a complex process that involves many different components. This task ranges from the design of image pre-processing to variant feature selection, fusion, and post-processing. For instance, when creating a noise filter for images, we need to design something like an adaptive median filter (AMF), Gaussian filter (GF), or Weiner filter (WF). Noisy images are very common in satellite imagery. When noise filters are applied, the image quality is improved and salt and pepper noise, speckle noise, etc., may be removed. Once these filters have been applied, image fusion modules are activated in order to improve overall image quality. These modules combine images taken from different sensor, like multiband panchromatic, and multispectral images. Combining these images gives you a final image that has aggregate information, like shape information, colour levels, edge information, crop contours, and more. In extraction process, a projector block, extract the features. These features can include a wide range of things such as local binary patterns, histogram features, colour maps, and edge maps.

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 1, March 2024

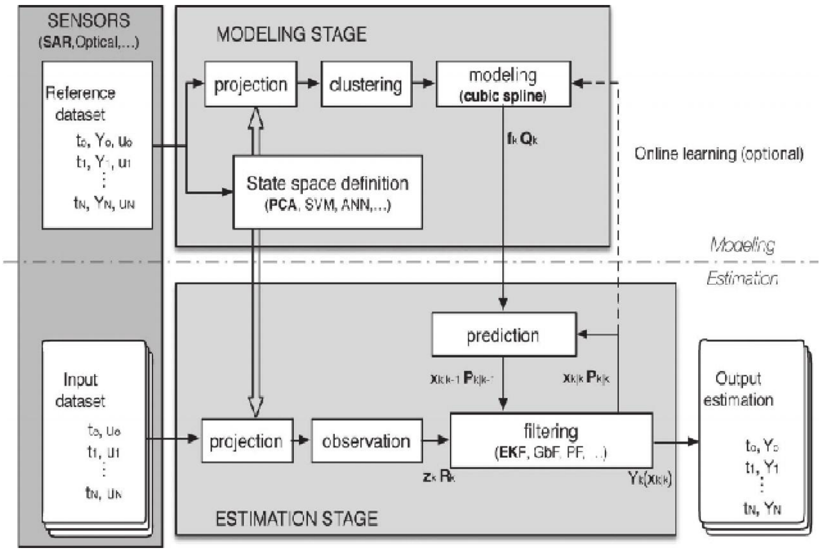

Figure 1. Crop Damage Detection System Model

Due to the large number of extracted features, the probability of feature redundancy increases. This redundancy reduces classification accuracy & increases processing delay. In order to avoid feature redundancy various feature selection models are implemented. Machine learning models are a great way to improve classification by analyzing the features of images. These factures should be varied widely for different types of photos and must be similar for images with similar content image. Classification engine is use to produce the crop damage system. Algorithms like SVM, NN, convolutional neural networks, and others are implemented in our model to classify the 'non-damage' and 'damage' categories as seen in figure 1. When the images get classified, they are sent to a post-processing block. From there, we do an estimation of the extent of the image. The algorithm like random forest, Naïve Bayes and neural networks are used for pattern recognition models. To divides the images into several categories of damage the proposed architecture makes use of the damaged image's temporal categorization data. The enormous variety of crop damage detection system models that have been proposed by researchers over the years will be examined in the next part, and their effectiveness will be discussed in this thesis. We first fabricated a model with the proposed system structure, and then we evaluated its performance using precision, accuracy, recall, delay and F-measure. To verify the effectiveness of the recommended system, the performance of several state-of-the-art models that are currently employed for crop damage detection is compared with the suggested model. At last observations were made about the suggested systemand recommended approaches to improve it.

II. LITERATURE SURVEY

Various approaches have been proposed by researchers in order to design highly efficient crop damage detection models. In this section a brief survey of these approaches along with their nuances is described. This is done in order to observe the efficiency of these approaches, and select the best performing approaches for comparison with our proposed model. Most of these approaches use deep learning for this purpose, for instance, the work in [1] proposes use of augmentation with region CNN model. This model segments a region of image and applies feature classification on that region using CNN for highly accurate classifications. The model is able to obtain an accuracy of 91.04% on different pest types, and can be extended to other classification tasks for better applicability. A similar model that uses unmanned aerial vehicles (UAVs) for capturing images, and then uses these low-resolution images for CNN training is observed in [2]. This model is able to obtain an accuracy of 95.1% on various image sets due to heat map generation from the captured images. The heat map is further used for evaluation of damage extent in near-field images, thereby assisting in its estimation for the entire field. This performance can be compared with different CNN models as described in [3], wherein models like fast CNN, and spiking CNN are described. The accuracy of these models can be further improved via use of deep convolutional neural network (DCNN), as described in [4], wherein LodgedNet architecture is defined. This model combines standard VGGNet-16 architecture with grey-level co-occurrence matrix (GLCM) & local binary pattern estimation and classification in order to obtain an accuracy of 97.7% for different crop damage types. This study can be used by the work in [5]& [6] to deploy high accuracy models for estimation of bird patterns & predator patterns, which are directly affected by crop damages.

Similar deep learning models can be observed from [7], [8], and [9]; wherein 9-fold cross-validation based CNN, Zeiler& Fergus CNN with region proposal network (RPN) & Non-Maximum Suppression (NMS) using parallel convolutions, and intersection-based CNN models are used respectively. These models provide accuracies between 90% to 98% depending upon number of layers, dataset used and the type of CNN architecture deployed in the system. These models can be used in wide agriculture applications as suggested in [10], wherein wide residual networks (WRN) are defined. These networks are extensions of CNN and are able to provide accuracies near to 99% when designed for specific applications. Another such model is described in [11], wherein s deep convolutional neural networks (DCNN) with transfer learning is used in order to improve classification performance of banana plantations. It is observed that this model can be extended to other crop types, and is able to obtain an accuracy of 99.7% in terms of damage detection. The model can also be used for detection of the extent to which the crops are damaged with over 90% accuracy, thereby making it a suitable choice for classification. Other applications of these networks can be observed from [12], wherein plant growth and protection are described. These applications are based on nanotechnology and thus can make use of deep learning models for efficient classification. Other applications like improving efficiency of insurance claims [13], detection of unreported damage pathogens [14], rice crop damage detection [15], and greenhouse insect pest detection [16] are also developed by researchers using deep learning models. In these applications, modification of CNN models, and their architectures is done in order to achieve accuracy levels in the range of 91% to 99% depending upon number of layers used classifier design. Unique applications like brown planthopper damage detection [17], general purpose damage detection [18], and super resolution image-based damage identification [19] also utilize deep learning and transfer learning models for improved accuracy. Machine learning architectures like Artificial Neural Networks, Support Vector Machines, AlexNet, VGGNet, GoogLeNet, InceptionNet, etc. are defined in [20], [21], [22], [23] along with GIS systems and Disaster Vegetation Damage Index (DVDI) are also discussed. These models provide similar accuracy performance, and can be used for real time crop damage detection applications.

Thus, it can be observed that deep learning models when combined with transfer learning approaches can be used for highly efficient crop damage detection. Based on this analysis, the proposed ensemble learning model using deep convolutional networks is described in the next section, which is followed by its performance evaluation & comparison with some of the recent models that are reviewed in this section.

III. PROPOSED METHOD

Transfer learning, several CNN architectures like VGGNet 16 network, and a deep feature extraction approach is combines in the proposed architecture. It generates extremely efficient features with significant interclass variation and low intraclass variance.Satellite crop datasets of Amravati District (India) which is generated after different disaster conditions such as floods and hailstorms in the year 2018 and 2019 is use to train the model. The model can be batter understood from following three steps:

- Multiple CNN architectures for Classification.
- Transfer learning block.
- VGGNet 16 network for Deep feature extraction.

This design has a few steps. The simplified version of it can be observed in Figure 2. The feature extraction model is directly provided with input images taken from our dataset. We got the result in form of tow class i.e., "non-damaged" or "damaged" by using the CNN classification model. This further aids in hyperparameter tuning of the proposed system via the transfer learning network. In order to fit the internal ImageNet model, input images are scaled to 224x224 and then features are extracted using a pre-trained VGGNet-16 architecture.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 1, March 2024

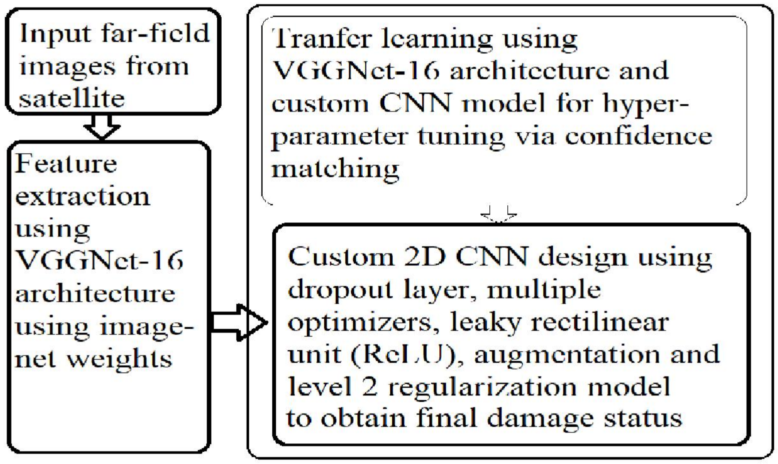

Figure 2. Damage Evaluation Models

To processes the images with a 64x64 window a 3x3 convolutional layer is used. 150K feature values are extracted from the image and then given to another 3x3 convolutional layer with 64-by-64-windows for more filtering features. It's often hard to find a certain filter when you're looking for multiple filters, but thankfully this equation will tell you which one would work for your needs. The first thing that it does is reduce feature variance for any similar features, and then it will increase the variance for images that are in different classes.

$$MP_{out} = Max\left(\frac{1}{X_k} * \sum_{i=1}^{X_k} x_i\right)^{1/l_r} \quad \dots (1)$$

Here, MP_{out} is the output of the maximum pooling layer, and X_k is the input of the layer with "k=224" various feature vectors. Learning rate is represented by l_r of the pooling layer (set between 0 and 1). Following convolutional layers with sizes of 128x128, 256x256, and 512x512 are applied to the layer once more to extract 800,000, 400,000, and 200000 features, respectively. In essence, these traits were turned into 1.5 million distinct features. The same max pooling, rectilinear unit (ReLU) procedure and a fully connected neural network are then used to retrieve a total of 25,088 features. The 150K different pixels of one image is converted into 25K different features. This feature set has low variance with same class feature sets and huge variance with feature sets of different class. Extracted characteristics are provided to an ensemble CNN classification model for the purpose of identifying crops with damage. An ensemble 2D CNN model made up of leaky rectilinear units (ReLUs), multiple optimizers, level 2 regularisation, and data augmentation receives the extracted features. This neural network model's architecture is shown in Figure 3. Encoder and decoder layers are among the specified layers. Prior to using the neural network, a data augmentation layer receives the output from the VGGNet 16 model. Every set of input features undergoes specialised calculations in this layer,
Using equation 2, data rotation up to 40 degrees is implemented.

$$d_{out_i} = \frac{d_{in_i} * \sin(\emptyset_i) + d_{in_i} * \cos\ (\emptyset_i)}{2} \dots (2)$$

Where $\emptyset_i$ indicates the angle and ranges from 40 to 0 degrees in steps of 1 degree, and, d_{out_i} and subscript are $d_{in_i}$are output, and input data for the specified angle.

• A typical autoregressive integrated moving average (ARIMA) model is used to enhance the samples when the width shifts between 0 and 0.2, as shown in equation 3.

$$d_{out_i} = R + \emptyset_1 * d_{in_i} + \emptyset_2 * d_{in_{i-1}} + \emptyset_3 * d_{in_{i-3}} \dots + \emptyset_p * d_{in_{i-p+1}} \dots . (3)$$

Where, 'R' stands for ARIMA constant, the i^{th} value of angle for width shifting is denoted by $\emptyset_i$. and *'p'* stands for the width shifting from 0 to 20 (20%).

Cropping with a range of 0 to 0.2 is used to enhance samples using the shearing operation as seen in equation 4. This operation is used to determine the feature's shearing stress value using statistical moment values.

$$d_{out} = {}^{d_{in} * M_{in}}\!/_{M_n * b} \dots (4)$$

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 1, March 2024

Where 'b' denotes the shearing range and M_{in} denote the moments that are evaluated using mean values and M_n denote the moments that are evaluated using around the neutral axis.

When the supplied features are zoomed in between 0 and 0.2, equation 5's detection of the zooming operator is used to enhance the given features. This operator enables the use of several values for the same feature vector, assisting in the assessment of enhanced variant features.

$$d_{out} = \frac{d_{in}}{2 * \tan\left(\frac{Z_f}{2}\right)} \dots (5)$$

In this case, Z_f is the zoom factor that is utilised to estimate the zooming values. The super feature vector may be created by combining all of these characteristics, which is then supplied to the ensemble CNN design. In order to create a deep, 21-layered network, this design syndicates many CNN models; separately, these layers are specified as follows:

Performance indicators including precision, recall, F-measure, and accuracy are obtained from this network by combining the outputs of all dense layers using a mode operation to get the final output class. By studying a pretrained architecture like VGGNet, the proposed architecture's hyper-parameters are optimised. The operation of this system is explained as follows:

The pre-trained VGGNet-16 model is trained with fewer layers than a fully convolutional network and makes use of the ImageNet architecture.

This model is used to classify images that have already been classified. Statistical analysis is then performed to compare the classification results with the original classification.

Leaky ReLU activation units are swapped out for regular ReLU activations.

Hyper-parameters are adjusted in accordance with the outputs of these models, i.e., the outputs of transfer learning ($C_{out_{TL}}$), leaky ReLU ($C_{out_{LR}}$), and normal ReLU ($C_{out_{NR}}$),

If, $C_{out_{TL}}$=$C_{out_{LR}}$ and $C_{out_{TL}}$=$C_{out_{NR}}$, then no hyperparameter tuning needed.

If $C_{out_{TL}}$=$C_{out_{LR}}$ and $C_{out_{TL}} \neq C_{out_{NR}}$, then adapt layer sizes to match the VGGNet-16 architecture.If not, we must adjust the hyper-parameters such that they gradually match the transfer learning model.

Else if$C_{out_{TL}} \neq C_{out_{LR}}$ and $C_{out_{TL}} = C_{out_{NR}}$, Change alpha in the hyper-parameters to match the non-leaky ReLU model since out-of-process computation time and in-process computation time are not equivalent. Alpha should be adjusted by a factor of 0.01 either up or down until it is equal to the value of a non-leaking ReLU architecture.

Otherwise, change the hyper-parameters to gradually match the non-leaky ReLU model if $C_{out_{LR}} = C_{out_{NR}}$. A 0.01 factor is used to enhance or reduce alpha. To match the layer sizes of VGGNet-16, layer sizes are also raised or lowered by a factor of 8.

Hyper-parameters are tuned continuously after every classification. In the next section results of these iterative tuning procedures can be observed.

IV. RESULT AND COMPARISON

To understand the work batter, we have divided the result on two sections visual analysis and quantitative analysis.

A. Quantitative Analysis

Because scientists can access LANDSAT images, collecting satellite data for different time periods has become easy. Here in this architecture, the data of Amravati District (India) from hailstorms during February 2018 and floods during March 2018 is evaluated. In this dataset, the selection of a region's farming population is important. Performance was evaluated for publications in [3], and [23], by putting the precises values from the literature so that we can compared the proposed model concerning the accuracy values. The results concerning the evaluation of different testing images as shown in Tables 2. The comparison of accuracy of different model is shown in table 2

Number of input images	Accuracy Values for VGG Net [16]	Accuracy Values for DCNN [3]	Accuracy Values for CNN [23]	Accuracy Values for Proposed Model
100	0.86	0.84	0.87	0.89
500	0.88	0.87	0.89	0.91

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 1, March 2024

1000	0.90	0.89	0.91	0.93
1500	0.92	0.90	0.93	0.95
2000	0.95	0.92	0.96	0.97

Table 2 Accuracy Scores of Various Algorithms

This improvement assists the model to be applied for high efficiency & large-scale applications that are accuracy aware like monitoring of remote areas. Thus, the proposed model can be applied to a wide variety of crop damage detection systems with high performance.

B. Visual Analysis

As demonstrated by figure 4, (a) Input Image and figure (B) DCNN [103] output, (C) VGG Net [116] output, (D) output of proposed model, which shows the batter results as compare to DCNN [103], VGG Net [116], CNN [123].

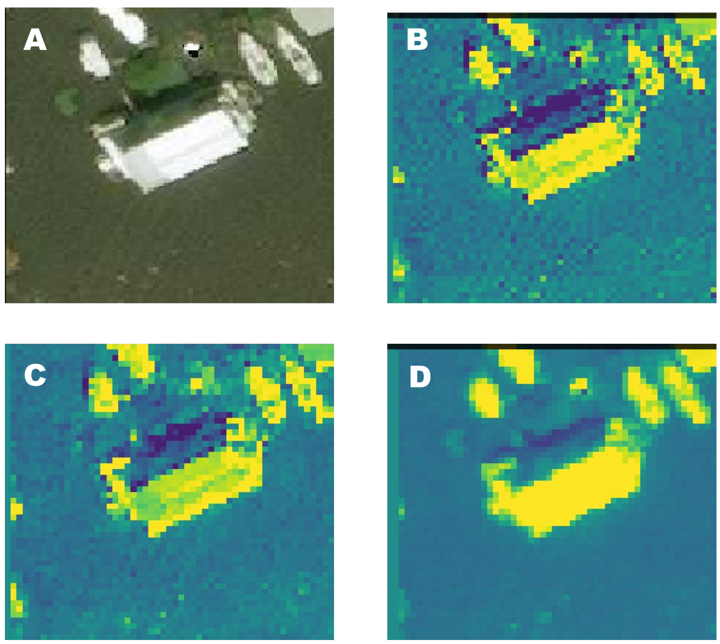

Figure 4 Experimental Results
(A) Input Image (B) DCNN (C) VGG Net (D) Proposed Model

V. CONCLUSION

CNN models help improve the performance of classification of existing as well as new systems. High-efficiency convolutional, ReLU, dropout layers and max pooling, are used for faster feature extraction, which is what helps make CNN models so effective. Each of these layers consists of a different neural network to extract features with more accuracy. In the suggested architecture combine several learning rate optimizers such as RMSProp, SGD, and Adam so that the accuracy performance of the dense layer may be enhanced. The transfer learning model and ensemble CNN classifier are used to improve accuracy, precision, recall, and F-measure automatically by iterative updating of its hyper-parameters. We can see that this is true in Tables 3.2, 3.3, 3.4, and 3.5. This thesis' suggested model outperforms existing deep learning models and can be implemented for high-efficiency applications like satellite-based crop damage detection. LSTM and GRU models may also improve performance. GANs (generative adversarial networks) are another option to investigate since they can increase the output of both near-field and satellite images when assessing damage in already classed damaged images.

REFERENCES

[1] Wu, H., Wiesner-Hanks, T., Stewart, E.L., DeChant, C., Kaczmar, N., Gore, M.A., Nelson, R.J. and Lipson, H. (2019), Autonomous Detection of Plant Disease Symptoms Directly from Aerial Imagery. Plant Phenome J., 2: 1-9 190006.

[2] Patel, Deven & Bhatt, Nirav. (2021). Improved accuracy of pest detection using augmentation approach with Faster R-CNN. IOP Conference Series: Materials Science and Engineering.

[3] Sharma, Parul & Berwal, Yash & Ghai, Wiqas. (2019). Performance Analysis of Deep Learning CNN Models for Disease Detection in Plants using Image Segmentation. Information Processing in Agriculture. 7. 10.1016/j.inpa.2019.11.001.

[4] S. Mardanisamani et al., "Crop Lodging Prediction From UAV-Acquired Images of Wheat and Canola Using a DCNN Augmented with Handcrafted Texture Features," 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2019, pp. 2657-2664, doi: 10.1109/CVPRW.2019.00322.

[5] Montras Janer, Teresa & Knape, Jonas & Nilsson, Lovisa & Tombre, Ingunn & Pärt, Tomas & Månsson, Johan. (2019). Relating national levels of crop damage to the abundance of large grazing birds: Implications for management. Journal of Applied Ecology. 56. 10.1111/1365-2664.13457.

[6] Schlötelburg, A., Plekat, A., Bellingrath-Kimura, S. and Jacob, J. (2020), Self-service traps inspected by avian and terrestrial predators as a management option for rodents. Pest. Manag. Sci., 76: 103-110. https://doi.org/10.1002/ps.5550

[7] Kasinathan, Thenmozhi & Singaraju, Dakshayani & Reddy, U. Srinivasulu. (2020). Insect classification and detection in field crops using modern machine learning techniques. Information Processing in Agriculture. 10.1016/j.inpa.2020.09.006.

[8] Li, Weilu& Chen (陈鹏), Peng & Wang, Bing &Xie, Chengjun. (2019). Automatic Localization and Count of Agricultural Crop Pests Based on an Improved Deep Learning Pipeline. Scientific Reports. 9. 10.1038/s41598-019-43171-0.

[9] Cuaran, Jose & Leon, Jose. (2021). Crop Monitoring using Unmanned Aerial Vehicles: A Review. Agricultural Reviews. 10.18805/ag.R-180.

[10] Yang, Haoxu& Gao, Lutao& tang, niansheng& Yang, Po. (2019). Experimental Analysis and Evaluation of Wide Residual Networks based Agricultural Disease Identification in Smart Agriculture System. EURASIP Journal on Wireless Communications and Networking. 2019. 10.1186/s13638-019-1613-z.

[11] SM, GOMEZ & Vergara, Alejandro & Ruiz, Henry & Safari, Nancy &Elayabalan, Sivalingam&Ocimati, Walter &Blomme, Guy. (2019). AI-powered banana diseases and pest detection. Plant Methods. 15. 10.1186/s13007-019-0475-z.

[12] Shang, Yifen&Hasn, Md.Kamrul&Ahammed, Golam Jalal & Li, Mengqi& Yin, Hanqin& Zhou, Jie. (2019). Applications of Nanotechnology in Plant Growth and Crop Protection: A Review. Molecules. 24. 2558. 10.3390/molecules24142558.

[13] Ceballos, Francisco & Kramer, Berber & Robles, Miguel. (2017). The Feasibility of Picture-Based Insurance (PBI): Smartphone Pictures for Affordable Crop Insurance.

[14] Bebber, DP, Field, E, Gui, H, Mortimer, P, Holmes, T, Gurr, SJ. Many unreported crop pests and pathogens are probably already present. Glob Change Biol. 2019; 25: 2703– 2713. https://doi.org/10.1111/gcb.14698

[15] Larijani, MR, Asli-Ardeh, EA, Kozegar, E, Loni, R. Evaluation of image processing technique in identifying rice blast disease in field conditions based on KNN algorithm improvement by K-means. Food Sci Nutr. 2019; 7: 3922–3930.

[16] Rustia, DJA, Chao, J-J, Chiu, L-Y, et al. Automatic greenhouse insect pest detection and recognition based on a cascaded deep learning classification method. J ApplEntomol 2021; 145: 206– 222. https://doi.org/10.1111/jen.12834

[17] D. Lakmal, K. Kugathasan, V. Nanayakkara, S. Jayasena, A. S. Perera and L. Fernando, "Brown Planthopper Damage Detection using Remote Sensing and Machine Learning," 2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA), 2019, pp. 97-104,

[18] O. Kulkarni, "Crop Disease Detection Using Deep Learning," 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), 2018

[19] Q. Dai, X. Cheng, Y. Qiao and Y. Zhang, "Crop Leaf Disease Image Super-Resolution and Identification With Dual Attention and Topology Fusion Generative Adversarial Network," in IEEE Access, vol. 8, pp. 55724-55735, 2020,

[20] L. S. Puspha Annabel, T. Annapoorani and P. Deepalakshmi, "Machine Learning for Plant Leaf Disease Detection and Classification – A Review," 2019 International Conference on Communication and Signal Processing (ICCSP), 2019, pp. 0538-0542,

[21] Y. Dong et al., "Monitoring and forecasting for disease and pest in crop based on WebGIS system," 2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics), 2019, pp. 1-5, doi: 10.1109/Agro-Geoinformatics.2019.8820620.

[22] R. Hari Shankar, A. K. Veeraraghavan, Uvais, K. Sivaraman and S. S. Ramachandran, "Application of UAV for Pest, Weeds and Disease Detection using Open Computer Vision," 2018 International Conference on Smart Systems and Inventive Technology (ICSSIT), 2018

[23] R. Kamesaka and Y. Hoshino, "Development of a Prevention System for Beast Damage of Agricultural Products Using Deep Learning," 2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS), 2018, pp. 747-752, doi: 10.1109/SCIS-ISIS.2018.00124.