LDDNet: An Efficient Neural Network Model for Plant Leaf Diseases Detection

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Abstract

The agricultural sector has a prominent role in contributing to the economy of many countries. Over the decades, production in the agricultural sector has decreased due to various factors such as leaf diseases, an overdose of chemical medication, natural disasters, and climatic changes. Majorly, the impact of plant diseases set a huge loss to the farmers compared to other kinds. Consulting an expert is a time taking and expensive process. Many machine learning and advanced deep learning algorithms are being implemented to identify diseases, more accurately, using the infected plant leaf image. The objective of this paper is to introduce a lightweight leaf disease detection Neural Network (LDDNet) that should be able to distinguish between diseased and healthy plants. The dataset contains 33 classes of different diseased and healthy plant leaves images, where each class has 1,680 training and 420 validating images. The accuracy obtained by the proposed LDDNet model is 99.30%. Since the performance of the model is high, it can be implemented in daily life to monitor plant diseases to have a healthy crop yielding.

Keywords
Classification, Convolution Neural Network, Data Augmentation, Machine Learning and Plant Disease Detection.

1. Introduction
Agriculture is one of the major sectors in India. It is a vital occupation of people in most developing and populated countries. India's economy contributed by the agricultural sector is fluctuating for a long time due to the loss of crop production. The majority of the losses are due to native and non-native diseases that plants get infected with. Plant diseases are generally caused due to biotic and abiotic matters. Bacteria, fungi, animals, etc, come under biotic matter. Soil, air, water, minerals, sunlight, etc, come under abiotic matters. Disease-causing organisms are also called pathogens, some of them are fungi, bacteria, and viruses (Kaur et al. 2018). Every year pathogens affect plants, resulting in less or sometimes low yield. Hence, it leads to food scarcity, and even consuming such products can be unhealthy. Many chemical medications and new cultivation techniques were introduced, and some are being implemented in daily life. Many studies have concluded that early detection and diagnosis result in better production. For early detection, in-depth knowledge and rigorous surveillance is needed that involves the deployment of a lot of the workforce. The most effective way to detect the disease is using computer-based knowledge, such as image processing techniques and computer vision, in which the image of plant leaves is involved in the detection. The improvement of technology and detection techniques in image processing revolutionized in improving accurate detection. Many machine learning algorithms came into use for the classification of diseases like SVM (Pantazi et al. 2016, Venkataramana et al. 2022), decision tree (Sabrol and Satish 2016), and KNN (Sabrol and Satish 2016). However, traditional machine learning algorithms aren't so capable of detecting complex patterns, which affects the performance of the overall model, and for large datasets, computation time also increases drastically. Later on, as technology advanced, many deep learning models, replacing traditional machine learning algorithms, came into use. This paper introduces a deep learning model called LDDNet, which was referenced from the Residual Network (ResNet) architecture, and presents an overview of its performance in classifying unseen data.

Section 2 contains the cited papers' work-study. The proposed model is described clearly in Section 3. Section 4 explains the dataset and simulation result of LDDNet. Finally, section 5 brings this paper's entire effort to a conclusion.

2. Literature Review

Pantazi et al. (2016) used Support Vector Machine (SVM), a traditional supervised machine learning algorithm used for both classification and regression problems. The results concluded that SVM achieved accuracy up to 96.25%. Sabrol and Satish (2016) used a decision tree as a classifier. The authors also compared the decision tree's performance with K-Nearest Neighbor (KNN), and SVM algorithms and concluded that the KNN works faster. But for large datasets, classifiers' performance degrades and the computation time also increases. To compensate for the drawbacks of traditional machine learning algorithms, deep learning algorithms are used to attain greater accuracies. Plant disease detection in Barbedo (2013) and Shrestha et al. 2020 is done using convolution neural networks (CNNs). A typical CNN model uses convolution layers, pooling layers, and fully connected layers. Ma et al. (2018) proposed a parallel combination of two classifiers, SVM and CNN, for cucumber leaf disease detection to get better accuracy. Khattak et al. (2021) proposed a basic sequential CNN model using Keras for differentiating healthy and diseased leaves of citrus plants. Liu et al. (2018) used AlexNet architecture to detect apple leaf disease and achieved an accuracy of 97.62%. Militante and Gerardo (2019) made a study on VGGNet for sugarcane disease detection and concluded that VGGNet achieved more accuracy, which is 95.4% when compared with the other two models namely StridedNet and LeNet. Suryawati et al. (2018) experimentally stated that VGGNet outperforms AlexNet and GoogleNet in tomato leaf disease detection. Ajra et al. (2020) compared the AlexNet model and ResNet-50 for tomato and potato disease detection, which achieved 96.5% and 95.3% accuracy respectively. Yuesheng et al. (2021) used the GoogleNet Inception model for circular fruit and vegetable classification by reducing the training parameters, introducing drop block and swish functions to increase the validation accuracy, and obtained an accuracy of 98.82% which is better than AlexNet, VGGNet, ResNet18, and DenseNet121 models. Marzougui et al. (2020) initially built a basic CNN sequential model, which consists of convolution layers, normalization layers, ReLU, and SoftMax activation functions. The model achieved an accuracy of 97.2%. Later, the model was modified into ResNet architecture by taking He et al. (2016) as a reference and achieved an accuracy of 98.96%. Li and Rai (2020) proposed ResNet18, and ResNet34 models, and achieved an accuracy of 99% and 97%, respectively. ResNet architecture counters the problem of model degradation by using skip connections and it is guaranteed that the model learns something new in the next layers (Alotaibi and Alotaibi 2020). Based on the statement mentioned by Alotaibi and Alotaibi (2020), use of skip connection, the LDDNet architecture is designed.

3. Proposed Model

LDDNet architecture, Figure 1-3, has 11 layers of which 10 are convolution layers and a fully connected layer. The model uses 7 convolution blocks without pooling, 3 convolution blocks with max pooling, one fully connected layer, and 2 skip connections. LDDNet, which was referenced from ResNet architecture, avoids the vanishing gradient problem by enabling gradients to flow through the skip connection. In addition to it, LDDNet uses Rectified Linear Unit (ReLU) as an activation function instead of the sigmoid. The sigmoid activation function enhances values nearer to zero and suppresses values farther from zero. Unlike sigmoid, ReLU enhances positive values and suppresses non-positive values. To prevent deep neural network architectures from overfitting, gradients must flow through the network, and in such cases using sigmoid degrades model performance. The output of the sigmoid function, when used as an activation function, is always less than 1, figure 1. In neural networks, the gradient gets multiplied many times to get the gradients of lower layers while backpropagation, hence making it even less. Thus, resulting in minimal or no change in the layer weights. Such issues can be avoided using ReLU activation functions since the derivative of ReLU is 1 for all positive values, figure 2.

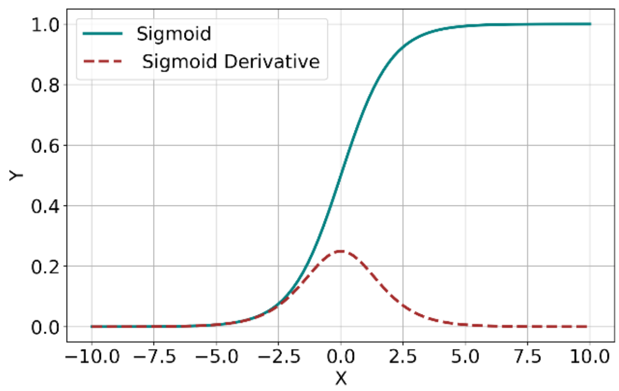

Figure 1. Sigmoid function

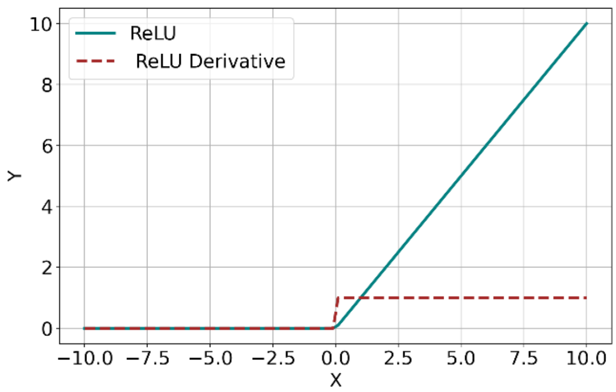

Figure 2. Rectified Linear Unit function

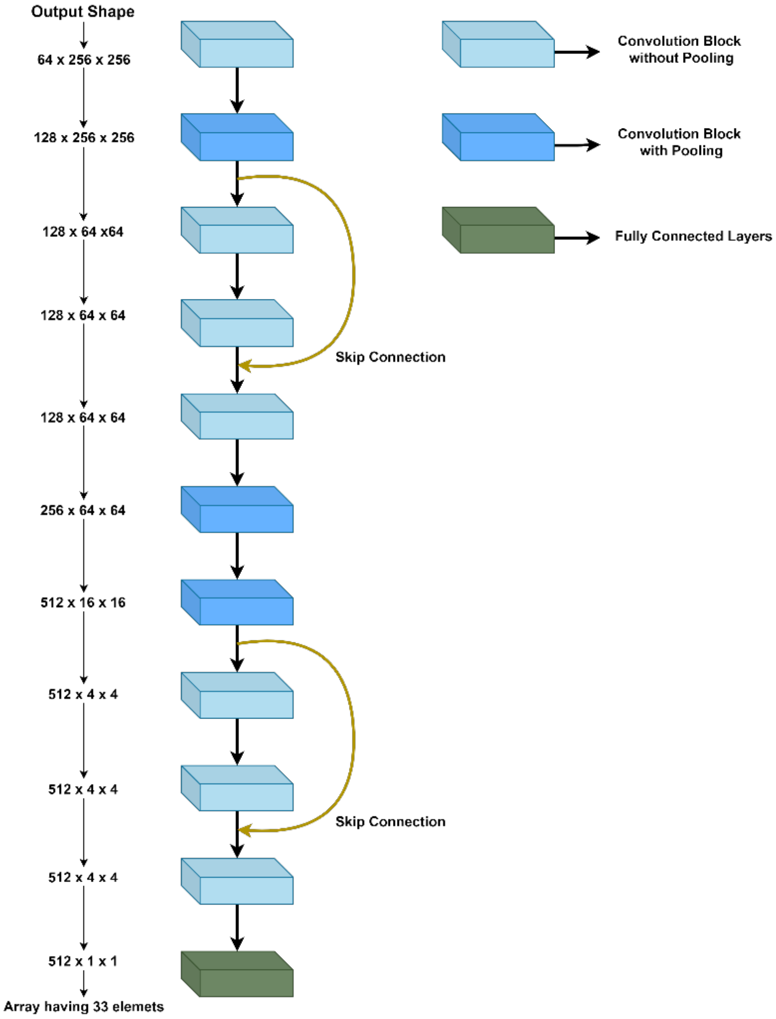

Figure 3. The architecture of LDDNet

Mathematically, the Sigmoid activation function can be given as

$$S(i) = 1/(1 + e^{-i})$$

Upon differentiating $S(i)$, we get $S'(i)$,

$$S'(i) = S(i) * \left(1 - S(i)\right) = e^{-i}/(1 + e^{-i})^2$$

ReLU activation function can be given as,

$$R(i) = \{0, for\ i \leq 0\ i, for\ i > 0$$

Upon differentiating $R(i)$, we get $R'(i)$,

$$R'(i) = \{0, for\ i \leq 0\ 1, for\ i > 0$$

4. Simulation Results

4.1 About Dataset

The dataset is derived from Mohanty et al. (2016) and has 38 classes of 54,306 images, where 12 are healthy and 26 are diseased classes. The derived dataset isn't balanced, so data augmentation is performed to balance the dataset. Also, plants are selected for training in such a way that a healthy class must exist in the derived dataset. Upon doing, 33 classes of 9 different plants are obtained. Plants that are considered are Tomato, Potato, Pepper, Apple, Corn, Grape, Cherry, Peach, and Strawberry. The total images present in the dataset after performing data augmentation are 69,300 images. On splitting them into training and validating images, each class has 1,680 training images and 420 validating images. The splitting is done in the ratio of 80% and 20% of the total images in the newly formed dataset. Image samples from the dataset are shown in figure 4.

Figure 4. Sample images from the dataset

4.2 Performance of LDDNet

LDDNet achieved a validation accuracy of 99.30% and a training accuracy of 99.96%, which is far better than many existing convolution neural network models and even some pre-trained models. Training of neural networks takes a lot of time, so using Graphical Processing Units (GPU) enhances the training time of the deep neural network models. The training time for the LDDNet using NVIDIA TESLA P100 GPU took around 215 minutes of the wall time for 19 epochs. The batch size is considered as 64 which implies that a unit of batch consists of 64 images. The model used the Adam optimizer, the best among the majority of the adaptive optimizers in most of the cases (Halgamuge et al. 2020), to prevent the overfitting of data. Accuracy and loss plots of LDDNet and other considered models are shown in figure 5 and figure 6, respectively. MobileNet and VGGNet-16 are pre-trained models loaded with the best weights. We used EarlyStopping class in "keras.callbacks" to monitor the improvement in validation accuracy for up to 6 epochs. The trained model is deployed as a web application using the flask framework, figure 7. Table 2 shows the classification report of the proposed LDDNet evaluated on precision, recall, and F1 score on the validation data. We further compared our model with other existing models namely MobileNet and VGGNet-16, loaded with the best weights of the ImageNet dataset, table 1.

Table 1. Comparison with other models

Models	Accuracy (%)		Epochs	Training time (min)
	Training	Validation		
MobileNet v1	99.84	99.38	20	230
LDDNet	99.36	99.30	19	215
VGGNet-16	97.25	96.19	23	329

Table 2. Classification report

Classes	Precision	Recall	F1 Score	Support
Apple__Apple_scab	1.00	1.00	1.00	420
Apple__Black_rot	1.00	1.00	1.00	420
Apple__Cedar_apple_rust	0.99	1.00	1.00	420
Apple__healthy	1.00	1.00	1.00	420
Cherry_(including_sour)__Powdery_mildew	1.00	1.00	1.00	420
Cherry__(including_sour)__healthy	1.00	1.00	1.00	420
Corn_(maize)__Cercospora_leaf_spot Gray_leaf_spot	0.99	0.97	0.98	420
Corn_(maize)__Common_rust	1.00	1.00	1.00	420
Corn_(maize)__Nothern_Leaf_Blight	0.97	0.99	0.98	420
Corn_(maize)__healthy	1.00	1.00	1.00	420
Grape__Black_rot	0.99	0.99	0.99	420
Grape__Esca_(Black_Measles)	0.99	1.00	1.00	420
Grape__Leaf_blight_(Isariopsis_Leaf_Spot)	1.00	1.00	1.00	420
Grape__healthy	1.00	1.00	1.00	420
Peach__Bacterial_spot	1.00	0.99	1.00	420
Peach__healthy	0.99	1.00	1.00	420
Pepper,_bell__Bacterial_spot	1.00	0.99	1.00	420
Pepper,_bell__healthy	1.00	0.99	0.99	420
Potato__Early_blight	1.00	1.00	1.00	420
Potato__Late_blight	0.99	1.00	0.99	420
Potato__healthy	1.00	1.00	1.00	420
Strawberry__Leaf_scorch	1.00	1.00	1.00	420
Strawberry__healthy	0.99	1.00	1.00	420
Tomato__Bacterial_spot	0.99	0.99	0.99	420
Tomato__ Early_blight	0.97	0.97	0.97	420
Tomato__ Late_blight	0.98	0.97	0.98	420
Tomato__Leaf_Mold	1.00	1.00	1.00	420
Tomato__Septoria_leaf_spot	0.99	0.98	0.98	420
Tomato__Spider_mites Two-spotted_spider_mite	0.99	0.99	0.99	420
Tomato__Target_Spot	0.99	0.98	0.98	420
Tomato__Tomato_Yellow_Leaf_Curl_Virus	1.00	1.00	1.00	420
Tomato__Tomato_mosaic_virus	0.99	1.00	1.00	420
Tomato__healthy	1.00	0.99	1.00	420
accuracy	-	-	0.99	13860
marco avg	0.99	0.99	0.99	13860
weighted avg	0.99	0.99	0.99	13860

Model's Performance is evaluated on the bases of F1 score, recall, precision, accuracy, weighted average, and macro average and can be given as,

$$\text{Precision} = \frac{TF}{TF+FF}$$

$$\text{Recall} = \frac{TF}{TF+FN}$$

$$\text{F1 Score} = \frac{2*P*R}{P+R}$$

$$\text{Accuracy} = \frac{TF+TN}{Total\ Predictions}$$

$$\text{Weighted Average} = \frac{\sum_{k=1}^{N} \quad (F1-score_k*Weight_k)}{\sum_{j=1}^{N} \quad (Weight_j)}$$

$$\text{Macro Average} = \frac{\sum_{k=1}^{N} \quad (F1{-}score_k)}{n}$$

Where TF = True Favourable, TN = True Non-Favourable, FF = False Favourable, FN = False Non-Favourable, P = Precision, R = Recall, and N = Number of classes.

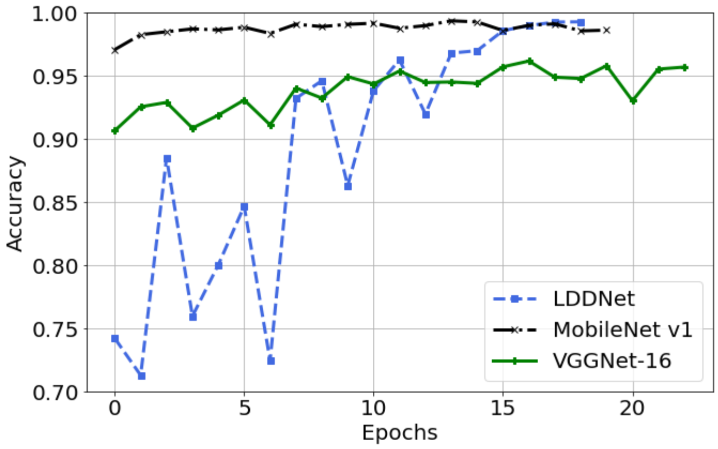

Figure 5. Combined validation accuracy plots of LDDNet, MobileNet, and VGGNet-16 have epoch count on the horizontal axis and accuracy readings on the vertical axis

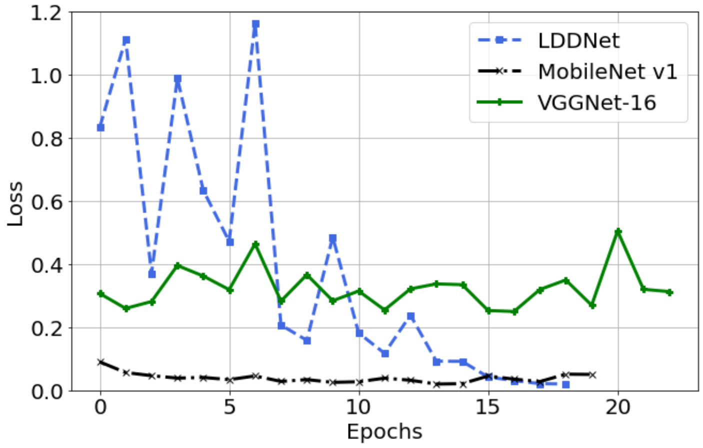

Figure 6. Combined validation loss plots of LDDNet, MobileNet, and VGGNet-16 have epoch count on the horizontal axis and accuracy readings on the vertical axis

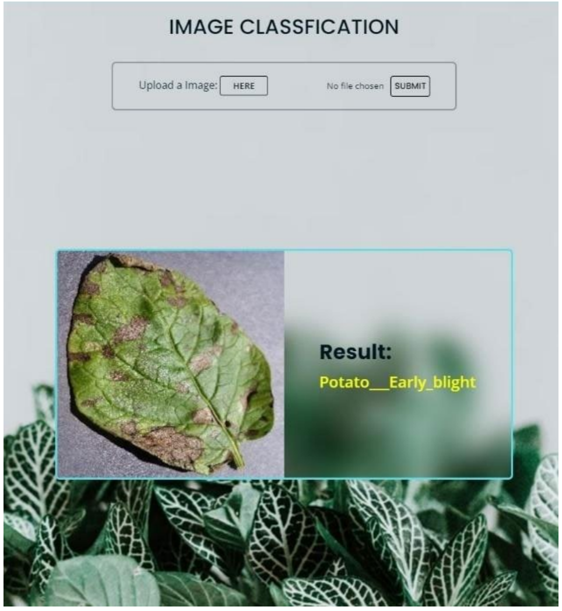

Figure 7. A Snapshot of the model deployed in the web application developed using the flask framework.
Flask framework gives the flexibility to develop quick and easy web applications using python. We have used REST APIs with HTTP methods GET and POST. The application has 2 buttons, one is for uploading the leaf image and the other is for submitting the uploaded image into the loaded model. The model evaluates the result upon clicking the submit button and displays the output along with the uploaded image in the block that was surrounded by sky-blue color.

5. Conclusion

Accurate classification of plant leaf disease is very essential to look for plants and soil health. The proposed novel architecture, LDDNet, can identify 24 different plant leaf diseases and 9 healthy plants with an accuracy of 99.30%. The model performs better than many other existing deep neural networks in the area of plant leaf disease detection in terms of accurate detection. LDDNet is extended further by developing a web application so users can access it easily at any time. This project can further be expanded by adding different diagnosis techniques along with the authorized purchasing links in the web application to buy organic products that slow down the rapid spread. Since the study on LDDNet shows that it is efficient enough to detect unseen data successfully, farmers can implement this model in daily life for monitoring crop health, thereby reducing unnecessary costs for detecting plant diseases.

References

Ajra, H., Nahar, M.K., Sarkar, L. and Islam, M.S., Disease detection of plant leaf using image processing and cnn with preventive measures. *In: 2020 Emerging Technology in Computing*, Communication and Electronics (ETCCE). pp. 1–6, 2020.

Alotaibi, B. and Alotaibi, M., A hybrid deep resnet and inception model for hyperspectral image classification. *PFG–Journal of Photogrammetry*, Remote Sensing and Geoinformation Science 88(6), 463–476, 2020.

Barbedo, J.G.A., Digital image processing techniques for detecting, quantifying and classifying plant diseases. *SpringerPlus* 2(1), 1–12, 2013.

Halgamuge, M.N., Daminda, E. and Nirmalathas, A., Best optimizer selection for predicting bushfire occurrences using deep learning. Natural Hazards 103, 845–860, 2020.

He, K., Zhang, X., Ren, S. and Sun, J., Deep residual learning for image recognition. *In: Proceedings of the IEEE conference on computer vision and pattern recognition*. pp. 770–778, 2016.

Kaur, M.G., Kaur, S. and Kaur, A., Plant disease detection: a review of current trends. *International Journal of Engineering and Technology* 7(3.34), 874–881, 2018.

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. *IEEE Access 9*, 112942–112954, 2021.

Li, X. and Rai, L., Apple leaf disease identification and classification using resnet models. *In: 2020 IEEE 3rd International Conference on Electronic Information and Communication Technology (ICEICT)*. pp. 738–742. IEEE , 2020.

Liu, B., Zhang, Y., He, D. and Li, Y., Identification of apple leaf diseases based on deep convolutional neural networks. Symmetry 10(1), 11, 2018.

Ma, J., Du, K., Zheng, F., Zhang, L., Gong, Z. and Sun, Z., A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. *Computers and electronics in agriculture 154*, 18–24, 2018.

Marzougui, F., Elleuch, M. and Kherallah, M., A deep cnn approach for plant disease detection. *In: 2020 21st International Arab Conference on Information Technology (ACIT)*. pp. 1–6, 2020.

Militante, S.V. and Gerardo, B.D., Detecting sugarcane diseases through adaptive deep learning models of convolutional neural network. *In: 2019 IEEE 6th International Conference on Engineering Technologies and Applied Sciences (ICETAS)*. pp. 1–5, 2019.

Mohanty, S.P., Hughes, D.P. and Salath ́e, M., Using deep learning for image-based plant disease detection. *Frontiers in plant science 7*, 1419 , 2016.

Pantazi, X.E., Moshou, D., Tamouridou, A.A. and Kasderidis, S., Leaf disease recognition in vine plants based on local binary patterns and one class support vector machines. *In: IFIP International Conference on Artificial Intelligence Applications and Innovations*. pp. 319–327, 2016.

Sabrol, H. and Satish, K., Tomato plant disease classification in digital images using classification tree. *In: 2016 International Conference on Communication and Signal Processing (ICCSP)*. pp. 1242–1246. IEEE (2016)

Shrestha, G., Das, M. and Dey, N., Plant disease detection using cnn. *In: 2020 IEEE Applied Signal Processing Conference (ASPCON)*. pp. 109–113, 2020.

Suryawati, E., Sustika, R., Yuwana, R.S., Subekti, A. and Pardede, H.F., Deep struc- tured convolutional neural network for tomato diseases detection. *In: 2018 inter- national conference on advanced computer science and information systems (IC- ACSIS)*. pp. 385–390, 2018.

Venkataramana, A., Kumar, K.S., Suganthi, N. and Rajeswari, R., Prediction of brinjal plant disease using support vector machine and convolutional neural network algorithm based on deep learning. *Journal of Mobile Multimedia* pp. 771–788, 2022

Yuesheng, F., Jian, S., Fuxiang, X., Yang, B., Xiang, Z., Peng, G., Zhengtao, W. and Shengqiao, X., Circular fruit and vegetable classification based on optimized googlenet. *IEEE Access 9*, 113599–113611, 2021.

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