Potato Leaf Diseases Detection Using Deep Learning

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Abstract:
Diagnosis of plant diseases is the key to prevent crop loss as well as value of agricultural output. Studies of the crop disease means studies of visible patterns observed in the plant. Monitoring of health and plant disease detection is critical for the sustainable agriculture. It is very difficult to monitor and detect plant diseases by observing them accurately. In India, it is estimated at 15-25 percentage of crop production that may be lost due to diseases, for this work to take that issue seriously, our country not only needs to increase productivity but also ensures food security as well nutrition. To detect plant diseases, we propose our automatic plant disease detection system which has been developed by integrating high level "Deep Learning" models like Convolution Neural Network (CNN) and Support Vector Machine (SVM). These model gives upto 98about detection on trained sample dataset which includes images of "healthy and unhealthy" plant leaves.

Keywords: Potato Leaf, Plant Disease, Disease Assessment, Disease Detection.

I. Introduction

India is a farm-based country and about 70 percent of the population depends on agriculture. Growers have a good range of selection of suitable crops and to search out the right pesticides for crops. Therefore, crop damage can cause significant losses in production and ultimately disrupt the economy. Leaves being the foremost sensitive segments for plants show signs of disease quickly. Plants have to be tested against diseases from the primary stage of their life cycle until they are able to be harvested[1]. Initially, the strategy accustomed monitor plants for disease was traditional eye contact which was a timeconsuming process that required specialists to look at plant fields. Leaves and stems can be used to detect the healthy status of potato leaf. This model is to develop a system that would be capable to detect and identify the types of diseases of that plant, by observing the dataset of that leaf, in recent years, a number of methods have been developed to improve plant diagnostic systems by recognizing the symptoms in plants that make the process of detection and identification easier and cheaper[2]. These systems have farreaching effects, and they are much more accurate than conventional monitoring methods. The leaf of the diseased plant is considered to be a sign of disease. There are many cases where farmers do not have complete information about the supply and the disease that may be affected by the supply. This is a work that is used effectively by farmers when increasing yields rather than visiting a specialist and getting their advice.

II. LITERATURE REVIEW

Surveying of different research paper on "Plant Disease Detection Using Deep Learning" during literature survey and some of them has been discussed below shortly. Survey of Related WorksIn depth study has provided many results with a solution for diagnosing plant diseases and stages.

- In [3], Nawaz, U., and Khan, A. , A. Ulhaq Robinson, R. W., and . Real-time plant health assessment utilising AWS DeepLens and cloudbased scalable transfer learning produced predictions with an accuracy of 98
- In [4] Abhishek Sharma, Mritunjay Ashish, Divyansh Tiwari, and Nitish Gangwar. Using an indepth study, the diagnosis of potato leaf disease Their VGG19 prediction accuracy was 97
- In [6] A. Chug, D. Singh, R. P. Singh, P. Sahu, and A. P. Singh. Implementation of CNN's plant disease research programme: Initial training vs pretraining of the model. And 97% of their predictions came true.
- In [7] Using a publicly available dataset of 54,306 photos of sick and healthy plant leaves, SP Mohanty et al. (2016) trained a convolutional neural network for a deep learning model and achieved a field test accuracy of 99%. Chapter 13 of 13. Research Review
- In [8,19] K.P. Ferentinos, 2018. Deep learning models for identifying and diagnosing plant diseases. With a dataset of 87,848 photos, computers and electronics in agriculture trained a convolutional neural network, which in a test run correctly identified a plant and its ailment with an accuracy of 99%.

- In [20] Niveditha M., Ramesh S., Hebbar R., Pooja R., and Shashank N. Vinod, P.V., 2018, built a Random Forest classifier to recognise papaya leaves from 160 photos, and obtained a classification accuracy of about 70%. This performance might be improved by enlarging the image dataset used to train the classifier model.
- In [10] The attached picture is used to extract a leaf using the YOLOv3 object detector, according to Venkataramanan, A., Honakeri, D.K.P., and Agarwal, P., 2019. A group of ResNet18 models examine the leaf that wasretrieved. Transfer learning was used to train these ResNet18 subtypes. The first layer determines the type of leaf, while the second layer investigates any potential plant illnesses.
- In [11,12] F. Mohameth and C. Bingcai Sada, K.A., 2020. The best layer to extract features for illness classification using SVM and KNN is VGG16.
- In [13] Dhakal, A. and Shakya, S., 2018, used artificial neural network with 20 epochs with accuracy of 98%.
- In [15] To identify and classify citrus plant diseases, Sharif, M., Khan, M.A., Iqbal, Z., Azam, M.F., Lali, M.I.U., and Javed, M.Y. (2018) propose a hybrid technique. M-SVM (Multi-class Support Vector Machine) was used to classify diseases, and it achieved an accuracy of 97% on the dataset for citrus illness, 89% on the combined dataset, and 90% on the local dataset.

A. Implementation of CNNs for Crop diseases classification

In [17], the focus is on erasing the concept of training CNN from scratch and using pre-trained models in the context of the agricultural sector. Testing research is done on the leaf pictures of the bean plant (infected / healthy). Demonstrated test the help of well-designed models over small samples training data, using training from the beginning and previous training a welldesigned model, with remarkable precision emerging 0.70 (approximately) to 0.9706. By using a layer-wise adjustment method, effective working depth of fine tuning can be decided to get the best results for segregation. to add data and exit methods added and a feature removal process [21]. Progress 78% were achieved with category accuracy diseases of bean plants. In addition, good preparation a pre-trained model is also made with the selection of hyperparameters are appropriate.It gave the best results from previous strategies withcategories 96% accuracy.

III. PROPOSED APPROACH

This system at firstly does “Data Partitioning” which is separately loaded image dataset of plant leaves into three division “Training”, “validation” and “Testing” than comes “Data Shuffling”, dataset is shuffled well to avoid any element of bias in the split dataset before training the “Deep Learning” model. Than “Data Augmentation”, where existing data is modified add modified. By creating fresh and unique instances for the training dataset, machine learning models can perform better and produce better results.

IV. MODEL SELECCTION

“Model Selecction”, in this process our system select a “Deep Learning” model (e.g. SVM, CNN, VGG-16 etc.) forthe further process of detection of disease. “Model Process”, system allows to find out the disease from the trained dataset to detect the disease.“Accuracy Evaluation”, evaluate the accuracy of the detection by the selected model process. After applying of SVM, CNN and VGG-16 on processed dataset,this work got three different accuracy. After evalution using, SVM the accuracy this work got 87%, using VGG-16 accuracy was 92% and using CNN theaccuracy was 98%.

A. Data Partitioning

There are several ways to separate the test data. The most popular methods are often called training, validation and classification testing. Data is often divided into three sets: a training set, a validation set, and a test set, with 80% of the data being used as a training set, 10% being used as a validation set, and 10% being used as a test set.

B. Data Augmentation

Data augmentation is the technique of creating additional data points from current data in order to artificially increase the amount of data. In order to amplify the dataset, this may involve making small adjustments to the data or utilising machine learning models to produce new data points in the latent space of the original data.

C. Data Shuffling

Techniques are intended to consolidate data and may voluntarily maintain meaningful relationships between columnsIn a column in simple flat format, for example, or collection of characteristics, shuffle data from databases at random (e.g. set of columns). It can change the values of the same attribute for a different record by manipulating sensitive data. Methods are generally well suited to mathematical contexts that ensure that any metrics or computer installed KPI across the database will still be fully operational. Then, since every mathematical distribution is still valid, it enables the secure use of production data for activities like testing and training.

V. RESULT ANALYSIS

Results analysis of outcomes of proposed models-

- The CNN is a class of in depth learning methods that dominate various computer vision functions and attract interest in all different fields, including radiology.

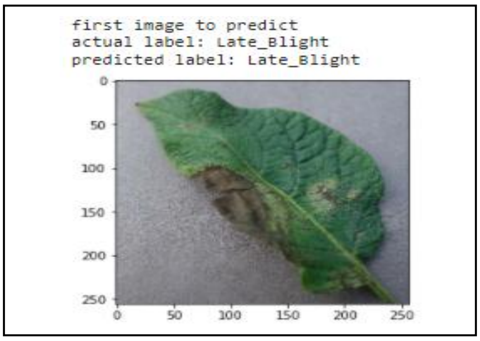

Fig. 1. Example of Data Prediction.

- The CNN is made up of multiple building blocks, such as convolution layers, integration layers, and fully integrated layers, and is designed to automatically and flexibly locate feature layouts using a back to back distribution algorithm [23].

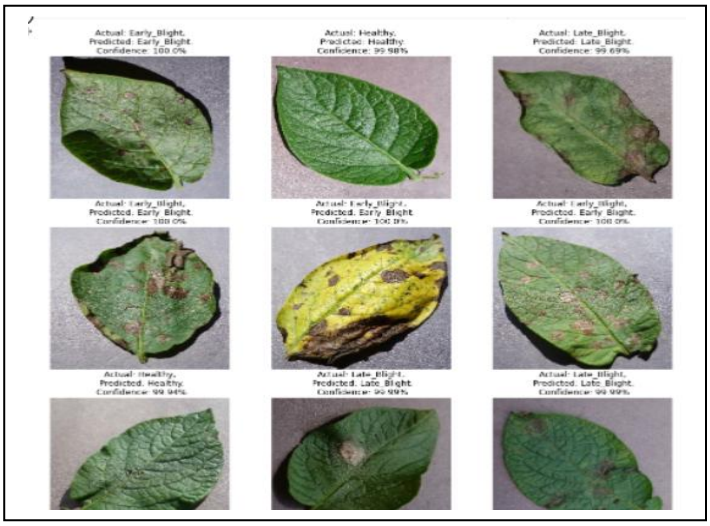

Fig. 2. Show Accuracy Prediction.

- Familiarity with the ideas and benefits, as well as the limitations, of the CNN is essential for utilizing its potential to improve the performance of the radiologist and, ultimately finding out the disease in the trained dataset. [18].

- Visualization of Training and validation accuracy ROC Curve Many plant diseases have distinct physical symptoms that can be used to diagnose and differentiate [22].

- This work introduces a potato disease classification algorithm using this unique look and the latest developments in computer vision that have been made possible by indepth study.

- The algorithm uses CNN that trains it to divide clusters into five stages, four disease stages and a healthy potato class.

Visualization of training and validation loss ROC Curve Data for the images used in this study, which contained potato of different shapes, sizes and diseases, were obtained, classified, and labeled by hand professionally. Models trained with different train test variants to better understand the amount of image data required for the use of in depth learning in such classification tasks.

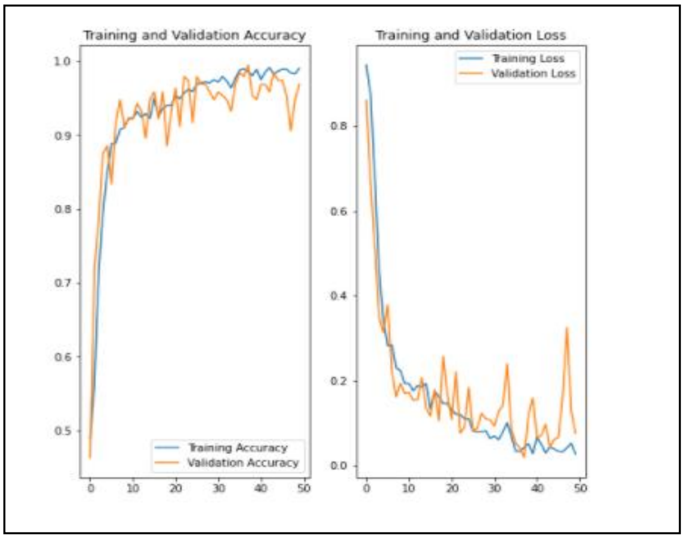

Fig. 3. Show Accuracy Prediction

VI. Evaluated Accuracy

Evaluated accuracy of SVM, CNN and VGG-16 are as follows - • 70 % of training and 30 % of testing data achieve accuracy of 49% using SVM. 45% using VGG-16 and 88% using CNN. • 60% of training and 40% of testing data achieve accuracy of 41% using SVM, 42% using VGG-16 and 60% using CNN. • 80% of training and 20% of testing data achieve accuracy of 56% using SVM, 48% using VGG-16 and 98% using CNN.

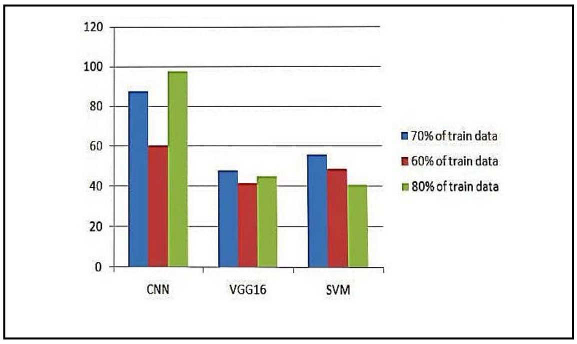

Fig. 4. Show Accuracy Prediction Comparison.

VII. ACCURACY EQUATION

Using two Deep learning models named VGG16 and CNN model on trained dataset the prediction level this work got approximate 97 . Where T.P. is true positives, T.N. is true negatives, F.P. is false positives and F.N. is false negatives. Here the T.P. and T.N. are the correct predictions while the F.P. and F.N. are the wrong predictions made by our model.

Accuracy = TP + TN / TP + TN + FN + FP.

VIII. SENSITIVITY PREDICTION

Precision and Recall-

- Precision is defined as the class of correctly predicted positive samples. And precision of CNN model that is 86% after classification of the plant leaves dataset. 42% and 45% precision are given for using of VGG-16 and SVG model.

- Recall is calculated as the ratio of the number of positive samples correctly classified as positive to the total number of positive samples. Recall mea- sures the ability of a model to detect positive samples. 89% recall has been classified of using CNN, 42% and 45% of using VGG-16 and SVM. 13.

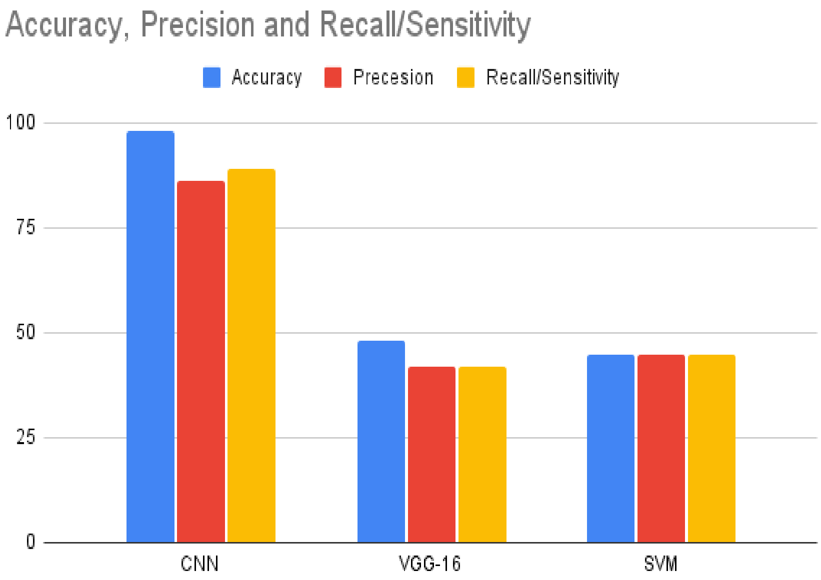

Fig. 5. Show Sensitivity Prediction Comparison.

CONCLUSION

The primary focus of the work on a study of analysis of plant diseases is to find the accuracy using several Deep Learning models and the primary form has been spotted on potato leaf found CNN is providing 98evaluation of processed data set. Some of the possible work training more data set for efficient accuracy, maybe a hybrid model using CNN, VGG16 and SVM, Using mobile net for scanning and detecting diseases.

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REFERENCES

[1] Bakay, Melahat Sevg¨ul, and ˙Umit A˘gbulut. ”Electricity production based forecasting of greenhouse gas emissions in Turkey with deep learning, support vector machine and artificial neural network algorithms.” Journal of Cleaner Production 285 (2021): 125324.

[2] Salim, Alaa Sabeeh, et al. ”Novel Image Caption System Using Deep Convolutional Neural Networks (VGG16).” 2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applica- tions (HORA). IEEE, 2022.

[3] Cruz, A.Ampatzidis, Y. , De Bellis, L. , Pierro, ,Panattoni, A. , Materazzi, A. , and Luvisi, A. . Automatic diagnosis of olive quick decline syndrome and grapevine yellows for the agriculture industry. In 2019 Second International Conference on Artificial Intelligence for Industries. (AI4I), pages 9–12. IEEE, 2019.

[4] Dhakal, A. and Shakya, S. . Image-based plant disease detection with deep learning. International Journal of Computer Trends and Technology, 61(1): 26–29, 2018.

[5] Ferentinos, K. P. . Deep learning models for plant disease detection and diagnosis. Computers and electronics in agriculture, 145:311–318, 2018.

[6] Islam, M. , Dinh, A. , Wahid, K. , and Bhowmik, P. . Detection of potato diseases using image segmentation and multiclass support vector machine. In 2017 IEEE 30th canadian conference on electrical and computer engineering (CCECE), pages 1–4. IEEE, 2017.

[7] Ji, M. , Zhang, L. , and Wu, Q. . Automatic grape leaf diseases identification via unitedmodel based on multiple convolutional neural networks. Information Processing in Agriculture, 7(3):418–426, 2020.

[8] Ji, M. , Zhang, L. , and Wu, Q. . Automatic grape leaf diseases identification via unitedmodel based on multiple convolutional neural networks. Information Processing in Agriculture, 7(3):418–426, 2020.

[9] Khan, A. , Nawaz, U. , Ulhaq, A. , and Robinson, R. W. . Real-time plant health assessment via implementing cloud-based scalable transfer learning on aws deeplens. Plos one, 15(12):e0243243, 2020.

[10] Kumari, C. U. , Prasad, S. J. , and Mounika, G. . Leaf disease detection feature extraction with kmeans clustering and classification with ann. In 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), pages 1095–1098. IEEE, 2019.

[11] Li, G. , Ma, Z. , and Wang, H. . Image recognition of grape downy mildew and grape powdery mildew based on support vector machine. In International Conference on Computer and Computing Technologies in Agriculture, pages 151– 162. Springer, 2011.

[12] Mohameth, F. , Bingcai, C. , and Sada, K. A. . Plant disease detection with deep learning and feature extraction using plant village. Journal of Computer and Communications, 8(6):10–22, 2020. 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.

[13] Ramesh, S. , Hebbar, R. , Niveditha, M. , Pooja, R. , Shashank, N., Vinod, P. , et al. Plant disease detection using machine learning. In 2018 International conference on design innovations for 3Cs compute communicate control (ICDI3C), pages 41– 45. IEEE, 2018.

[14] Sahu, P. , Chug, A. , Singh, A. P. , Singh, D. , and Singh, R. P. Implementation of cnns for crop diseases classification: A comparison of pre-trained model and training from scratch. IJCSNS, 20(10):206,2020.

[15] Saleem, M. H. , Potgieter, J. , and Arif, K. M. . Plant disease detection and classification by deep learning. Plants,8(11):468, 2019.

[16] Sharif, M. , Khan, M. A. , Iqbal, Z. , Azam, M. F. , Lali, M. I. U. , and Javed, M. Y. . Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection. Computers and electronics in agriculture, 150:220–234, 2018.

[17] Simonyan, K. and Zisserman, A. . Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

[18] Sun, Y. , Lu, R. , Lu, Y. , Tu, K. , and Pan, L. . Detection of early decay in peaches by structured illumination reflectance imaging. Postharvest Biology and Technology, 151:68–78, 2019.

[19] Tiwari, D. , Ashish, M. , Gangwar, N. , Sharma, A. , Patel, S. , and Bhardwaj, S. . Potato leaf diseases detection using deep learning. In 2020 4th Interna tional Conference on Intelligent Computing and Control Systems (ICICCS), pages 461–466. IEEE, 2020.

[20] Tiwari, Divyansh, et al. ”Potato leaf diseases detection using deep learning.” 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE, 2020.

[21] Wu, Xiongwei, Doyen Sahoo, and Steven CH Hoi. ”Recent advances in deep learning for object detection.” Neurocomputing 396 (2020): 39-64.

[22] Liu, Hongyu, and Bo Lang. ”Machine learning and deep learning methods for intrusion detection systems: A survey.” applied sciences 9.20 (2019): 4396.

[23] Farsad, Nariman, and Andrea Goldsmith. ”Detection algorithms for communication systems using deep learning.” arXiv preprintar Xiv:1705.08044 (2017).