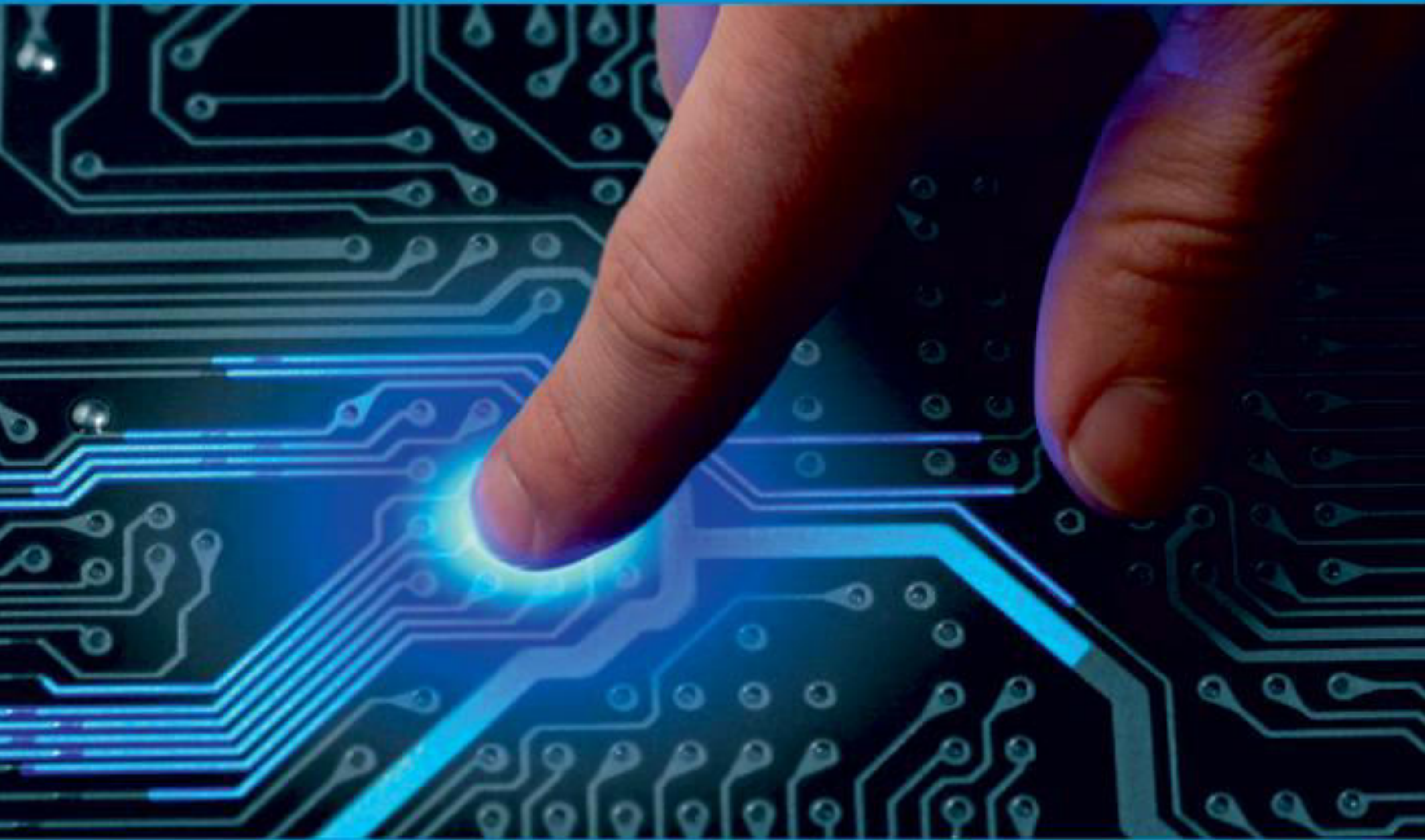
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 12, December 2021

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.542

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542

|| Volume 9, Issue 12, December 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0912023 |

Review on Plant Disease Detection Using Deep Learning Model

Prakash Sahu, Vivek kumar sinha

PG Student, Dept. of CSE., Raipur Institute of Technology, Raipur, Chhattisgarh, India

Assistant Professor, Dept. of CSE., Raipur Institute of Technology, Raipur, Chhattisgarh, India

ABSTRACT: Agriculture and agricultural production play an important role in India's economy. In the ecosystem, many pathogens are present, which significantly affect the plant's health and the soil they are planted, affecting crop production. This kind of misfortune can show a negative impact on an agriculture-dominated nation. The most common practice to identify those pathogens is by observing the plant via naked eyes, which neither provide information regarding the disease that affects plant's leaves nor provides information regarding precautionary measures to prevent them from being harmed. There are several solutions to detect cotton plant leaf disease using transfer expertise as a methodology. However, each of them is limited to just two or three disease detection patterns with maximum accuracy of 77%.
In this dissertation work a fully automated method for the recognition of medicinal plants leaf detection using computer vision and machine learning techniques has been presented. On first section leaves from 20 different medicinal plant species were collected and photographed using a smart phone in a laboratory setting. A large number of features were extracted from each leaf such as its length, width, perimeter, and area, number of vertices, color, perimeter and area of hull. Several derived features were then computed from these attributes. The best results were obtained from a CNN classifier using Relu activation. The model is able to detect 6 types of disease with an accuracy of 98.57%, CNN performed better than other machine learning approached methodology.

KEYWORDS: Convolutional neural network, Relu, Deep learning, VGG16, Alexnet, Resnet

I. INTRODUCTION

In today’s era, the crop production not limited to just food source. India’s economy is heavily relied upon agricultural production. Hence identification of disease on plants has become more essential in the agricultural industry. The implementation of an automated disease detection method is advantageous for detecting plant diseases at their earliest occurrence. Considering a example, in US tiny fungal disease is one the most dangerous illness that affects oak trees. The effected tree has limited development and will die within few years. A method which can detect the disease at early-stage might will be beneficial in this condition. On the other side irrigation plays and important role in yield production. Proper irrigation can help to achieve higher yield production.

The only feasible method now available for identification and recognition of illness in plant is observation of disease by human eyes. To perform observation by human eyes proper examination on regular interval is require by a team of agricultural scientist. Consider the large farms it can be very expensive and time consuming. In some countries availability of agricultural specialist can be also an issue. In this kind of circumstances, a method which is capable of detecting disease automatically can be useful. An automated identification of infections by simply matching characteristics of plant leaf with healthy leaf’s and unhealthy leaf’s is simpler and less expensive technique. Applying this technique will add AI on agriculture, which can be used for automated fertilization, agricultural machine guiding. The existing method of crop yield irrigation is also highly depended on human interaction. A proper investigation of crop field water level is required by human. A method which provides real time information regarding water level of field and provides control over irrigation machineries can be helpful in such situation.

Plant infection detection and irrigation dependent on human interaction can be strenuous, time consuming, not much efficient and restricted to some region.in contrast, if an automated disease detection and irrigation system is deployed it will surely help to solve the above-mentioned issues. In same species of plants several common illnesses observed are various colour strains, curly leaf’s and pathogenic disease. In order to identify the infection region and type of infection image processing is employed.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542

|| Volume 9, Issue 12, December 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0912023 |

Splitting or dividing a picture into multiple distinct segments is known as image segmentation. Several image segmentation techniques are currently available including basic picture segmentation and sophisticated colour picture segmentation. Typically, such

components are related to things that human can easily identify and see that as distinct thing. Because computers are incapable of properly identifying things, a variety of techniques have already been devised in order to separate pictures into distinct segments. Because machines lack the ability to identify things sensibly, many techniques for segmenting pictures have already been devised. The picture segmentation method involves different characteristics that may be discovered when the picture being processed. Color data, picture borders, or a region of pictures can be these characteristics. Color picture segmentation is accomplished via the use of a genetic algorithm in our proposed model the picture segmentation was accomplished via CNN algorithm.

Major Processes To Be Followed In Leaf Disease Detection

To achieve the goal of leaf disease detection following procedures needs to be followed.

1. Image Acquisition. In Image processing this can be defined as process of retrieving digital picture from camera or from storage device. During image acquisition step pre-processing operation like image scaling is performed
2. Image Enhancement. Image enhancement methods are used to pull out important information which has been hidden. It performs some basic transformation like brightness adjustment or contrast adjustment to pull out hidden information.
3. Image Restoration. It is Process of Enhancing the overall look of a photograph. Its majority of picture transformation operations are based on mathematical models
4. Morphological Operation. The Morphological Operation provides components extraction techniques on picture elements that can be used to characterize and describe shapes.
5. Image Segmentation. In image segmentation technique digital image is partitioned into different subsets called classes. Transformation on image segmentation process reduces the computational complexity and simplifies its analysis.

II. RELATED WORK

Dheeb Al Bashish et al.[1] They developed a prediction models trained on the imagenet networks and discovered that it is successful at detecting leaf illness, and K-means grouping gives more effective outcome for Colour image classification.

Anand Kulkarni et al [2] created a classification scheme for leaf disease identification.Clustering is accomplished using the Gabor filter, and illness categorization is accomplished using an ANN.ANN based classifier is used for detection and recognition of various plant leaf diseases.combination of colour characteristic and shape is used.The experimental results shows performance gained using ANN is superior, achieving 91% accuracy.

Mamta Gahlot et al. [3] AlexNet, VGG16, GoogleNet, ResNet-101, and DenseNet- 121 are five different convolution neural network models that are used to categories tomato leaf disease into ten different classifications without utilizing a lot of resources. DenseNet-121, the smallest of the five models, has the highest accuracy of 99.694% and the smallest size of 113.29MB. With 14529 photos, Plant Villages photographs were used for the suggested system. Because loading 14529 photos with 256 × 256 sizes was challenging, Data Generator was utilized to reduce memory usage.

Xin Li et al.[4] A model was presented utilising a dataset of apple grey-spot disease, black star disease, and cedar rust disease, as well as healthy leaves, to investigate the identification and classification of apple leaf disorders. Picture segmentation was done with an SVM classifier, while image classification was done with ResNet and VGG convolutional neural network models. This article compares the two models, and the results demonstrate that ResNet-18, which has less layers of ResNet, has a greater accuracy rate of 98.5% when compared to other architecture.

Muhammad Sufyan Arshad et al. [5]Potato, tomato, and corn diseases were identified using ResNet50 and Transfer Learning. The suggested system compares ResNet50's performance to that of VGG16 and MCNN, both of which were created and trained from the ground up, with ResNet50 achieving the greatest performance of 98.7% for plant disease detection. The programme can identify 16 types of distinct plant diseases from the Plant Village dataset. The work can be extended by using the training model on a larger number of classes.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542

|| Volume 9, Issue 12, December 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0912023 |

Anshuman Singh et al [6] suggested a novel disease detection approach that provides a feature extraction strategy for distinguishing between healthy and diseased wheat plants. The system was trained using a deep convolutional neural network (DCNN) and a transfer learning approach. Different CNN models such as VGG16, VGG19, AlexNet, ResNet-34, ResNet-101, ResNet-50, and ResNet-18 are applied with the CIMMTY dataset, and a comparison of the models shows that the RESNET-101 has the highest accuracy of 98%.

Kirti et al. [7] The proposed method for identifying Black Measles Disease in Grape Plants is based on the Plant Village Database's Grape Plant dataset. There are 1807 photos in total in the dataset (healthy and diseased). The suggested model uses the ResNet 50 Deep Neural Network architecture in conjunction with Transfer Learning and Fine Tuning to compute the findings, resulting in an accuracy of more than 97%, outperforming previous approaches based on feature extraction methods.

Philomina Simon1[8] et al Propose a method for texture classification that uses Convolution Neural Network (CNN) features for feature extraction and a Support Vector Machine as a classifier. We employed cross entropy as the loss function to evaluate the error during training, and classification was used to investigate the efficiency of CNN features extracted from several pre-trained models such as DenseNet201 and ResNet50. A dominant discriminative classifier that can conduct classification is the support vector machine. The model's performance is calculated using grey and color texture databases like KTH-TIPS, CURET, and floral datasets. With various datasets,the results demonstrate good and superior accuracy of t of about 85% to 95%. The proposed methods take less time to compute.

Mohit Agarwala, at al.[9] Using the Plant Village dataset, a CNN-based algorithm to identify disease in tomato crops has been constructed. There are three convolution and max pooling layers in the proposed CNN-based architecture, each with a different number of filters. There are 9 disease classifications in the collection, as well as a healthy image class. Because the photos inside the class are unbalanced, data augmentation techniques were used to balance the images within the class. The average testing accuracy of the model is 91.2%, according to experiments. The suggested model requires only 1.5 MB of storage space, whereas pre-trained models require roughly 100 MB, demonstrating the proposed model's advantage over pre-trained models.

Junde Chena et al.[10] Investigate utilizing a pre-trained model learned from usual masssssive datasets, and then transferring to a specific goal educated by our own data, and employing deep convolutional neural networks to identify plant leaf diseases through transfer learning. VGGNet pre-trained on ImageNet was used in the suggested model, and the Inception module was used for further categorization. Instead of starting from the beginning and randomly initialising the weights, ImageNet used pre-trained networks on a large labeled dataset to initialize the weights. The proposed method achieves a validation accuracy of no less than 91.83% on the publicly available dataset, which is a major improvement over previous state-of-the-art methods. Even under tough backdrop conditions, the suggested method achieves a 92% average accuracy for class prediction of rice plant pictures.

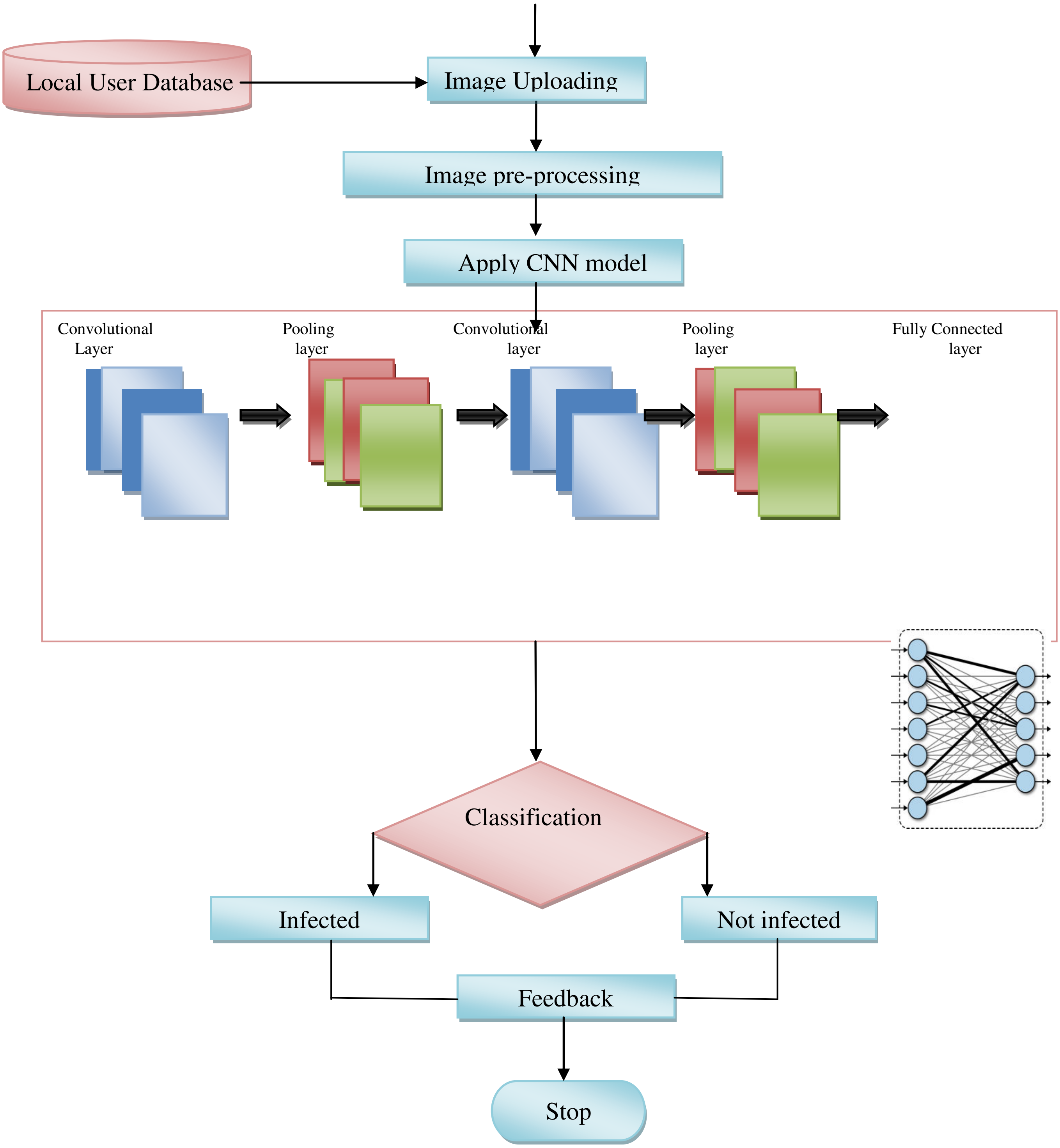
III. PROPOSED METHODOLOGY

Step In brief the research technique used is about as follows. In beginning, the user uploads a picture of the diseased leaf. Secondly, submitted pictures are segmented prior to being processed. Thirdly, the uploaded image's characteristics are extracted. Fourth, the picture is processed using CNN model. Lastly, disease is predicated based on the performance of CNN model.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542

|| Volume 9, Issue 12, December 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0912023 |



3.1 Convolutional Neural Network

CNN is kind of NN that has shown to be very effective in image detection and diagnosis.[1]. Rather of individually collecting high-level solid characteristics, CNNs may obtain them immediately from the original image.

In the identification of plant varieties and pathogens, CNNs have really been demonstrated to outperform traditional feature extraction algorithms. It has been shown how CNNs outperform conventional image segmentation approaches in the detection of plant varieties and pathogens [11]. Convolution layers, pooling layers, and fully connected layers

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542

|| Volume 9, Issue 12, December 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0912023 |

make up a standard CNN architecture. Consider n_h = Height Size, n_w = Width Size, n_c = Channel Quantity, The CNN model configuration is shown is table 4.1 and CNN architecture is shown in figure 4.2.

Table 3.1 – Layers Details of proposed CNN Model

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_1 (MaxPooling2	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_2 (MaxPooling2	(None, 17, 17, 128)	0
conv2d_3 (Conv2D)	(None, 15, 15, 256)	295168
max_pooling2d_3 (MaxPooling2	(None, 7, 7, 256)	0
dropout (Dropout)	(None, 7, 7, 256)	0
flatten (Flatten)	(None, 12544)	0
dense (Dense)	(None, 128)	1605760
dropout_1 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 256)	33024
dropout_2 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 4)	1028

Total params: 2,028,228
Trainable params: 2,028,228
Non-trainable params: 0

3.1.1 Convolutional Layers: The first layer is convolutional layer which is an essential part of a CNN since it collects the image's basic features using various convolution kernels of various sizes. From input image, a collection of features can be retrieved by applying convolutional layers repeatedly. We know that on convolutional layer, we perform convolutional operation and then we apply activation function to the output of convolutional operation.

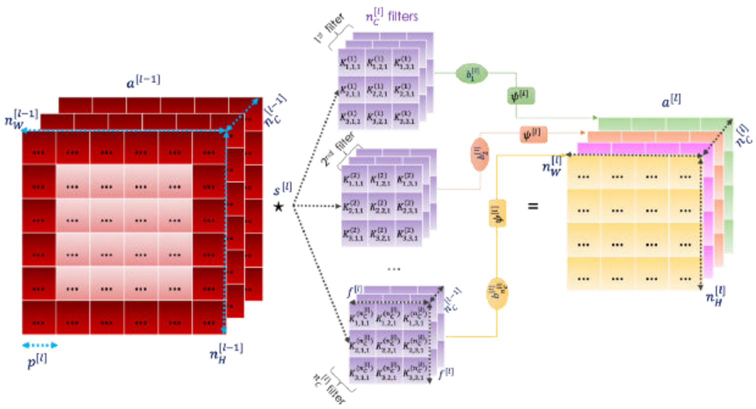


Fig. 3.2 [13]Convolutional Layer Operation

3.1.2 Pooling Layers: Pooling layers have the benefit of reducing the non-linear measurements, which reduces numerical complexity and efficiently controls the probability of over-fitting.[12]The process of reducing complexity is known as down sampling. Down sampling doesn't have any impact over number of channels. Pooling layer operation is described in below algorithm. There is no learning from Pooling layer.

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542

|| Volume 9, Issue 12, December 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0912023 |

The operation of pooling layer can be summarized in below graph.

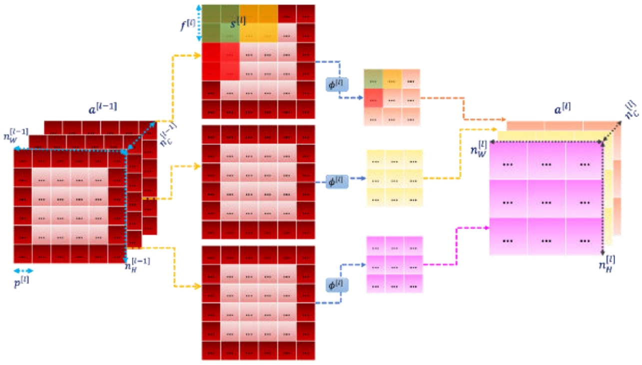


Fig. 3.3 [13]Pooling Layer Operation

3.1.3 Fully-connected Layers : –Following the PO layer after convolutional layer there are many FC layers but number of neurons in FC layers is limited. This layer is used to classify the images based on features retrieved. [14]SoftMax function is used for classification of model which is based on the output collected from pooling layers and convolutional layers.

The FC layer can be summarized in following illustration:

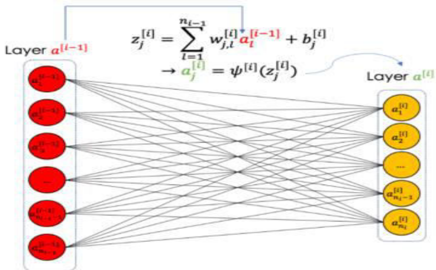


Fig. 3.4 [13]Fully Connected Layer Operation

We need to apply convolutional operation multiple times afterward we need to perform pooling operations repeatedly. Convolutional operation and pooling operation will extract the features from the picture which has been given as input to the NN. [13]The main agenda of these operation is to reduce n_h & n_w and expand n_c while performing the layers operations.

IV. CONCLUSION AND FUTURE WORK

Deep learning methodologies plays an important role in Agriculture industry. Deep learning algorithms are easy to implement, and capable of solving complex problem using these techniques. We have seen that many researcher uses the deep learning technique to classify and diagnosing the illness of the different leaf all model uses the existing dataset and result and accuracy are good using DL model.
Hence in future we can create a deep learning model with real time image or new dataset like Plant village dataset and for optimal accuracy we can use Resnet Model to identify the disease in leaf.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542

|| Volume 9, Issue 12, December 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0912023 |

REFERENCES

1. Dheeb Al Bashish, Malik Braik and Sulieman Bani Ahmad "Detection and classification of leaf disease using K-mean based segmentation and neural network based classification," International Technology Journal, vol.10, Issue 2, 2014, pp. 267- 275.
2. Anand Kulkarni & Ashavin Patil R. K. "Applying image processing technique to detect plant diseases," International Journal of Modern Engineering Research (IJMER), Vol. 2, Issue 5, Sep-Oct 2012, pp. 3661- 6264.
3. M. Gehlot and M. L. Saini, 'Analysis of Different CNN Architectures for Tomato Leaf Disease Classification', *2020 5th IEEE Int. Conf. Recent Adv. Innov. Eng. ICRAIE 2020 - Proceeding*, vol. 2020, 2020, doi: 10.1109/ICRAIE51050.2020.9358279.
4. X. Li and L. Rai, 'Apple Leaf Disease Identification and Classification using ResNet Models', *ICEICT 2020 - IEEE 3rd Int. Conf. Electron. Inf. Commun. Technol.*, pp. 738–742, 2020, doi: 10.1109/ICEICT51264.2020.9334214.
5. M. S. Arshad, U. A. Rehman, and M. M. Fraz, 'Plant Disease Identification Using Transfer Learning', *2021 Int. Conf. Digit. Futur. Transform. Technol. ICoDT2 2021*, pp. 1–5, 2021, doi: 10.1109/ICoDT252288.2021.9441512.
6. Singh and M. Arora, 'Wheat Crop', no. Icosec, pp. 121–125, 2020.
7. K. Kirti, N. Rajpal, and J. Yadav, 'Black measles disease identification in grape plant (vitis vinifera) using deep learning', *Proc. - IEEE 2021 Int. Conf. Comput. Commun. Intell. Syst. ICCCIS 2021*, pp. 97–101, 2021, doi: 10.1109/ICCCIS51004.2021.9397205.
8. P. Simon and V. Uma, 'Deep Learning based Feature Extraction for Texture Classification', *Procedia Comput. Sci.*, vol. 171, no. 2019, pp. 1680–1687, 2020, doi: 10.1016/j.procs.2020.04.180.
9. M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, 'ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network', *Procedia Comput. Sci.*, vol. 167, no. 2019, pp. 293–301, 2020, doi: 10.1016/j.procs.2020.03.225.
10. J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, 'Using deep transfer learning for image-based plant disease identification', *Comput. Electron. Agric.*, vol. 173, no. November 2019, p. 105393, 2020, doi: 10.1016/j.compag.2020.105393.
11. Basvaraj S. Anami, J.D. Pujari, Rajesh Yakkundinath, "Identification and classification of normal and affected agriculture / horticulture produce based on combined color and texture feature extraction," International Journal of Computer Applications in Engineering, vol 1, Sept 2015,pp.356-360.
12. Militante, Sammy V., Bobby D. Gerardo, and Nanette V. DIonisio. 2019. "Plant Leaf Detection and Disease Recognition Using Deep Learning." 2019 IEEE Eurasia Conference on IOT, Communication and Engineering, ECICE 2019, 579–82. https://doi.org/10.1109/ECICE47484.2019.8942686.
13. Agarwal, Mohit, Abhishek Singh, Siddhartha Arjaria, Amit Sinha, and Suneet Gupta. 2020. "ToLeD: Tomato Leaf Disease Detection Using Convolution Neural Network." *Procedia Computer Science* 167 (2019): 293–301. https://doi.org/10.1016/j.procs.2020.03.225.
14. [S. Zhang, X. Wu, Z. You, and L. Zhang, "Leaf image based cucumber disease recognition using sparse representation classification," Comput. Electron. Agric., vol. 134, pp. 135–141, Mar. 2017, doi: 10.1016/j.compag.2017.01.014.

INNO SPACE
SJIF Scientific Journal Impact Factor
Impact Factor: 7.542

doi cross ref

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

निस्केयर NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

Scan to save the contact details