International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10s
DOI: https://doi.org/10.17762/ijritcc.v11i10s.7687
***Article Received:** 07 June 2023 **Revised:** 28 July 2023 **Accepted:** 15 August 2023*

Rice Leaf Disease Detection Using Convolutional Neural Network

Dr. Rajani P.K[1], Dr. Vaidehi Deshmukh[2], Dr. Sheetal U. Bhandari[3], Dr. Roshani Raut[4], Dr. Reena Kharat[5]
[1]Department of Electronics and Telecommunication,
Pimpri Chinchwad College of Engineering, Pune, India
e-mail: rajani.pk@pccoepune.org
[2]Department of Electrical and Electronics Engineering,
Dr. Vishwanath Karad MIT World Peace University Pune, India
e-mail: vaidehi.deshmukh@mitwpu.edu.in
[3]Department of Electronics and Telecommunication,
Pimpri Chinchwad College of Engineering, Pune, India
e-mail: sheetal.bhandari@pccoepune.org
[4]Information Technology Department,
Pimpri Chinchwad College of Engineering, Pune, India
e-mail: roshani.raut@pccoepune.org
[5]Computer Department,
Pimpri Chinchwad College of Engineering, Pune, India
e-mail: reena.kharat@pccoepune.org

Abstract—In the agriculture sector, the rice crops getting diseased has become a significant concern recently, especially in India, where rice is one of the primary meals. Precise and early-stage detection of various diseases observed in the rice crops can help farmers to provide proper treatment to the crops. This paper presents a Convolutional Neural Network (CNN) based approach is used to detect rice plant leaf disease. CNN is one of the deep learning algorithms that help in image processing and classification with significant accuracy. The proposed algorithm is used for an image dataset of the diseased rice plant leaves, available on Kaggle. Two types of rice leaf diseases are considered for the analysis: brown spot and bacterial leaf blight. The images of these two diseases were pre-processed, segmented, and classified to identify the caused disease. The proposed model can also be used for the detection of the diseases present in other types of crops, faces recognition system, classifying animals, and car models. The overall accuracy of the developed model is nearly 67%.

Keywords: Rice leaf disease detection, Deep learning, Convolutional Neural Network (CNN), Brown spot, Bacterial leaf blight.

I. INTRODUCTION

Agricultural plays an important role in our livelihood as it provides food and raw material. Plant disease is one of the challenges faced by farmers. Crop diseases are getting more severe and prevalent as global weather patterns shift as a result of climate change. As a result, technologies that can rapidly and readily evaluate crops and diagnose the illness must be developed in order to prevent future crop loss [1][2]. Rice is a staple cereal farmed mostly in Asia, Africa, and South America, but it is susceptible to a number of pests and diseases. However, the symptoms of plant diseases are varied with the type of plant. The diseases in the leaf differ due to changes in color, size, and shape. Every leaf disease has individual features and properties. The physical characteristics like changes in the color of leaves are used to identify several diseases affecting the crop. Brown spot is a fungus that attacks the leave's protective covering. As illustrated in Figure 1, the leaves have a number of little oval brown markings [3][4][8] The fungus attacks the seedling, which stops the seed germination, and seed mortality and reduces the quality of grain and its weight. This disease dries up the leaf and causes a yield loss of 50%.

Figure 1: Brown Spot

Bacterial blight generates a yellow color on the leaf, which later dries the leaf. This disease occurs mostly in rainfed areas. This disease is one of the most critical diseases in the rice field. The bacterial leaf blight can cause yield loss of around 70%[1][5][7]. The yellowish rashes are generated over the leaf, as shown in Figure 2.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10s
DOI: https://doi.org/10.17762/ijritcc.v11i10s.7687
***Article Received:** 07 June 2023 **Revised:** 28 July 2023 **Accepted:** 15 August 2023*

Figure 2: Bacterial blight

In the paper, the proposed model is written in Python on Jupiter Notebook and gives an accurate classification. The classifier was processed after the dataset was trained, and the output was predicted with the highest accuracy possible using Convolution Neural Networks.

II. METHOD

Recently, artificial intelligence is a widely recognized field of computer science for building smart machines that are capable of performing tasks that require humans. Learning based on artificial intelligence applications has achieved productive mechanisms. Machine learning techniques have good performance in image processing applications. This technique trains the system in a way that it learns automatically and improves the result with its own experiences. It has been observed many times that plant diseases are difficult to control as it varies according to environmental conditions. The Convolutional Neural Network (CNN) is a class of deep learning which is applied to analyze visual imagery [8][10][11]. A CNN takes in an input image, extracts important objects in the image, and classifies the difference.

After studying the literature survey, it is observed that there is a need to have a model that will detect rice leaf diseases. The CNN approach is a suitable tool object detection tool. Hence, Convolutional Neural Network can be used to detect rice leaf disease.

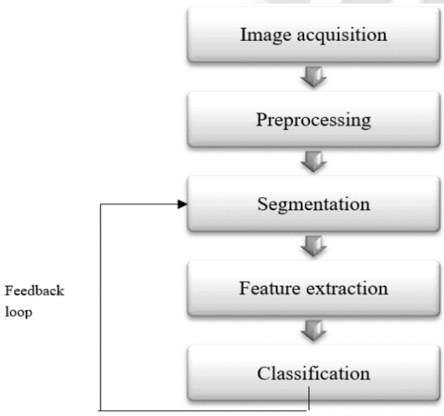

Figure 3: Flow Chart of the model

Image Acquisition: it is a process of collecting images used for this study. From the farm field to real-world conditions, rice crop leaf photo datasets were loaded from Kaggle.

Pre-processing: it is a memory reduction, and power input images in the database are enlarged and cut. At this stage, it is important to eliminate the background of the image using hue-based fusion.

Segmentation: the model utilizes selective search to extract a large quantity of objects proposal. The diseased part is collected from leaf images and grouped into brown spots and bacterial leaf blight.

Feature Extraction: this is a process of pulling the relevant features from input images. These features can be analyzed for classification. Color features include subtraction of used values and standard values. The R, G, and B components are extracted from the diseased portion of the leaf image. The mean and standard deviation is calculated by using the formula:

$$My = \frac{1}{n}\sum_{x=1}^{n} Pyx \quad (1)$$

$$Sy = \sqrt{\frac{1}{n}\sum_{x=1}^{n}(Pyx - My)^2} \quad (2)$$

where n represents the total number of pixels, and Pyx represents the pixel values.

Classification: the images based on color features and feature extraction values are classified into the diseases like brown spot and bacterial leaf blight. Hence, the model gives an accurate classification of the leaf disease.

The image dataset from the Kaggle was split into training and testing image sets. There are 608 images of the training set containing both brown spot and bacterial leaf blight disease and 109 images of the test set of both diseases. To prevent overfitting, the training images were modified by scaling and flipping them. Transfer Learning is a method for learning the features of the training images that involves removing the 'top' layers of a pre-trained model and replacing them with layers that can learn the characteristics particular to the training dataset.

One of CNN's most well-known applications is image recognition. It's used to categorize photos and recognize faces, patterns, and other visual information. Using TensorFlow, the convolutional neural network model is implemented on Anaconda's Jupiter Notebook. The notebook is used to code in Ruby and Python. Here, the programming language used is Python. The libraries imported were Keras, OpenCV, NumPy, and Matplotlib. The CNN is based on the assumption that data

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10s
DOI: https://doi.org/10.17762/ijritcc.v11i10s.7687
***Article Received:** 07 June 2023 **Revised:** 28 July 2023 **Accepted:** 15 August 2023*

is arranged in rows and columns. CNN works well on image data because images are a matrix of pixel data. Three channels contribute up a digital colour image: red, blue, and green. Each channel is a pixel intensity matrix ranging from 0 to 255, with 0 become the brightest and 255 become the darkest. Each pixel value represents the many shades of grey in a grayscale image, which has only one channel.

Flattening the matrix into a one-dimensional vector and presenting it to a fully connected neural network is one way to train the model to classify an image. The test image is scanned frame by frame in this approach, and the data from each frame is put into the network for prediction. This works well if the object is in a different location, but if the object is too large to fit in one window, a different window size must be used. If the filter size does not match the image, the image will not be recognized. One option is to scan the image with many filters of various sizes, but this would be computationally expensive. Because CNN's predictions are spatially invariant and irrespective of image size, it solves this constraint. The number of parameters necessary to train the network is likewise reduced.

The common operations performed on an image when it flows through a CNN network are striding, convolution, pooling, flattening, and feeding to a fully connected network. In this paper, building the CNN to identify if the leaf disease is the brown spot or bacterial leaf blight. In striding, the image breaks down to an overlapping frame using a sliding window. The window size is a hyperparameter that needs to be chosen. The window size here is a 3×3 filter matrix.

$$\begin{array}{|c|c|c|c|c|}\hline 1&0&0&1&1\\\hline 0&0&1&1&0\\\hline 1&1&1&0&1\\\hline 0&1&1&1&0\\\hline 0&0&1&1&1\\\hline\end{array} \times \begin{array}{|c|c|c|}\hline 1&1&0\\\hline 0&0&1\\\hline 1&1&1\\\hline\end{array}$$

Figure 4: Image Matrix Filter Matrix

In the convolution layer, the image data is passed from each frame into a smaller neural network, also known as a feature vector which performs a convolution operation. To keep the track of original frames, the result of each convolutional network is stored in a grid, preserving the same position as the original image.

The input to CNN is N-dimensional data. For digital images its dimension is

(number of rows ×number of columns ×number of channels) (3)

An additional dimension is added for input which represents the number of samples, so the final dimension would be

(number of samples × number of rows × number of columns × number of channels) (4)

That is represented as,

$$m \times nh \times nw \times nc \qquad (5)$$

Convolution in CNN is an element-wise multiplication between two matrices and adding all the elements of the resulting matrix to output scalar numbers.

$$\text{Output} = a1 \times w1 + a2 \times w2 + a3 \times w3 + (a4 \times w4 + a5 \times w5 + a6 \times w6) + (a7 \times w7 + a8 \times w8 + a9 \times w9) \qquad (6)$$

To preserve the size of image after convolution, zero padding is performed on images. For image dimension m × m × n and the output are convolved to be the same dimension of input, then two borders of zero are padded around the images symmetrically. For dimension f, the padding P = (f-1)/2 in order to preserve the dimension of the output image providing striding.

$$\text{Output dimension} = \left(\frac{w-f+2p}{s}+1\right) \times \left(\frac{h-f+2p}{s}+1\right) \times d \qquad (7)$$

Where w is width, h is height and d is depth.

Soon after convolution, the feature map is still large. To reduce the size of output, there is a technique called pooling. In pooling, the convolution extracts the most notable features from the image. Here, the pool size of 2×2 is convolved over the matrix, and the maximum value is selected. This is called Max Pooling, one type of pooling. Pooling reduces the input dimension but preserves the essential features. This makes the CNN especially invariant when classifying the images. Pooling prevents overfitting as it provides generalization by extracting only the notable features. If the input image has nh × nw × nc dimension, the output dimension after pooling will be

$$\left(\frac{nh-f}{s}+1\right) \times \left(\frac{nw-f}{s}+1\right) \times nc\ d \qquad (8)$$

As the images are successfully reduced to a fairly small array, the next step is to flatten. Flattening is resizing the array into one dimension to feed it to a fully connected neural network. The flattened array is a bunch of numbers that are readily fed to the fully connected network. The fully connected network is a densely connected layer; its function is to analyze the input features and combine them with different attributes. These attributes are activated in response to the input image.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10s
DOI: https://doi.org/10.17762/ijritcc.v11i10s.7687
***Article Received:** 07 June 2023 **Revised:** 28 July 2023 **Accepted:** 15 August 2023*

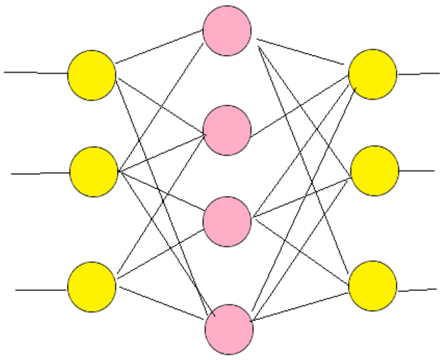

Figure 5: Fully Connected Network

III. RESULTS AND DISCUSSION

The paper is implemented using python programming with Jupyter platform. The image is classified into brown spot and bacterial leaf blight. After performing convolution, each element is of convolved output is activated by applying the activation function. ReLU activation is widely used in CNN. TensorFlow makes it easy for beginners and experts to create machine learning models for desktop, mobile, web, and cloud. The below figure is a summary of the convolution layers in TensorFlow.

LAYER (TYPE)	OUTPUT SHAPE	PARAM #
CONV2D_2 (CONV2D)	(None, 62,62,32)	896
MAX_POOLING2D_2 (MAXPOOLOING2)	(None,31,31,32)	0
FLATTEN_2 (FLATTEN)	(None, 30752)	0
DENSE_4 (DENSE)	(None,128)	3936384
DENSE_5 (DENSE)	(None,1)	129
TOTAL PARAMS:3,937,409		

Figure 6: Convolutional Layer Information

The model was then tested on the sample test images. The prediction for the image of bacterial blight disease was predicted as shown below. This is the shown in Jupyter Notebook with python programming.

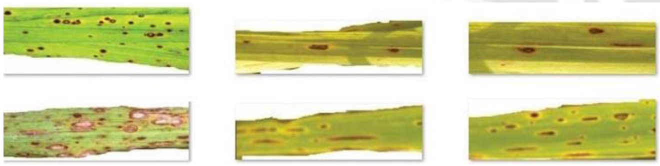

Figure 7: Result Image of Brown Spot

Similarly, the result for Bacterial Leaf Blight is predicted with output as shown. This is the shown in Jupyter Notebook with python programming.

Figure 8: Result Image of Bacterial Leaf Blight

Hence, the model classified the rice leaf as diseased with bacterial blight and brown spot, respectively. Thus, it was analyzed that the CNN model predicted and classified the images of diseased leaves successfully. This model can be further used to detect various leaf diseases in various crops. This work will be helpful to framers to recognize the disease by capturing the images of the leaf. Accuracy and cross-entropy can be used as parameters for evaluation [6][12].

The accuracy of the prediction is given as,

$$Accuracy = \frac{(\text{True Positive} + \text{True Negative})}{(\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative})} \quad (9)$$

Binary cross-entropy is often calculated as the average cross-entropy across all data examples. For cross-entropy, the loss is

$$\mathrm{L} = -\frac{1}{\mathrm{N}}\ \{\ \sum_{\mathrm{i}=1}^{\mathrm{N}} [\mathrm{ti}\log(\mathrm{pi}) + (1-\mathrm{ti})\log(1-\mathrm{pi})] \quad (10)$$

For N data points, where ti is the true vale taking value 0 or 1 and pi is the activation probability for i^{th} data point.

The image accuracy and loss obtained for each image are given in the table for both diseases.

Brown Spot images in .jpg	Accuracy	Loss	Bacterial Leaf Blight Images In .Jpg	Accuracy	Loss
DSC_0106	62.5	59.44	blight-_0_432	50.46	46.55
DSC_0109	70.31	58.58	blight-_0_546	63.96	51.56
DSC_0300	60.4	58.59	blight-_0_1602	79.84	49.22
DSC_0302	67.97	58.41	blight-_0_1905	79.23	50
DSC_0305	65.62	57.47	blight-_0_1988	72.45	45.31
spot-_0_14	70.31	54.55	blight-_0_2019	67.31	51.56
spot-_0_74	61.72	58.9	blight-_0_2094	72.66	64.33
spot-_0_93	67.97	54.25	blight-_0_2316	65.57	53.28
spot-_0_1063	65.62	60.09	blight-_0_2441	69.92	51.56
spot-_0_1206	66.41	55.66	blight-_0_2659	65.12	60.94
Average	65.883	57.594	Average	68.652	52.431

Table 1: Accuracy and loss of leaf images

The accuracy and loss model for the training set and test set for epoch = 10 is as follows.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10s
DOI: https://doi.org/10.17762/ijritcc.v11i10s.7687
***Article Received:** 07 June 2023 **Revised:** 28 July 2023 **Accepted:** 15 August 2023*

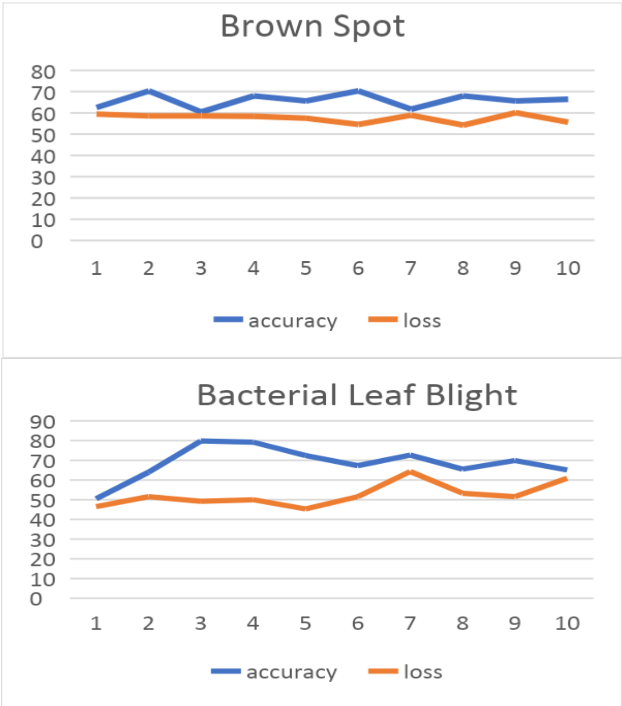

Figure 9: Accuracy and Loss mode

IV. CONCLUSION

The diseases like bacterial blight and brown spots found in rice leaves were studied. The convolutional neural network is a very good tool for image processing and classification. The dataset was obtained from Kaggle. The image of the leaf was captured and processed to the array of the pixel. The Anaconda Jupyter Notebook was used for coding in Python for creating the model. The CNN model was trained for these diseases. The trained model was tested to predict the result, that is, to classify if the image of the leaf is bacterial blight or brown spot disease. In Future Scope, this model can have better accuracy and less percent of loss parameter. The CNN model can be configured to classify the other types of image datasets, including other crops, human face, animals, and many more.

REFERENCES

[1] Hardikkumar S. Jayswal and Jitendra P. Chaudhari; Plant Leaf Disease Detection and Classification using Conventional Machine Learning and Deep Learning; International Journal on Emerging Technologies; 23 May 2020.

[2] Emma Harte; Plant Disease Detection using CNN; publication at: www.researchgate.net/publication/344155605 ; September 2020.

[3] Jayesh Kolhe, Guruprasad Deshpande, Gargi Patel, “Crop Decision using Various Machine Learning Classification Algorithms”, published in conference proceedings by Springer SIST. ISSN Number - 2190-3018, Smart Innovation, Systems and Technologies, 312, pp. 495–502, 2023.

[4] Anshul Dhingra; Multimodal Transfer Learning Outlook for Plants Disease Prognosis; publication at: https://www.researchgate.net/publication/348500780, January 2021.

[5] Dhabliya, P. D. . (2020). Multispectral Image Analysis Using Feature Extraction with Classification for Agricultural Crop Cultivation Based On 4G Wireless IOT Networks. Research Journal of Computer Systems and Engineering, 1(1), 01–05. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/10

[6] Alameady, M. H. ., George, L. E. ., & Albermany, S. . (2023). Energy Theft Detection with Determine Date Theft Period for State Grid Corporation of China Dataset. International Journal of Intelligent Systems and Applications in Engineering, 11(1s), 01–13. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2491

[7] Adnan Mushtaq Ali Karol, Drushti Gulhane, Tejal Chandiwade, Plant Disease Detection using CNN & Remedy; International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering; March, 2019.

[8] P. K., Rajani, Neha Motagi, Komal Nair, and Rupali Narayankar. "Autonomous Smart Device for COVID-19 Detection Using Artificial Intelligence." In Handbook of Research on Applied Intelligence for Health and Clinical Informatics., 128-147. Hershey, PA: IGI Global, 2022. http://doi:10.4018/978-1-7998-7709-7.ch008

[9] Ms. Madhuri Zambre. (2012). Performance Analysis of Positive Lift LUO Converter . International Journal of New Practices in Management and Engineering, 1(01), 09 - 14. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/3

[10] Aliyu M. Abdu, Musa M. Mokji, Usman U. Sheikh; Machine learning for plant disease detection: an investigative comparison between support vector machine and deep learning; IAES International Journal of Artificial Intelligence; Vol. 9, No. 4, December 2020.

[11] Manish Chandra, Saurav Roy; "Classification of Various Plant Diseases Using Deep Siamese Network", publication at: https://www.researchgate.net/publication/341322315 May 2020.

[12] Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk and Darko Stefanovic; Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification; Hindawi Publishing Corporation; 29 May 2016.

[13] Johnson, M., Williams, P., González, M., Hernandez, M., & Muñoz, S. Applying Machine Learning in Engineering Management: Challenges and Opportunities. Kuwait Journal of Machine Learning, 1(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/90

[14] D. Shen, G. Wu, H. Suk., "Deep learning in medical image analysis". Annual Revised Biomedical Engineering 19, page 221–248, 2017.

[15] Sharada Prasanna Mohanty, David Hughes and Marcel Salathé; Using Deep Learning for Image-Based Plant Disease Detection; April 15, 2016.

[16] Mondal , D. (2021). Green Channel Roi Estimation in The Ovarian Diseases Classification with The Machine Learning Model . Machine Learning Applications in Engineering Education and Management, 1(1), 07–12.

[17] Nair, K., Motagi, N., Narayankar, R., Rajani, P.K.," Error Detection and Error Concealment of Medical Images Using Frequency Selective Extrapolation (FSE) Algorithm, in 6th International Conference on Information and Communication Technology for Competitive Strategies (ICTCS 2021) held at Jaipur, Rajasthan during 17th -18th December 2021.