IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Deep Learning Based Tobaco Leaf Disease Detection

Ms. B.Anitha (M.C.A). Rajeev Gandhi Memorial college Of Engineering and Technology, Nandyal

*Mr. P. Murthuja (Ph.D). Rajeev Gandhi Memorial college Of Engineering and Technology, Nandyal

Abstract

Only after the initial fermenting phase were some of the tobacco leaf insect bites visible. Pest attacks on tobacco leaves cause the quality to decrease. To preserve quality, it is necessary to separate diseased and pest-affected leaves from healthy leaves. Typically, sorting is done by hand, which leaves room for human error. In this work, we attempted to automatically classify the leaves impacted by various pest infestations. One of the most recent classification techniques suggested in this paper makes use of the well-known VGG19 architecture: the convolutional neural network (CNN). If trained with random weight initialization, VGG19 training can take a while. To increase accuracy and shorten training time, we chose beginning weights using transfer learning. Considering the outcomes, We achieved a very good accuracy by training with a single class of the disease using VGG19 and transfer learning. To achieve the best outcomes, some scenarios are examined depending on a combination of the number of learnable parameters and types of the optimizer. As a result, it was established that the suggested architecture can accurately identify all training and validation data.

KEYWORDS: Tobacco Leaf Pest, VGG19, Transfer Learning.

1. INTRODUCTION

1.1 Introduction

Only after the initial fermenting phase were some of the tobacco leaf insect bites visible. Pest attacks on tobacco leaves cause the quality to decrease. To preserve quality, it is necessary to separate diseased and pest-affected leaves from healthy leaves. Typically, sorting is done by hand, which leaves room for human error. In this work, we attempted to automatically classify the leaves impacted by various pest infestations. One of the most recent classification techniques suggested in this paper makes use of the well-known VGG19 architecture: the convolutional neural network (CNN). If trained with random weight initialization, VGG19 training can take a while. To increase accuracy and shorten training time, we chose beginning weights using transfer learning. Considering the outcomes The Convolutional Neural Network (CNN) is suggested in this study as a way to sort or categorize the presence of different pests on tobacco leaves. The most recent categorization technique in the area of computer vision based artificial intelligence is CNN. CNN has shown to be more effective than the previous standard classification approach. To classify data, CNN has been utilized in a lot of studies. For some forms of attacks, like Glassy, the contrast between healthy areas and those infested by the pest is also not particularly noticeable. As a result, it is challenging to extract crucial characteristics, and when conventional feature extraction is used, the resulting features frequently overlap. The hidden network's features can be automatically extracted by CNN using raw image input data. One of CNN's benefits is that it is challenging to accomplish via the old conventional way. As a result, this study suggests using CNN to deliver the best categorization outcomes.

CNN's architecture has expanded quickly in the last year. The well-known one is VGG19. Despite having a straightforward layer design, VGG19 outperforms Alexne and ZF-Net in terms of accuracy on the ImageNet dataset. The dataset used in this investigation for tobacco leaves is substantially smaller than the ImageNet dataset. VGG169was selected for this investigation since it was examined and shown to be extremely competent at classifying a dataset of tobacco leaves. italicized at random. CNN acknowledges that transfer learning can shorten training periods. Transfer learning initializes the weights of numerous layers on the new architecture using weights from the prior training. Several layers in the new architecture are identical to those in the previous architecture in order to accommodate the new dataset.

2. Literature Survey

[1] A. Ferreira and G. Giraldi, "Convolutional Neural Network approaches to granite tiles classification," Expert Syst. Appl., vol. 84, pp. 1-11, 2017:, The procedure of quality control in the stone industry is a difficult issue to solve nowadays. Due to the similar visual appearance of several rocks with the same mineralogical content, industry losses might occur if customers are unable to correctly identify the supplied rocks as the ones they originally purchased. In this article, we propose the first data-driven method used to categorize granite tiles in order to move toward the automation of rock-quality assessment in various picture resolutions. Convolutional neural networks that are specifically designed for this issue are used in our method to comprehend intrinsic patterns in small image patches. The effectiveness of the suggested method and its feasibility for applications in various uncontrolled settings, such categorizing images, are demonstrated by experiments comparing it to texture descriptors in a well-known dataset..

[2] S. Ruder, "An overview of gradient descent optimization algorithms, " arXiv:1609.04747v2 [cs.LG] 15 Jun 2017, 2017: Although they are becoming more and more common, gradient descent optimization algorithms are frequently utilized as "black-box" optimizers since it is difficult to find concrete justifications for their advantages and disadvantages. The purpose of this article is to give the reader intuitions about how various algorithms behave so that she can use them. Throughout this overview, we examine various gradient descent variations, list problems, introduce the most popular optimization algorithms, analyze parallel and distributed architectures, and look into further gradient descent optimization techniques..

D.P. Kingma and J.L. Ba, "Adam: A method for stochasti c optimization," arXiv:1412.6980v9 [cs.LG] 30 Jan 2017, 2017

We introduce Adam, a technique for optimizing stochastic objective functions using first-order gradients that is based on adaptive estimations of lower-order moments. The method is simple to use, computationally effective, requires little memory, is invariant to diagonal rescaling of the gradients, and works well for issues with a lot of parameters or data. The approach is also suitable for non-stationary goals and issues with extremely noisy and/or sparse gradients. The hyper-parameters may usually be tuned to a reasonable degree and have intuitive interpretations. Adam was inspired by some connections to related algorithms, which are explained. Additionally, we examine the algorithm's theoretical convergence characteristics and offer a regret bound on the convergence rate that is equivalent to the most well-known outcomes under the online convex optimization.

3. OVERVIEW OF THESYSTEM

3.1 Existing System

With the current techniques, it is quite challenging for farmers to manually and reliably diagnose numerous diseases given their minimal training. Deep learning techniques can be used to get around this challenge.

3.1.1 Disadvantages of Existing System

It takes less time to identify and detect the disease.

Results are accurate.

Easy to handle.

3.2 Proposed System

In the system under consideration, we suggest a Deep Learning technique using a transfer learning model based on VGG19 that automatically recognizes photos using Convolution Neural Network (CNN) models can be very helpful in such issues. These methods make it simple to find and recognize diseases.

3.3 Methodology

In this project work, I used five modules and each module has own functions, such as:

1. System Module
2. User Module

3.3.1 Dataset Collection:

The dataset containing images of the desired objects to be recognize is split into training and testing dataset with the test size of 20-30%.

3.3.2 Preprocessing:

Resizing and reshaping the images into appropriate format to train our model.

.

3.3.3 *Training:*

Use the pre-processed training dataset is used to train our VGG19 model using CNN algorithm.

3.3.4 Classification

The results of our model is display of X-ray images are either with pneumonia or normal.

3.3.5 User Module

Register

The user needs to register and the data stored in MySQL database.

Login

A registered user can login using the valid credentials to the website to use a application.

About-Project

In this application, we have successfully created an application which takes to classify the images.

Upload Image

The user has to upload an image which needs to be classify the images.

Prediction

The results of our model is displayed as either Healthy or Green Spot.

Logout

Once the prediction is over, the user can logout of the application.

.

4 Architecture

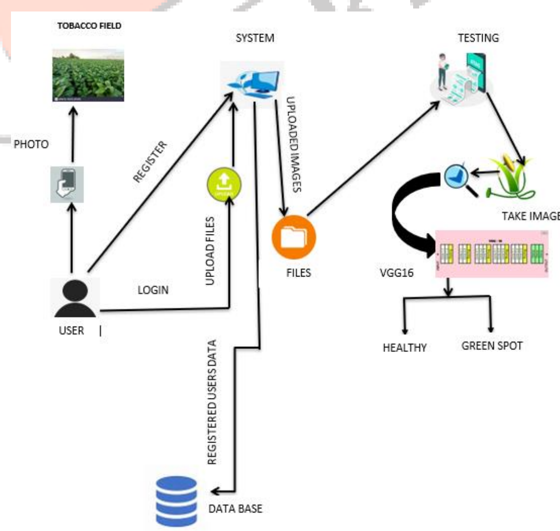

Fig 1: Frame work of proposed method

5 RESULTS SCREEN SHOTS

Home Page:

Upload image:

Choose options:

Predict Result:

7. CONCLUSION

✓ In subsequent studies, we'll attempt to apply CNN on entire leaves rather than just sub-images. Using CNN object detection, it is very likely. CNN object detection is anticipated to be able to simultaneously detect the existence of pest diseases and pinpoint their location. To segment the boundaries of pest diseases and determine their area, CNN semantic image segmentation may also be used. The CNN architecture can use the most recent, most sophisticated architectures or the appropriate bespoke design.

Future Enhancement

- ✓ The sorts of pest attacks were successfully and highly accurately classified using the suggested method utilizing transfer learning VGG19
- ✓ architecture. Accuracy, precision, specificity, and sensitivity performance can all be improved by adding more learnable characteristics. With a few or many learnable parameters for the dataset on tobacco leaf pest, Adam optimizer was able to demonstrate superior performance to SGD.

8. References

[I] T. Youwen, L. Tianlai, and N. Yan, "The recognition of cucumber disease based on image processing and Support Vector Machine," Proc. - 1st Int. Congr. Image Signal Process. CISP 2008, vol. 2, pp. 262-267,2008.

[2] S. Weizheng, W. Yachun, C. zhanliang, and W. Hongda, "Grading method of leafspot disease based on image processing," Proc. - Int. Conf. Comput. Sci. Softw. Eng.CSSE 2008,vol.6,pp. 491-494,2008.

[3] A.Ferreira and G.Giraldi, "ConvolutionalNeural Networkapproaches to granite tiles classification," Expert Syst. Appl., vol. 84, pp. 1-11, 2017.

[4] Y. Lu, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, "Identification of rice diseases using deep convolutional neural networks,"Neurocomputing, vol. 267, pp.378-384,2017.

[5] M. Dyrmann, H. Karstoft, and H.S. Midtiby, "Plant species classification using deep convolutionalneural network,"Biosyst. Eng., vol. 151,no.2005,pp.72-80,2016.

[6] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 1-14. doi:l0.l016/j.infsof.2008.09.005,2014.

[7] A. Krizhevsky,I. Sutskever, and G.E.Hinton, "Imagenetclassification with deep convolutional neural networks," Adv. Neur. Inf . Process. Syst. 1097Cl105,2012.

[8] M. D. Zeiler and R. Fergus, "Visualizing and understanding convolutional networks," in: European Conference on Computer Vision, Springer, pp. 818-833,2014.

[9] S. Ruder, "An overview of gradient descent optimization algorithms," arXiv:1609.04747v2 [cs.LG] 15Jun 2017, 2017

[10] D.P. Kingma and J.L. Ba, "Adam: A method for stochastic optimization," arXiv:1412.6980v9 [cs.LG] 30 Jan 2017, 2017.

.