Applied GIS

ISSN: 1832-5505

Vol-11 Issue-04 Oct 2023

PREDICTING THE RICE LEAF DISEASES USING CNN

B.HARITHA LAKSHMI[1], Y.CHAITHANYA2, SHREYA SAMALA3, R.RUCHITHA4, P.BHAVANI5

[1]Assistant Professor, Department of Information Technology, Malla Reddy Engineering College for Women (UGC-Autonomous), Maisammaguda, Hyderabad, TS, India.

[2,3,4,5] UG Students, Department of Information Technology, Malla Reddy Engineering College for Women (UGC-Autonomous), Maisammaguda, Hyderabad, TS, India.

ABSTRACT:

A variety of diseases attack rice, one of India's most widely planted crops, at various phases in the growing process. It is exceedingly difficult for farmers with poor understanding to identify these diseases manually. Automated picture identification systems based on Convolutional Neural Network (CNN) models are showing considerable promise in deep learning research recently. Our deep learning model was created using Transfer Learning on a small dataset because it was difficult to find an image dataset of rice leaf disease. VGG-16 is utilized to train and assess the proposed CNN architecture, which is based on rice field and internet datasets. The proposed model has a 95 percent accuracy rate. Deep Learning, Convolutional Neural Network (CNN), fine-tuning and rice leaf diseases are some of the terms in this index.

Keywords: CNN, VGG. SVM, ANN.

1. INTRODUCTION:

In India and around the world, rice is the primary source of nutrition. Throughout the course of its development, it is plagued by a wide range of ailments. A high-quality crop depends on early diagnosis and treatment of these diseases, but this is challenging due to the enormous tracts of land controlled by individual farmers, the great variety of diseases they carry, and the likelihood of many diseases in a single crop. It's tough and time-consuming to locate agricultural experts in remote areas. As a result, Automated Systems are required. To help farmers in need and improve the precision with which plant illnesses can be identified, artificial neural networks (ANNs) and support vector machines (SVMs) have been utilised in studies. But the accuracy of these

ISSN: 1832-5505
Vol-11 Issue-04 Oct 2023

systems depends greatly on the features that are selected. Images may now be recognised using convolutional neural networks, which eliminates the requirement for picture preprocessing and provides built-in feature selection. Another issue is that huge datasets for these kinds of challenges are extremely difficult to come by. In situations where the dataset size is relatively small, it is preferable to use a model that has been trained on a large dataset. When developing a new model using Transfer Learning, it is possible to delete the final layer of connections or to fine tune the final layers to be more specific to the dataset under consideration. Farmers can send photographs of infected leaves taken using their smartphones to our server, where our neural network will identify the illness and return to the farmers with a diagnosis and treatment recommendations. This notion came to us as a result of the widespread availability of cell phones. A disease classification component for an automated system is presented in this paper. Convolutional neural network work has helped us build a deep learning technique in this work... Transfer Learning has been utilised to fine-tune the fully connected layers so that we can fit our own datasets into the VGG-16 model's fully connected layers. At the end, we looked at our mistakes and tried to figure out why they happened.

2. LITERATURE SURVEY

2.1 Using Deep Learning for Image-Based Plant Disease Detection

AUTHORS: V. Singh, A. Misra

ABSTRACT: Lack of infrastructure makes it difficult to detect agricultural diseases rapidly, despite their considerable threat to global food security. Because of the extensive usage of smartphones around the world and recent improvements in computer vision made possible by deep learning, disease diagnosis by smartphone is becoming a reality. We train a convolutional neural network to recognise 14 crop species and 26 illnesses from a publically available dataset using 54,306 pictures of damaged and healthy plant leaves (or absence thereof). Using a held-out test set, the trained model achieves an accuracy of 99.35%, demonstrating the validity of the approach. Using a set of shots that were not taken in the same conditions as those used for training, the model's accuracy is just 31.4 percent The total accuracy can still be improved by using a more diversified set of training data, though. For crop disease diagnosis on a global scale, training deep learning models on increasingly large and publically available image datasets provides a clear path.

2.2SVM classifier based grape leaf disease detection

AUTHORS: P. B. Padol and A. A. Yadav

ABSTRACT: Grapes are one of India's most popular fruit crops. Grape yields fall as a result of disease infections on the fruit, stems, and leaves. Toxins from bacteria, fungus or virus are the most common causes. There are many factors that limit the amount of fruit that can be produced, including illness. It's impossible to implement effective control measures without an accurate diagnosis of the disease. For the identification and categorization of plant leaf diseases, image processing is a commonly employed technique. SVM classification is used in this work to aid in the detection and categorization of grape leaf diseases. Segmentation by K-means clustering is used to locate the sick area, and then colour and texture features are extracted. Leaf disease can finally be identified using a classification system. Accuracy in the suggested approach is 88.89 percent for the condition being studied.

2.3 Very Deep Convolutional Networks for LargeScale Image Recognition

AUTHORS: Karen Simonyan, Andrew Zisserman

ABSTRACT: Using a large-scale image identification task, we investigate how a convolutional network's depth influences its performance. Using an architecture with extremely small (3x3) convolution filters, we examined networks of increasing depth and found that raising the depth to 16-19 weight layers significantly improved performance over prior-art setups. This is the main contribution of our study. As a result of these discoveries, our team was able to take first and second place in the 2014 ImageNet Challenge in the categories of localization and classification. A wide range of datasets can benefit from our representations' state-of-the-art results. Two of our finest ConvNet models have been provided so that further research into deep visual representations in computer vision can take place.

2.4Hyper-class augmented and regularized deep learning for fine-grained image classification

AUTHORS: S. Xie, T. Yang, X. Wang, and Y. Lin

ABSTRACT: Deep convolutional neural networks have shown significant success in large-scale object recognition (CNNs). Due to the high cost of fine-grained labelled data (usually necessitating domain expertise), as well

ISSN: 1832-5505
Vol-11 Issue-04 Oct 2023

as the huge intra-class and moderate inter-class variance, fine-grained image classification (FGIC) is significantly more challenging than generic object identification. Using an external dataset (like ImageNet) to pre-train the CNN and then fine-tuning it on the small target data to meet a specific classification goal is one of the most prevalent ways. Two new aspects of the problem of learning a deep CNN are introduced in this paper: identifying easily annotated hyper-classes inherent in the fine-grained data and collecting numerous images with hyper-classes labelled from readily available external sources (such as image search engines), formulating the problem as multitask learning; and (iii) a novel learning modality, which is based on the idea of a "multitask learning" paradigm. Two small, fine-grained datasets (Stanford Dogs and Stanford Cars) as well as a big, automotive-specific dataset have all been used to evaluate the proposed approach.

EXICITING SYSTEM:

In the past, the only way to identify a disease was to manually examine the leaf. The illness was discovered using a combination of visual inspection of plant leaves and consulting a reference book. This method has three key drawbacks: limited accuracy, the inability to analyse every leaf, and a lengthy time investment. As science and technology progress, new methods for accurately diagnosing these diseases emerge. Image processing and deep learning are two methods to consider. Filtering, clustering and histogram analysis are some of the approaches used in image processing to identify the diseased area. Deep learning neural networks, on the other hand, are used to detect disorders.

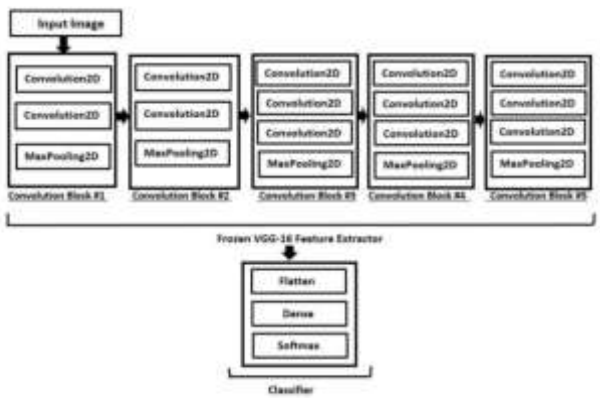
PROPOSED SYSTEM:

A VGG16 transfer learning neural network is used in this paper to train a dataset of rice diseases, and the trained model may be used to predict disease from new photos. Because the Rice Leaf dataset from KAGGLE was too tiny for author to train the VGG16 model, he turned to the transfer learning CNN algorithm, which transfers an existing CNN model to a new dataset and then uses the new data to train the model.

It has been shown that VGG16 transfer learning improves prediction accuracy in both a normal CNN model and a normal CNN model with VGG16 transfer learning.

Applied GIS

ISSN: 1832-5505
Vol-11 Issue-04 Oct 2023



3. METHODOLOGY

MODULES:

A. Experimental Setup

A 64-bit Windows 10 PC was used in the experiment. The CNN model was built with Keras 2.2.4 deep learning framework, Tensor Flow 1.14.0 backend, and Python 3.7.2.

B. Processing of images.

In addition to being taken in the field, all of the images were taken online. The dataset description includes images of leaf blast, leaf blight, brown spot, and healthy plants. Image Enhancement and Retouching As a result of applying various enhancement techniques such as zoom, rotation, and horizontal and vertical shift to the collected photos with Image Data Generator in Keras, new images are generated at 224*224 pixel resolution.

C. CNN's Modeling School

The picture data set must be loaded in order to do training and testing. Class labels and images are kept in distinct arrays for training reasons. Due to the train-test split technique, training consumes 70% of the data, while testing consumes 30%. 30% of the data is utilized for validation and 70% of it is divided up again after that. The class labels are encoded as integers using a one-hot encoding procedure, and each label is represented as a vector rather than an integer. Finally, the final fully linked layers are erased from Keras. Additions to the system that cannot be trained are made. To finish, we applied a softmax filter to the feature extractor's flattened output before applying the softmax filter. Our model was designed from the ground up using the Adam optimizer with categorical cross entropy as the loss function for classification. Since the results remained stable after 25 epochs, we've stopped here. Figure 3 depicts the classification procedure steps that we've taken.

In support of the selected model, provide justification

What we call "transfer learning" is the process through which what we learn in one setting can be applied to a different one. Due to the fact that most real-world situations don't contain millions

ISSN: 1832-5505
Vol-11 Issue-04 Oct 2023

of labeled data points, transfer learning is extremely beneficial in training neural network models. In order to train a neural network from scratch, a large amount of data is required, however this data is not always available. Because the model has already been pre-trained, it is possible to build a robust machine learning model using only a small amount of training data. A VGG Net that has been pre-trained on our little dataset was utilized instead.

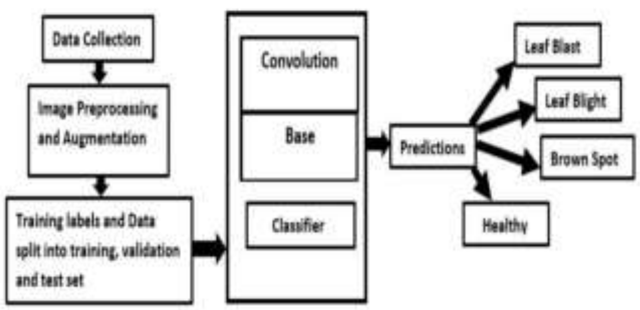


Fig. Overview of the steps of the proposed model

OPERATION:

To run project install python 3.7 and tensorflow package 1.14.0 and then install Django==2.1.7

After installation run below command from 'RiceDisease' folder

Python manage.py runserver

Then open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below screen

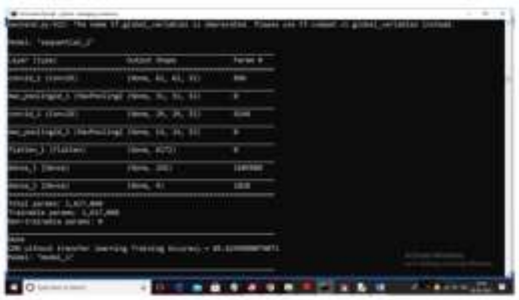
In above screen click on 'Login' link to get below login screen

In above screen enter username as 'admin' and password as 'admin' and then click on 'Login' button to get below screen

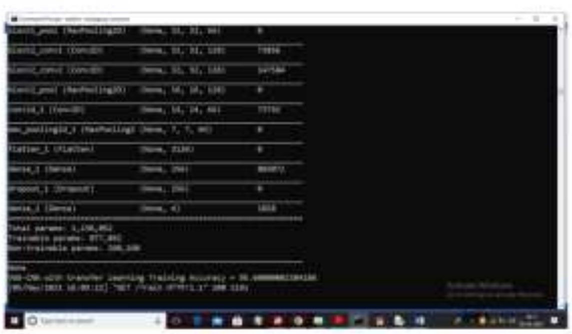
In above screen click on 'Train CNN Algorithms' link to train both VGG16 and normal CNN without transfer learning on rice dataset and then calculate prediction accuracy

ISSN: 1832-5505
Vol-11 Issue-04 Oct 2023

In above screen CNN with transfer learning VGG16 got 95% accuracy and without transfer learning got 85% accuracy so VGG16 is giving better result. In below console you can see layer details of VGG 16 and Normal CNN



In above screen normal CNN created 4 layers and got 85% accuracy and in below screen you can see VGG16 layers



In above screen VGG16 contains so many layers and its accuracy is 95% and now in below screen click on 'Upload Rice Image' link

Now in above screen click on 'Choose File' button to upload leaf test image from 'testImages' folder

In above screen selecting and uploading '6.jpg' file and then click on 'Open' button then click on 'Submit' button to get below result

In above screen in uploaded image disease predicted as 'Leaf Blast' and now test other image

In above screen leaf predicted as healthy and similarly you can upload other images and test them

CONCLUSION

In this research, we present a deep learning architecture that classifies 95% of the test photos correctly after training on 40 photographs of rice leaves and then testing on another 20 images. As a result of fine-tuning the VGG16 model, we were able to significantly increase the model's performance on such a short dataset. We capped the number of epochs employed at 20 after receiving data showing no improvement in accuracy or decrease in loss on either the training or validation sets.

In the future:

More photos from agricultural areas and agricultural research organizations are needed in the future to further increase the accuracy of our results. In the future, we want to include a cross-validation mechanism to further verify our findings. It would also be beneficial if we could compare the findings achieved with those of more advanced deep learning models and other current efforts in progress. Other plant leaf diseases, which are significant crops in India, can be detected using the model described here.

REFERANCES

1. T. Gupta, ”Plant leaf disease analysis using image processing technique with modified SVM-CS classifier,” Int. J. Eng. Manag. Technol, no. 5, pp. 11-17, 2017.

2. Y. Es-saady,T. El Massi,M. El Yassa,D. Mammass, and A. Benazoun, ”Automatic recognition of plant leaves diseases based on serial combination of two SVM classifiers,” International Conference on Electrical and Information Technologies (ICEIT) pp. 561-566, 2016.

3.P. B. Padol and A. A. Yadav, “SVM classifier based grape leaf disease detection,” Conference on Advances in Signal Processing (CASP), pp. 175-179, 2016.

4. L. Liu and G. Zhou, “Extraction of the rice leaf disease image based on BP neural network,” International Conference on Computational Intelligence and Software Engineering ,pp. 1-3,2009.

5.S. Arivazhagan and S.V. Ligi, “Mango Leaf Diseases Identification Using Convolutional Neural Network,” International Journal of Pure and Applied Mathematics, vol. 120,no. 6, pp. 11067-11079,2008.

6.B. Liu,Y. Zhang, D. He and Y. Li, “Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks Symmetry,” X. X. &Suen, C. Y. A novel hybrid CNN–SVM classifier for recognizing handwritten digits. Pattern Recognition,vol. 45,pp. 1318–1325,2012.

7.Y. Lu, S. Yi,N. Zeng,Y. Liu, and Y. Zhang, “Identification of Rice Diseases Using Deep Convolutional Neural Networks,” Neurocomputing, 267, pp. 378-384,2017.

8.R. R. Atole, D. Park, “A Multiclass Deep Convolutional Neural Network Classifier for Detection of Common Rice Plant Anomalies,” International Journal Of Advanced Computer Science And Applications,vol. 9,no. 1,pp. 67–70,2018.

9.V. Singh, A. Misra, “Detection of Plant Leaf Diseases Using Image Segmentation and Soft Computing Techniques,” Information Processing in Agriculture,vol. 4 ,no. 1,pp. 41–49,2017.

10. P. Konstantinos Ferentinos, “Deep Learning Models for Plant Disease Detection and Diagnosis,” Computers and Electronics in Agriculture ,vol. 145,pp. 311–318,2018.