Analysis on Various Plant Disease Identification Deep Learning Techniques - A Survey

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DOI:- https://doi.org/10.47531/SC.2022.21

Abstract

Plant Identification of the plant ailments is the key to stopping the losses in the yield and extent of the agricultural product. The research of the plant ailments implies the research of visually observable patterns viewed on the plant. Health monitoring and ailment detection on the plant is very imperative for sustainable agriculture. It is very hard to screen the plant illnesses manually. It requires a first-rate quantity of work, expertise in plant diseases and additionally requires immoderate processing time. Hence, image processing is used for the detection of plant diseases. Plant Disease Identification includes photo acquisition, picture pre-processing, picture segmentation, characteristic extraction and classification. In our proposed work, AlexNet, which is used as a feature extractor, plays a very crucial role in helping to classify plant diseases. We have proposed an image-processing based technique to identify plant diseases. This method takes an image of the affected plant disease as input. It will extract the key features using filters, and extracted features are then compared with the trained model (contains datasets of sample images) to detect the type of plant disease. Our Proposed work is simple, quick, and does not require any costly equipment.

Keywords: - *Image Processing, AlexNet, Skin diseases, Feature Extraction*

INTRODUCTION

Modern applied sciences have given human society the capability to produce sufficient food to meet the demand of greater than 7 billion people. However, meals safety stays threatened by way of several elements, which include local weather changes. Plant illnesses are no longer solely a hazard to meals protection on the world scale. However, they can additionally have disastrous penalties for smallholder farmers whose livelihoods rely on healthy crops. In the growing world, more than eighty per cent of the agricultural manufacturing is generated by using smallholder farmers[1].

Various efforts have been developed to forestall crop loss due to diseases. Historical processes of the huge utility of pesticides have increasingly been supplemented by built-in pest administration

(IPM) approaches in the previous decade. Identifying an ailment successfully when it first seems is an integral step for environment-friendly disorder management. Historically, disorder identification has been supported by agricultural extension agencies or different institutions, such as neighbourhood plant clinics. In greater current times, such efforts have moreover been supported by presenting records for ailment analysis online, leveraging the growing Internet penetration worldwide. Even extra recently, equipment is primarily based on cellular.

Telephones have increased, benefiting from the traditionally unparalleled fast uptake of cell cellphone technological know-how in all components of the world [2].

Smartphones in specific provide very novel procedures to assist in discovering ailments due to their computing power, high-resolution displays, and massive built-in units of accessories, such as superior HD cameras. It is broadly estimated that there were between 5 and 6 billion smartphones on the globe in 2020. At the cease of 2015, 69% of the world's populace had to get entry to cell broadband coverage, and cell broadband penetration reached47%in2015. The blended elements of large smartphone penetration, HD cameras, and excessive overall performance processors in cell gadgets lead to a state of affairs. The place disorder analysis based totally on computerised photograph recognition, if technically feasible, can be made on hand at an unheard of scale. Here, we show the technical feasibility of using a deep gaining knowledge of method utilising 54,306 pictures of 14 crop species with 26 illnesses (or healthy) made overtly accessible via the assignment Plant Village[3]. These days, deep neural networks have been correctly utilised in various domains as examples of stop to stop learning. Neural networks provide a mapping between an input—such as a photo of a diseased plant—to output— such as a crop ailment pair. The nodes in a neural community are mathematical features that take numerical inputs from the incoming edges and grant a numerical output as an outgoing edge. Deep neural networks are indeed mapping the enter layer to the output layer over a sequence of stacked layers of nodes. The project is to create a deep community so that each the shape of the community as correctly as the features (nodes) and aspect weights efficiently map the entrance to the output. Deep neural networks are skilled by tuning the community parameters so that the mapping improves at some point in the coaching process. This technique is computationally tricky and has, in the latest instances, been accelerated dramatically via a wide variety of conceptual and engineering breakthroughs.

To address the issues caused by limited access to agricultural specialists, especially in developing countries, considerable research has focused on developing automated image analysis systems that can detect plant diseases based on images. This work applies machine learning classifiers to use a portion of the images from the dataset for training and the rest of the images, which were not used in training, to classify the skin diseases. Depending on the features, the classification is performed using AlexNet classifier.

OBJECTIVES AND SCOPE OF THE STUDY

The objective of our project is to use the modern technology of machine learning and deep learning to identify Plant Disease. Using the technology, we can increase the accuracy for identifying Plant Disease.

So our focal point will be strategies that can assist us in higher apprehend the educated fashions to keep away from the black field impact and ensure the reliability of the acquired results.

The system can help for practising plant disease. Plant disease can be done in a better way, with more accuracy, and with more safety. In the future, we can upgrade it to identify more plant diseases.

RELATED WORK

In this research paper, they propose using a deep convolutional neural network (CNN) for plant identification from leaf vein patterns. In particular, they consider classifying three different legume species: white bean, red bean, and soybean. The introduction of a CNN avoids using handcrafted feature extractors as in a state of the art pipeline. Furthermore, this deep learning approach significantly improves the accuracy of the referred pipeline. They also show that this accuracy is reached by increasing the depth of the model. Finally, by analysing the resulting models with a simple visualisation technique, they can discover which vein patterns are relevant [1].

In this research paper, they have used deep convolutional neural networks to identify the plant species captured in a photograph and evaluate different factors affecting the performance of these networks. Three powerful and popular deep learning architectures, namely GoogLeNet, AlexNet, and VGGNet, are used for this purpose. Transfer learning is used to fine-tune the pre-trained models using the plant task datasets of Life CLEF 2015. Their best-combined system has achieved an overall accuracy of 80% on the validation set and an overall inverse rank score of 0.752 on the official test set. A comparison of their results against the results of the LifeCLEF 2015 plant identification campaign shows that they have improved the overall validation accuracy of the top system by 15% points and its overall inverse rank score on the test set by 0.1 while outperforming the top three competition participants in all categories[2].

In this research paper, they have proposed using two methods for the problem of plant species identification from leaf patterns. Firstly, they use a traditional recognition shallow architecture with extracted features histogram of oriented gradients (HOG) vector, then those features used to classifying by SVM algorithm. Secondly, they apply a deep convolutional neural network (CNN) for recognition purposes. They experimented on leaves data set in the Flavia leaf dataset and the Swedish leaf dataset. They want to compare a traditional method and a method considered as current state-of-the-art. And get finally, a result showing that the CNN-based neural network depth model, which they propose, works very well on the classification problem of leaves based on the shape of veins [3].

This research paper studies convolutional neural networks (CNN) to learn unsupervised feature representations for 44 different plant species. To gain intuition on the chosen features from the CNN model, a visualisation technique based on the deconvolutional networks (DN) is utilised. It is found that venations of different orders have been chosen to uniquely represent each plant species. The experimental results justified that learning the features through CNN can provide better feature representation for leaf images than handcrafted features. Moreover, they demonstrated that venation structure is an important feature to identify different plant species with a performance of 99.6%, outperforming conventional solutions [4].

In this research paper, the purpose of the study is to develop an efficient baseline automated system, using image processing with a pattern recognition approach, to identify three species of Ficus, which have similar leaf morphology. Artificial neural network (ANN) and support vector machine (SVM) was then implemented, recognition models. Evaluation results showed the ability of the proposed system to recognise leaf images with an accuracy of 83.3%. However, the ANN model performed slightly better using the AUC evaluation criteria. The system developed in the current study can classify the selected Ficus species with acceptable accuracy [5]

Deep Learning for plant identification using vein morphological patterns proposes using a deep convolutional neural network (CNN) for the problem of plant identification from leaf vein patterns. In particular, they consider classifying three different legume species: white bean, red bean, and soybean. The introduction of a CNN avoids using handcrafted feature extractors as in a state of the art pipeline.

Furthermore, this deep learning approach significantly improves the accuracy of the referred pipeline. The approach also shows that this accuracy is reached by increasing the depth of the model. Finally, by analysing the resulting models with a simple visualisation technique, they can discover which vein patterns are relevant[6].

This research paper has an approach that can help control the growth of diseases on Plants using pesticides in the required quantity so that excessive pesticides can be avoided. Automatic identification of plant diseases is an important task. It may prove beneficial for farmers to monitor large plants and identify the disease using a machine learning approach [7].

In this research paper, they have proposed to provide an automated and reliable economic solution for nutrient deficiency identification. The dataset for deficient leaves and healthy leaves are created using an image processing approach for RGB colour feature extraction, real-time texture detection, edge detection, etc. This created dataset will be given to supervised machine learning as a training dataset for further detection and identification of exact nutrient deficiency and healthy plants to take preventive measures to maximise the yield [8].

In this paper, they propose to use the concept of plant electrodes to automatically identify whether different environmental cues cause specific changes in the electrical signals of soybean plants. They considered using machine learning algorithms and arithmetic intervals to verify such a hypothesis, a branch of mathematical tools that allows one to extend standard numbers to an interval representation [9].

To make an easy and reliable plant identification tool, it will require collecting a huge amount of data about thousands of species. So it will most likely require collaborative efforts of analysts in this field interested in the proposed identification strategy as it was with many databases for recognition/identification algorithms. They also show that this accuracy is reached by increasing the depth of the model, finally, by analysing the resulting models with a simple visualisation technique [10].

As machine learning technology advances, sophisticated models have been proposed for automatic plant identification. With the popularity of smartphones and the emergence of Plant- Net mobile apps, millions of plant photos have been acquired. Mobile-based automatic plant identification is essential to real-world social-based ecological surveillance, invasive exotic plant monitor, ecological science popularisation, and improving the performance of mobile-based plant identification models attracts increased attention from scholars [11].

To test this hypothesis, quantifications of various Abiotic soil characteristics and the taxa in a soil microbiome are needed. Abiotic soil characteristics can be measured by different chemical and physical analyses, but quantification of taxa can be technically challenging because of the complexity of the soil microbiome. Recent advances in metagenomics, which uses the power of next-generation sequencing technology, provides for an approach to quantify taxa in the soil microbiome [12].

Combinatorial use of multiple sensors to acquire various spectra has allowed us to noninvasively obtain a series of datasets, including those related to plants' development and physiological responses throughout their life. Automated phenotyping platforms accelerate the elucidation of gene functions associated with traits in model plants under controlled conditions. Remote sensing techniques with image collection platforms, such as unmanned vehicles and tractors, also emerge for large-scale field phenotyping for crop breeding and precision agriculture. Computer vision-based phenotyping will play significant roles in both the now-casting and forecasting of plant traits by modelling genotype/phenotype relationships [13].

The combination of macro-environmental factors that determine diversity likely varies at continental scales; thus, as climate change alters the combinations of these factors across the landscape, the collective effect on regional diversity will also vary. Our study represents one of the most comprehensive examinations of plant diversity patterns to date. It demonstrates that our ability to predict future variety may benefit tremendously from the application of machine learning [14].

We assess the robustness of our findings to the presence of endogenous factors by estimating a Heckman two-stage sample selection model. When implementing the Heckman procedure, it is generally recommended that the exogenous variables in the choice model and the outcome model not be identical for identification purposes. This requirement is amply satisfied in our implementation: the variables for automobile life cycles and plant utilisation before launch are specific to choice. At the same time, variables for launch experience and utilisation after launch are specific to outcomes [15].

METHODOLOGY

Images from her barium specimens of three Ficus species: F. benjamina, F. pellucidopunctata and F. sumatrana, were taken from University of Malaya Herbarium (acronymKLU), situated in the RimbaIlmu Botanic Garden. A total of54 sheets of herbarium specimens (F. benjamina, 21; F. pellucidopunctata, his section presents a survey on approaches used in reference research papers taken into consideration. The given table analyses and illustrates all significant aspects of the classification of plant diseases. 12; F. sumatrana, 21) were used in this study. These specimens are collections from Kuala Lom-pat, Pahang, except for a few F. benjamin, specimens collected from Kluang, Johor. The specimens were collected between the years 1961 and 2010, with most specimens being collected in 1986. All specimens have been identified and had annotation tags on her barium sheet.

Data used in this study are available at https://data.mendeley.com/datasets/tvw4g y5ywy/draft?a=67c0cb 84-80cb-4b41-a19d-38e29c3141b9.

Images of the specimens used in this study were captured using the Canon EOS 5D Mark II digital SLR camera, coupled with Canon EF 16–35 mm f/2.8L USM II lens. The computer workstation used to conduct this study was Intel® CORETM2 CPU, 4 GB RAM with a Windows 7 professional (32 bit) operating system. Image processing and features extraction were performed using an open source image processing program, ImageJ (Schneider et al. 2012[)] and MATLAB (MAT-LAB R2013a, The MathWorks, Inc., Kuala Lumpur, Malaysia)[5].

Leaf selection

Sample images in this study consist of many plant structures, e.g. branches, stems, leaves, syconium and others. Where possible, only intact leaves were selected with no apparent tearing and free of damage from pest or disease. Young leaves that are evidently small-sized were ignored. Selected leaves were cropped out and saved as new images with a standard resolution (1800×1800pixel). The stem was removed as it varies in length and would affect feature extraction. The leaves cropping and stem removing steps were done manually using ImageJ. Twenty images were selected for each species totalling 60 leaf images [5]. Image pre-processing the leaf images contain only one object, the leaf. Since all leaves are not perfectly flat, image capturing would always cast a shadow underneath the leaf. The shadow would disrupt the edge detection as it has a stark contrast with the background, confusing the algorithms to draw the boundary based on shadow instead of the leaf. Thus, it should be removed before image segmentation. Firstly, the image RGB value was changed to HSV value. Then, the channel with the clearest contrast between object and shadow was selected and used to identify the object boundary. HSV value conversion alters the original colour. This step serves as guidance for the subsequent edge detection of RGB value leaf images rather than producing a final image for feature extraction [5].

Feature extraction

Processed images from previous steps were transformed into a set of parameters that describe the leaf features. Four classes of features are extracted in this study: morphological features (shape), Hu moment invariants feature, texture features, and histogram of oriented gradients. These features were explicitly selected to obtain the important properties for image leaves and the numeric values that can be used to distinguish between the different types of image leaves. Several feature methods, as described below, were implemented to improve the accuracy of detection and matching criteria [5].

CONCLUSIONS

Plant disease is one of the most common diseases caused by a fungal infection, bacteria, allergy, viruses, etc. In general, plant diseases are chronic, infectious and sometimes may develop to damage plants, which would lead to unpleasant circumstances. Therefore, the plant disease must be detected at a very early stage. The deep learning algorithms have a huge potential in their plant disease identification endeavour. The authors are focused on automating plant disease identification, and classification can be beneficial and takes less time for identified as well. Several irrelevant variables can be reduced through image filtering, rotation, and Euclidean distance transformation applied in image pre-processing.

Image Processing with SVM classifier and CNN classifier: According to the result obtained, the CNN classifier proved to be accurate and efficient in detecting plant disease as compared to SVM Classifier, and it can be concluded that the method of detection was designed by using pre-trained convolutional neural network (AlexNet) and SVM.

FUTURE WORK

Our system takes pictures of various plants as input and gives output about the disease, which is related to the provided picture by the user and some suggestions about the diseases that how it will be a cure. It will help the agriculture sector, particularly the farmers; get an idea about the plants' diseases to take proper measurements to grow plants. Our system's main objective is to work for a social cause.

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